Available online at www.qu.edu.iq/journalcm
JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS
ISSN:2521-3504(online) ISSN:2074-0204(print)

A Review of Techniques for Muscle Fatigue Analysis and the Associated Noise Challenges

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ARTICLE INFO

Article history:
Received: 07/12/2025
Rrevised form: 22 /01/2026
Accepted : 25 /01/2026
Available online: 30/03/2026

Keywords: Electromyography (EMG) biosignal, noise, muscle fatigue, machine learning, deep learning.

ABSTRACT

To reduce the risk of impression muscle fatigue in the medical field, sports, and rehabilitation of disorders and it is muscles are a critical neuromuscular phenomenon. Electromyography (EMG) is the most important Bio signal used to detect muscle fatigue. Many studies over the past few years have been conducted to address the challenge of muscle fatigue (detection, recognition, and prediction). This study presents a review of various approaches to build models, and evaluation metrics, and applications for each structure begins with exploring artificial intelligence (AI) methods such as machine learning (ML) and deep learning (DL), as well as hybrid model showing the way of data acquisition (sensors types, techniques, preprocessing, models…) specially noise affected of data collection of each type of power spectrum. Furthermore, this review compares fatigue detection, recognition, and prediction approaches, highlighting their performance, strengths, and limitations. Finally, a discussion of various aspects of bio-signal-based muscle fatigue, with specific applications and descriptions, and analyses of the datasets used in muscle fatigue to address the most trending issues and challenges in applying upper limb muscle fatigue. The synthesis presented here aims to guide future developments toward robust, interpretable, and real-time neuromuscular fatigue monitoring systems.

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https://doi.org/10.29304/jqcsm.2026.18.12484

1. Introduction

Fatigue is a common non-specific symptom caused by depletion of physical and mental energy experienced by many people with various conditions, while muscle fatigue is biochemical, which signifies alterations in the electrical power of muscle and mechanical qualities. fatigue is a state of exhaustion caused by depletion [1]. There are many assessment of fatigue types: 1) fatigue severity scale (FSS) [2] 2)fatigue impact (FIS)[3] 3)visual analog fatigue scale (VAFS) [4] 4) brog rating of perceived exertion (RPE)scale 5) multidimensional fatigue inventory (MFI) [5] 6)brief fatigue inventory (BFI) [6] each one is differ from other in term of: measure, scaling and items, features, populations, administration, and time in minute. Figure (1) a and b show the statistically increasing number of research papers per year based on (sEMG and muscle) and (Ninapro db1-10 and muscle fatigue), respectively.

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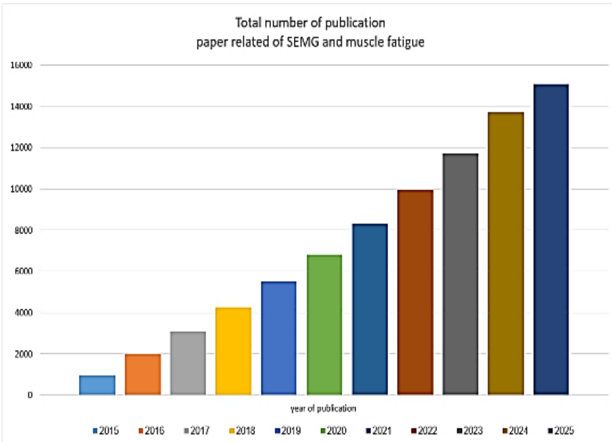

Fig. 1 (a) Number of sEMG studies on muscle fatigue in the years (2015) to (2025)

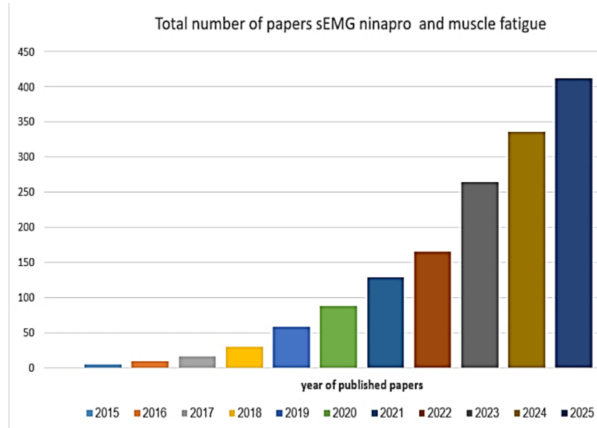

Fig.1 (b) Number of Ninapro dataset studies on muscle fatigue in the years (2015) to (2025)

Fatigue level can be described by three scales: non-fatigue that perform task without difficulty, transition fatigue that addressed muscle aware, then start feel warm difficult to maintain exercise, hard activity that mean it's very difficult to maintain exercise intensity which is no longer execute the movement correctly [7], can be explore to predict the muscle fatigue, Figure 2 shows how fatigue happen.

Fig.2 Individual's self-assessed fatigue level description.

Surface electromyography (sEMG) measures the electrical activity of skeletal muscles by capturing the action potentials of active motor units beneath the skin's surface electrodes [8].

Problems arise from the complexity of signal detection and processing during dynamic tasks and in finding clear and quantitative criteria for muscle fatigue. Generally, the features used in analyzing the (sEMG) signal can be divided into three main groups: 1) time domain, 2) frequency domain, and 3) time–frequency or time-scale representations. Various signal-processing methods have been applied to the raw sEMG signals to derive an accurate muscle fatigue index and some of these methods have also been tested for detecting muscle fatigue. The methods and parameters include the root mean square (RMS) [9], the integrated sEMG [10], mean and median frequency [11], muscle fiber con duction velocity (MCV) [12], parameters based on the Hilbert transform [13], higher order temporal and spectral moments [14], kepstrum analysis [15], multi-component AM–FM decom position [16], and variational mode decomposition [17] (see Table 1 for the list of abbreviations and acronyms).

This paper presents a systematic narrative review of muscle fatigue detection, recognition, and prediction methods, with particular emphasis on non-invasive bio-signals, noise sources, signal processing techniques, and artificial intelligence–based modeling approaches.

2. Methods

Muscle fatigue detection has progressed from classical EMG signal-processing methods to advanced AI-driven predictive models. Early approaches quantified fatigue through amplitude and spectral indicators—such as RMS, ARV, MDF, and MNF—which change systematically as motor-unit recruitment increases and conduction velocity declines [18]. Machine-learning classifiers, including SVM and Random Forest, later used these handcrafted features to distinguish fatigued from non-fatigued states [19]. Deep-learning architectures such as CNN, LSTM, CNN–LSTM, TCN, and multitask networks further improved performance by learning spatial–temporal fatigue patterns directly from raw sEMG signals [20].

Recent work incorporates physiological structure using graph-based synergy models, where GAT-LSTM and MSGAT-LSTM integrate attention with muscle-synergy graphs and achieve state-of-the-art accuracy on Ninapro datasets ($R^2 \approx 0.98$) [21]. Parallel advancements in Transformer-based models, including PET and Conformer architectures, provide low-latency continuous EMG regression suitable for wearable systems ($R^2 \approx 0.95$) [22]. Collectively, these developments support reliable real-time fatigue monitoring for rehabilitation, prosthetics, ergonomics, and sports applications. Figure 2 shows various aspects of the muscle fatigue detection and prediction framework.

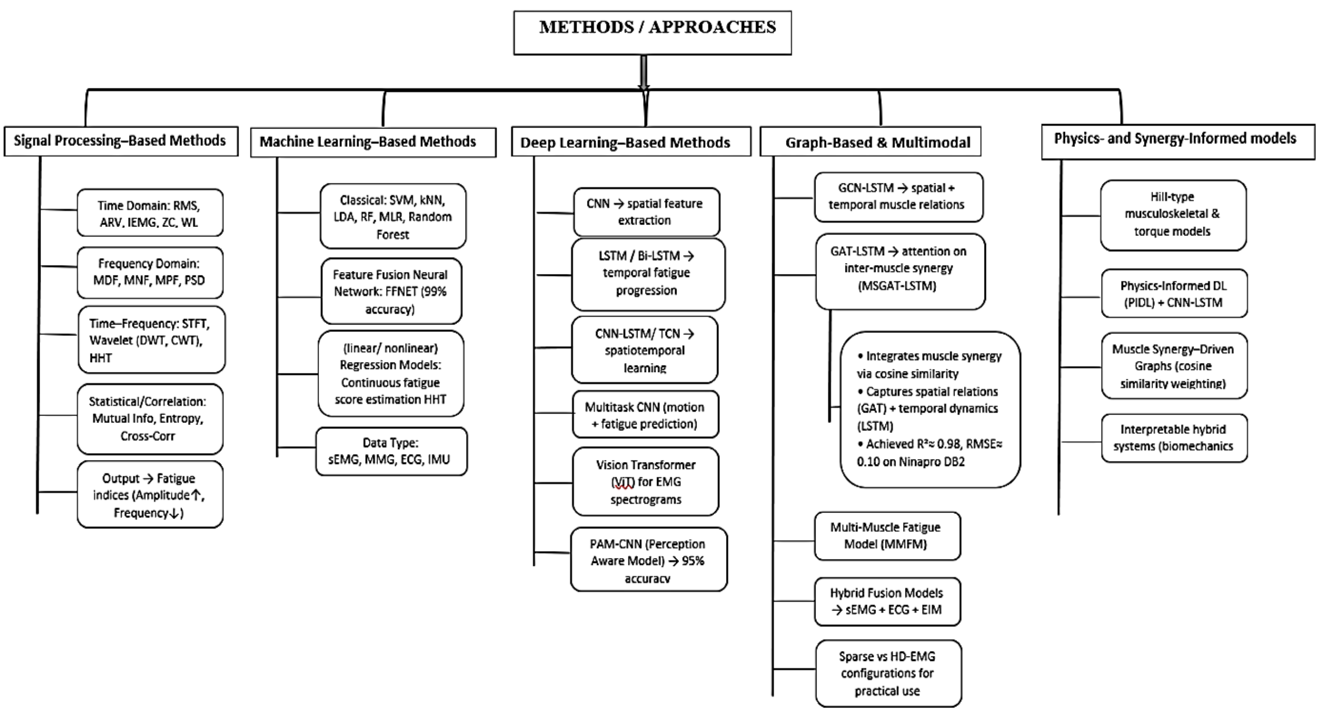

Fig. 2: Muscle fatigue techniques for detection and prediction framework.

2.1. Systematic Review Methodology

This review was executed utilizing a methodical framework to pertinent literature to guarantee precision and extensive inclusivity. Its principal aim was to scrutinize the methodologies employed in contemporary investigations pertaining to the detection, identification, and prognostication of muscular fatigue through non-invasive, noise-related, and signal processing methodologies.

The systematic inquiry was performed across prominent scientific repositories, including ScienceDirect, PubMed, IEEE Xplore, Google Scholar, Scopus, and SpringerLink, and encompassed publications released between 2010 and 2025. Eligibility criteria stipulated that studies were deemed suitable if they (i) documented the analysis, detection, recognition, or prediction of muscular fatigue; (ii) utilized non-invasive sensing modalities, particularly surface electromyography (sEMG); (iii) incorporated signal processing techniques that included noise reduction or

AI/ML/DL-based modeling frameworks; and (iv) were published in peer-reviewed journals or esteemed conference proceedings. Studies if they concentrated on invasive procedures, excluded. were not associated with muscle fatigue.

Following the removal of duplicate records, titles and abstracts were screened for relevance. Subsequently, full-text articles were evaluated based on the predefined inclusion criteria. The selected studies were then organized into thematic categories, including sensor technologies, data acquisition protocols, signal processing and denoising techniques, machine learning approaches, deep learning and hybrid frameworks, dataset characteristics, and evaluation metrics. This structured approach enhances transparency and reproducibility while enabling a comprehensive narrative synthesis of current research trends, methodological challenges, and future directions in muscle fatigue analysis.

2.2. Non-invasive Sensor technologies

For analyzing and assessing muscle fatigue for non-invasive techniques can see found in Figure 3, based on the application used for measures, data processing, features, tool, and application.

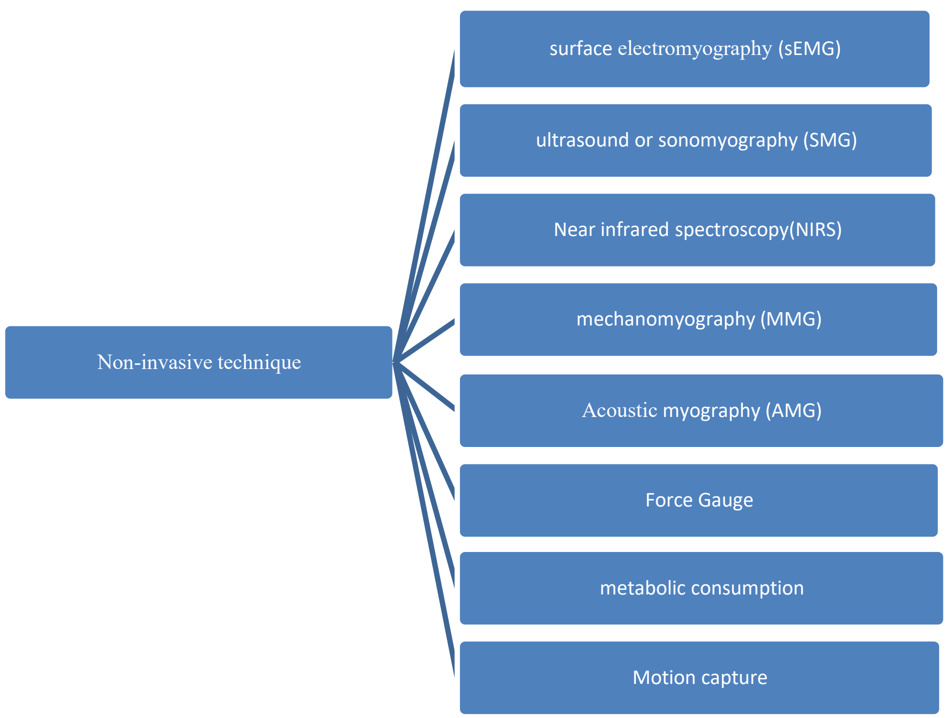

Fig.3 Describes the number of non-invasive techniques.

2.2.1 Surface electromyography (sEMG)

It is a non-invasive method (electrical activity generated during muscle contractions) that uses electrodes placed on a specific area to record the muscle's electrical activity during contraction. Through this recording, changes in muscle EMG signals can be identified, leading to muscle fatigue, which scientifically means a decrease in the speed of muscle fiber diffusion and an increase in the synchronization of movement units [23]. Changes in the amplitude of the EMG signal also indicate muscle fatigue; that is, during the fatigue process, the EMG amplitude increases [24].

2.2.2 Sono-myography (SMG) or Ultrasound

Researchers have used ultrasound to assess deep muscles and detect their activity, recording structural and morphological changes during voluntary contraction due to movement or electrically stimulated contractions [25]. Ultrasound Sono-myography facilitates the extraction of contraction and peak stress measurements [26], thus enabling the assessment of tissue stress and muscle fatigue. While SMG assesses muscle fatigue induced by neuroelectric stimulation, it induces fatigue rapidly. Speckle tracking is also used to monitor muscle fatigue during NMES-induced fatigue [27].

2.2.3 Near-Infrared Spectroscopy (NIRS)

Muscle contractions require increased oxygen delivery to boost blood flow. Physical activity restricts blood flow due to intramuscular pressure, thus reducing blood volume and oxygenation. NIRS is a non-invasive method used to determine the absorption of light by blood hemoglobin, which absorbs light at wavelengths between 760 nm and 800 nm. Therefore, the changes in blood volume and oxygenated hemoglobin observed during muscle contractions by NIRS can help identify muscle fatigue [28].

2.2.4 Mechanomyography (MMG)

Non-invasive techniques that capture the low-frequency vibrations produced by muscle fibers during contraction, typically using sensors like accelerometers or piezoelectric devices [28]. Because it reflects the mechanical response of the muscle, MMG is highly sensitive to fatigue—RMS values usually rise while MNF and MDF decrease as the muscle tires [29]. MMG also benefits from reduced signal cross-talk and less sensitivity to skin impedance, although it can be influenced by environmental noise and measurement protocols [30].

2.2.5 Acoustic Myography (AMG)

A non-invasive method that records the low-frequency sounds produced by contracting muscle fibers to assess muscle activity and fatigue [29]. As fatigue develops, the RMS increases while MDF and MNF decrease over time [30]. AMG is simple to use and provides real-time feedback, though it can be affected by external noise and has limited depth penetration [31].

2.2.6 Force Gauge

Direct measurement of force from muscle by the use of a simple tool such as force gauge takes into account muscle strength and fatigability, as well as the degree of muscle contraction [28]. It senses output voltage from a calibrated load cell or strain gauge to measure force in isometric and isotonic applications. With increasing fatigue, muscle force usually decreases, frequently accompanied by enhanced tremor perception. Force gauges, however, are not without limitations such as sensitivity to gravity, joint angle, and sensor drift so they are commonly paired with bio-signals like EMG, MMG, or AMG to distinguish true fatigue from reduced voluntary effort [32].

2.2.7 Metabolic Consumption (MC)

Represents the energy cost of an activity usually expressed in terms of oxygen consumption or metabolic cost [33]. It is commonly used to measure physical performance in walking, cycling and exercise [34]. MC increases with muscle fatigue progression in general, as fatigued muscles need more oxygen to maintain the same effort [35]. Nevertheless, the MC measurement is also influenced by stress and emotional situation [36] and thus normalization procedures are frequently required.

2.2.8 Motion Capture (Mocap)

Mocap systems assess fatigue by tracking movement patterns and joint kinematics using tools like IMUs [37], infrared cameras [38], or AI-based vision systems [39]. These systems detect fatigue-related changes in gait and posture and can classify fatigue levels with machine-learning models in walking, industrial, and construction tasks [40]. Wearable Mocap devices, such as smart helmets and sensor-embedded clothing, also enable real-time fatigue monitoring [41]. Although useful, Mocap systems face limitations like sensor drift (IMUs) and high cost or occlusion issues (camera systems).

2.3. Data Acquisition

Data is collected according to specific criteria that take into account different conditions, ages, genders, and time periods to assess the feasibility of generalizing the use of the techniques. Initially, it is ensured that the area where muscle strain is to be measured is clean and free from any factors that could affect the stability of the electrodes in their correct position.

For the purpose of collecting (EMG) and full-body EMG (F-EMG) signals, athletes and sEMG are used, which serve as the data source for upper limb muscle strain projects [42]. The data source is usually participants performing various movements, such as basic wrist movements, basic finger movements (flexion and extension), isometric and isotonic hand configurations ("hand positions"), and coherent and functional movements such as opening, closing, and pressing. Each participant is instructed to perform a series of these movements, which are collected as separate files in separate sessions using bipolar EMG sensors with rest periods, and a specific number of sessions corresponding to all muscle states (no fatigue, pre-fatigue, fatigue) [43].

2.4. Signal Processing–Based Methods

Early detection of muscle fatigue relied primarily on signal-processing analysis of (sEMG) signals to quantify physiological changes in amplitude and frequency. Researchers have long shown that time-domain features, including Root Mean Square (RMS) and Average Rectified Value (ARV), increase progressively as muscle fatigue develops, reflecting enhanced motor-unit recruitment and synchronization [44]. Frequency-domain parameters, such as the Median Frequency (MDF) and Mean Power Frequency (MPF), were shown to decline as the conduction velocity of active fibers decreases [45]. To handle the non-stationary nature of EMG during dynamic or repetitive contractions, several studies introduced time–frequency analysis, including the Short-Time Fourier Transform (STFT) [46], Discrete and Continuous Wavelet Transforms (DWT/CWT) [47], and Hilbert–Huang Transform (HHT) to localize spectral changes in time [48]. These findings, drawn from early and modern research, established that muscle fatigue is characterized by an increase in amplitude-related indices (RMS, ARV) and a reduction in spectral-frequency parameters (MDF, MNF, MPF), forming the quantitative basis for machine- and deep-learning fatigue models. As describe in Figure 4.

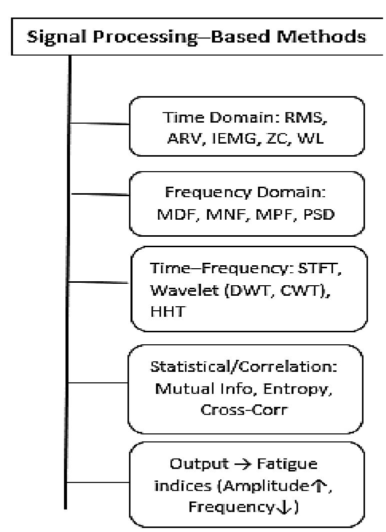

Fig. 4 Various Methods of Signal Processing for Muscle Fatigue.

2.5. Machine-Learning-Based Approaches

Following the extraction of EMG features, researchers began employing machine-learning (ML) algorithms to automate the classification or prediction of fatigue levels. Classical supervised methods—including Support Vector Machines (SVM), k-Nearest Neighbors (kNN), Linear Discriminant Analysis (LDA), and Random Forests (RF)—were frequently trained on RMS, MDF, and wavelet-derived features to separate *fatigued* from non-fatigued states [19].

Regression based techniques have subsequently been used to estimate continuous fatigue indices, which also allows for smoother tracking of the progression of fatigue during dynamic tasks [49]. In order to further improve robustness, some researches introduced feature-fusion scheme that concatenates features of different domains (time, frequency and non-linear entropy).

A representative example is the Feature-Fusion Neural Network (FFNET), which concatenated handcrafted descriptors before classification and obtained close to 99 % accuracies in multi channel sEMG experiments [20]. More recent work explored transfer learning and domain adaptation to improve inter-subject generalization. By fine-tuning pretrained fatigue classifiers on new user data, these studies demonstrated consistent performance across subjects and recording conditions [50]. Together, these developments transitioned fatigue analysis from descriptive spectral observation to data-driven prediction, forming a bridge between traditional feature engineering and deep-learning architectures. As shown in the Figure 5.

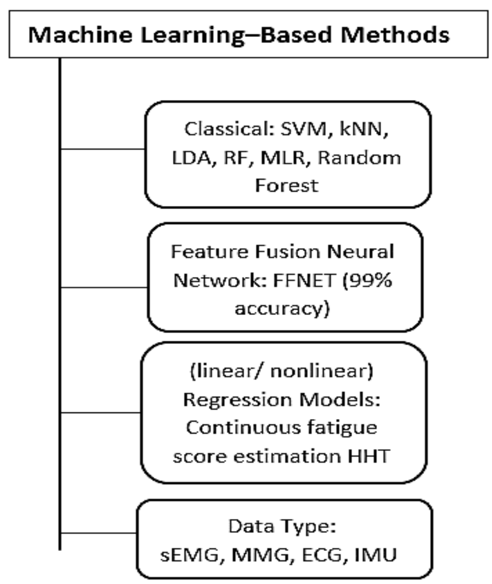

Fig. 5 Various Methods of Machine learning based methods.

2.6. Deep-Learning-Based Models

With the expansion of annotated EMG databases and the need for higher robustness, research in muscle-fatigue analysis has moved toward deep-learning architectures capable of learning discriminative features directly from raw or minimally processed sEMG signals. Unlike machine-learning classifiers that rely on handcrafted features, these models automatically extract hierarchical spatial temporal representations that describe fatigue progression. Convolutional Neural Networks (CNNs) were among the first deep models adopted for this task. They efficiently learn spatial activation patterns across multiple EMG channels and have proven effective for both static and dynamic contractions [51]. To elucidate the temporal dynamics, Recurrent Neural Networks (RNNs)—notably Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM)—have been employed in the analysis of sequential electromyographic (EMG) data to effectively model fluctuations in firing rates and the decay of frequency attributable to fatigue [52].

Hybrid architectures such as CNN–LSTM and Temporal Convolutional Networks (TCNs) amalgamate the advantages of convolutional feature extraction and sequential memory, thereby yielding more refined estimations of fatigue trends across varying load conditions [53].

Further progress introduced Multitask Learning (MTL), where motion intention and fatigue state are predicted jointly within one network. Tu et al. demonstrated that shared representation learning across both tasks increases accuracy and stability of fatigue classification [20]. Another important direction involves Perception-Aware CNNs (PAM-CNN), which integrate biomechanical context for occupational-fatigue detection and achieved ≈ 95.6 % accuracy in industrial scenarios [54].

Recently, Vision Transformers (VITs) have been used to transform EMG spectrograms into 2-D images and leverage self-attention to model long-range dependencies between spectral components, improving fatigue-stage discrimination compared to CNNs [55]. Across these studies, deep networks consistently outperformed classical ML algorithms by learning from large-scale datasets such as Ninapro DB1–DB3, delivering more robust and generalizable fatigue prediction systems suitable for real-time applications. Which is shown below in Figure 6.

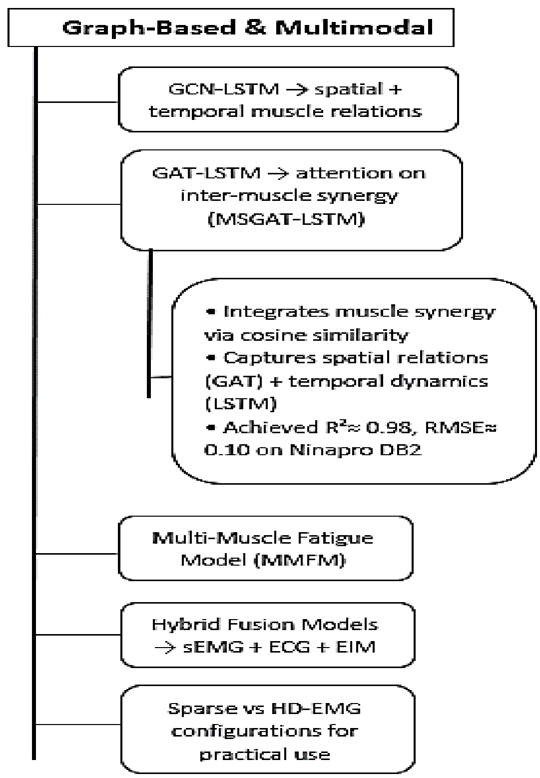

Fig. 6 Various Methods of Deep Learning Based Models

2.7. Graph- and Synergy -Based Frameworks

Recent work models' multi-channel sEMG as a graph to encode physiological coordination between muscles (muscle synergy) and to improve temporal-spatial fatigue prediction. In the GAT-LSTM approach, each sEMG channel is a node, and edges are weighted by cosine-similarity between channel activations to represent inter-muscle synergy; a Graph Attention Network (GAT) then learns data-driven edge weights (attention coefficients) that emphasize the most informative muscle relations while suppressing noisy or redundant links. An LSTM layer captures the temporal evolution of fatigue-related dynamics over sliding windows, producing continuous predictions (e.g., joint kinematics and fatigue-related trends) from sparse sEMG rather than dense/high-density grids.

On Ninapro DB2, the synergy-weighted MSGAT-LSTM achieved $R^2 \approx 0.98$ and RMSE ≈ 0.10, and outperformed CNN and GRU baselines, demonstrating that (1) explicitly encoding synergy improves accuracy and robustness, and (2) attention facilitates adaptation to subject variability and electrode configuration changes [56]. This graph-temporal design also interfaces naturally with newer attention backbones (e.g., transformer blocks) for real-time continuous estimation on embedded targets, enabling fatigue-aware control in prosthetics/rehab pipelines detailed in your other attached work [60]. Where Figure 7 shows that.

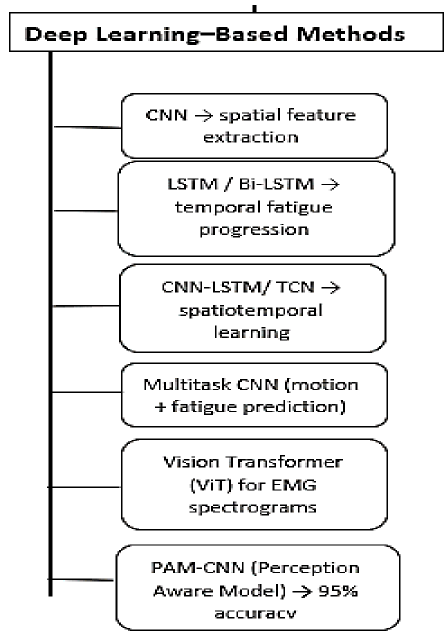

Fig. 7 Various Methods of Deep-Learning-Based Models.

2.8. Transformer and Physics-Informed Hybrid Models

The most recent advances described in your attached research, particularly the Parallel Efficient Transformer (PET) paper and the GAT-LSTM synergy paper, demonstrate a shift toward attention-driven architectures and biomechanically meaningful hybrid systems. The PET model replaces recurrent operations with multi-head self-attention, allowing parallel processing of long sEMG sequences and dramatically reducing inference latency. According to the study, PET achieves $R^2 \approx 0.95$ on Ninapro DB2 and DB7 while lowering computational load, making it suitable for real-time, on-device fatigue and kinematics estimation [57]. Such Transformer blocks outperform traditional CNN-LSTM pipelines in edge scenarios where continuous monitoring is required.

Synergy-based GAT-LSTM file also points to future integration between graph reasoning and Transformer attention, since both rely on attention mechanisms; this allows combining global dependency modeling (from Transformers) with local muscle-synergy structure (from GAT) for richer fatigue interpretation. Furthermore, works referenced inside your files highlight the emerging role of Physics-Informed Deep Learning (PIDL), in which neural networks are constrained by biomechanical priors such as Hill-type muscle models, torque-angle relations, or physiological activation curves.

By embedding these constraints, fatigue prediction becomes not only data-driven but also physiologically interpretable, allowing models to reflect real muscle behavior rather than purely statistical patterns [20]. These hybrids represent the frontier of fatigue modeling, combining attention-based sequence modeling, synergy-aware graph layers, and biomechanical constraints for robust fatigue-aware human-machine interaction. Which is shown below in Figure 8.

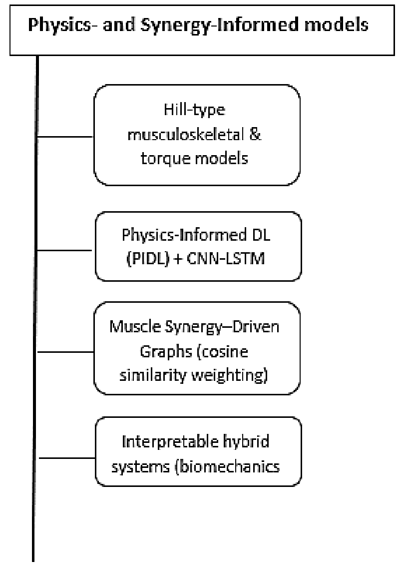

Fig.8 Various Methods of Physics-Informed Hybrid Models

Hybrid muscle-fatigue recognition systems combine volitional (sEMG) with neuromuscular electrical stimulation (NMES) to enhance control stability, reduce fatigue, and improve functional performance in assistive robotics. The uploaded study presents a real-time closed-loop architecture that integrates an SVM-based fatigue classifier with a fuzzy logic hand-grip estimator to adapt stimulation parameters dynamically during bionic hand operation. Frequency-domain features (Mean Frequency and Mean Power) extracted from EMG signals enable accurate detection of fatigue states, achieving 95.4% accuracy, while fuzzy logic classification of grip effort reaches 93% accuracy. Experimental trials with ten healthy users show that the hybrid EMG–NMES approach reduces muscle fatigue by 28.6%, improves grip force consistency by 22%, and enhances long-term task stability compared to EMG-only control. These results demonstrate that hybrid EMG–NMES frameworks can effectively recognize fatigue in real time and actively counteract its progression, offering substantial advantages for prosthetic control, rehabilitation, and fatigue-aware human–machine systems [58].

Recent advancements in the analysis of muscle fatigue elucidate the advantages and constraints inherent in both machine learning and deep learning methodologies. Conventional machine learning techniques continue to be appealing for real-time and wearable applications owing to their inherent simplicity and interpretability; however, their dependence on manually crafted features restricts their robustness in the presence of inter-subject variability and signal noise. Conversely, deep learning models exhibit enhanced proficiency in discerning intricate patterns associated with fatigue from surface electromyography (sEMG) signals; nevertheless, their elevated computational demands and diminished interpretability limit their applicability in clinical environments and resource-constrained scenarios.

Furthermore, the characteristics of the dataset significantly influence the reported performance metrics, as numerous publicly available sEMG datasets depend on indirectly inferred fatigue labels and exhibit considerable variability in their acquisition protocols. As a result, no singular modeling strategy can be deemed universally optimal. Subsequent research endeavors should emphasize the development of physiology-informed models, standardized definitions of fatigue, and validation processes conducted under realistic operational conditions to enhance generalizability and practical usability.

2.9. Muscle fatigue dataset types

Biological datasets constitute a pivotal component in the exploration of muscle activity dynamics and fatigue evaluation, as they furnish quantitative insights into the physiological responses of the human body during physical exertion. With the progression of sensing and modeling technologies, these datasets have proliferated to encompass direct muscle signal acquisition, non-invasive measurement techniques, and an array of physiological and behavioral indicators. This heterogeneity fosters a more holistic comprehension of muscular functionality and fatigue, thereby laying the groundwork for the formulation of robust analytical and predictive models pertinent to biomedical and sports science applications.

2.9.1 Electromyography dataset

EMG is widely used to measure muscle function. It is based on the principle that muscle contractions generate bursts of electrical activity. The combined action potentials from all muscle fibers within a single motor unit are known as the motor unit action potential (MUAP) [BDL85]. These signals can be detected using either surface electrodes (non-invasive) or needle electrodes (invasive) placed near the muscle's electric field [59].

2.9.2 Surface Electromyography dataset

sEMG is non-invasive and wieldier than conventional needle EMG. Such signals are often time dependent and characterized by the amplitude, frequency, and phase. They are complex signals, being directly governed by the nervous system, and depending on both the anatomical and physiological properties of the performing muscle. Such signals give detailed information about muscle and nerve function, which is helpful in diagnosing nerve damage or muscle disease [60]. Biological and neurological applications EMG In the biomedical sciences, EMG is used widely for research, as well as for clinical testing (e.g. the diagnosis of degenerative diseases such as amyotrophic lateral sclerosisEMG is further used for prosthetic control, e.g. in the development of evolvable hardware (EHW) chips for prosthetic hand control \citeOH07 where grip control is a sophisticated application. Further, amputee and those with disabilities often wear sensors to record sEMG signals produced during muscle contraction as part of operator interfaces.

These signals are useful in recognizing human muscle activities, and improve the accessibility function [PPL11]. As muscle activity is involved in most activities of human, and sEMG signal can be utilized for various measurement purposes, it should not be surprising that sEMG has been widely utilized for HAR research. For instance, facial muscle activity is applied in expression recognition [VLK+24] and silent communication [MHD+18]. Lower limb EMG is used to recognize lower limb movements [WDC+21], while hand EMG facilitates gesture recognition and detection of finger movements [Lor24].

2.9.3 Athlete Fatigue Risk Dataset

Another type of data set involves predicting overall fatigue in athletes. The AFR-1000 (Athlete Fatigue Risk Dataset) contains 1,000 samples with 15 features covering: Demographics (Age, Gender), Training load (Training Hours, Training Intensity), Physiological monitoring (Resting Heart Rate, Heart Rate Recovery, Lactate Level, HRV), Subjective assessments (RPE, Sleep Quality, Muscle Soreness), Recovery indicators (Sleep Hours, Hydration Level, Cortisol Level, Protein Intake), and target variable: Fatigue Risk (0=Normal, 1=Fatigued). This is a synthetic dataset generated based on exercise physiology principles and sports medicine standards. Feature values and ranges follow international guidelines (ACSM, ISSP). Labels were created using physiological logic linking training load, recovery, and stress indicators to fatigue risk [61].

2.10. Data processing

The signals obtained, as described in Section 2.3, undergo basic preprocessing, including amplification, initial filtering (Bandpass + Notch)., windowing, and conversion. The data are then processed to extract the signal characteristics most relevant to distinguishing muscle fatigue.

If the data is readily available on popular websites, such as those mentioned in Section 2.9, which are presented as groups of participants and their recorded movements. The data is then uploaded to Google Drive and used to run the Collab Python program. This program performs a series of signal processing steps, including filtering, noise reduction, and wavelet feature extraction, based on the techniques mentioned in Section 2.12, which operate within a time-frequency range to eliminate random noise affecting the recording of actual muscle activity [42].

2.11. Noise and conformant types

The sEMG is widely employed for evaluating neuromuscular activity; however, its reliability is significantly affected by various noise sources and artifacts inherent to biological and electronic acquisition systems [62]. EMG recordings are contaminated by baseline noise, interference noise, and motion-related artifacts, each introducing distortions that complicate accurate analysis and feature extraction.[63] Baseline noise, arising from thermal, electrochemical, and instrumentation factors, degrades signal quality even in resting conditions. Interference noise, including power-line interference, ECG contamination, and crosstalk from adjacent muscles, introduces structured disturbances that overlap with the EMG spectrum. In addition, non-stationary artifacts such as electrode movement, skin–electrode impedance variation, and mechanical vibration contribute low-frequency distortions that can mask physiological muscle activity. Understanding the characteristics, frequency ranges, and sources of these noise types is essential for designing robust preprocessing pipelines, ensuring accurate detection, recognition, and prediction of muscle fatigue in clinical and engineering applications.

2.12. Denoising data acquisition

The small amplitude of basic (EMG) activity presents a challenge in distorting the true pattern of muscle activity, including noise pollution, which is often caused by: 1) EEG recording; 2) the power of ambient electrical equipment; 3) the influence of the interconnected muscular environment; and 4) electrode misalignment during movement. This makes the overall medical analysis unreliable. Therefore, we must develop models or techniques to reduce noise before the processing stage. There are several noise reduction techniques, such as software methods that help eliminate negative effects on signal quality, or improvements to measuring devices. These include high-qu0061lity amplifiers, device filters, power supplies, and software using digital filtering to suppress high-frequency fluctuations, smoothing (signal contrast), and waveform restoration [64].

2.13. Active Noise Cancellation (ANC)

Anti-Noise where refers to the concept of generating an inverse (180° phase-shifted) signal to cancel out unwanted noise through destructive interference. This is commonly known as Active Noise Cancellation (ANC). Although ANC is widely used in audio devices, similar principles can be applied to biomedical engineering for removing predictable noise patterns such as power-line interference.[65]

3. Assessment, Evaluation metrics, and application

Understanding neuromuscular function is essential for accurately assessing muscle fatigue, improving rehabilitation strategies, enhancing human-machine interaction, and preventing injuries. Measures for reporting and recording vital signs, such as sEMG (synthetic electromyography), are used to measure, identify, and characterize muscle fatigue. This section provides an overview of the most important fatigue assessment approaches, the measures used to evaluate detection and prediction models, and their practical applications in various fields.

3.1 Assessment of fatigue

Muscle fatigue assessment framework mainly divided into two aspects objective and subjective, objective mainly divided into two parts which are described in (2.1) section and robotic divices for assessing patients during rehabilitation training[66] , many end effectors and exoskeletons have been developed for upper and lower limb where upper limb refers to the part of the human body that stretches from the shoulder all the way down to the fingertips. It is made up of the shoulder region, the arm, the forearm, the wrist, and the hand. What makes the upper limb unique is its ability to perform precise and delicate movements, such as grasping objects, writing, lifting, and rotating the hand or forearm. This wide range of motion is possible because of the complex structure of its muscles, joints, and bones [67]. Several research studies in this field that appeared the importance and feasibility of implementing robotic training protocols, Masia et al. in developed WRISTBOT [68], a 3-degree of-freedom (DoF) manipulator. It was used to perform wrist f lexion and extension movements in a resistive visco-elastic force field until muscle fatigue was reached. Kanal et al. [69] introduced an adaptive robotic system that uses both fatigues perceived by the user and objective fatigue metrics.And the lower limb extends from the hip region down to the foot. It includes the hip joint, the thigh, the knee, the leg, the ankle, and the foot. Unlike the upper limb, the lower limb is built for support, stability, and movement. Its strong muscles and connective tissues allow the body to walk, run, maintain balance, and bear weight throughout the day. Because of these functions, the lower limb plays a central role in mobility and everyday physical activities [70]. Chen et al. [71] developed a real-time system to quanti tatively monitor the onset and progression of muscle fatigue in lower limbs during bipedal cyclic movements by varying external loads. Chaparro et al. in [72] led a pilot study to determine muscle fatigue based on maximal voluntary contraction (MVC) using a Walking Fatigue Detection (WFD) protocol, an instrumented orthosis with sEMG sensors (MyoWear) and a treadmill. Radecka et al. [73] found that MS patients exhibited increasing EMG amplitudes in wrist flexor and extensor muscles during prolonged contraction, indicating fatigue. Similarly, Beretta-Piccoli et al. [74] investigated the effects of rehabilitation on the biceps brachii and vastii muscles in MS patients.

3.2 Evaluation metrics and Application

Muscle fatigue is a fundamental neuromuscular phenomenon that adversely affects force production, motor control, and task performance across clinical, athletic, and industrial domains. Accurate assessment of fatigue is therefore essential for preventing injuries, optimizing training, and enhancing rehabilitation outcomes. sEMG has emerged as a primary non-invasive modality for monitoring fatigue-related changes in muscle activation, supported by recent advances in signal decomposition, multimodal sensing, and machine-learning techniques. Contemporary studies employ analytical frameworks spanning fatigue detection, recognition, and prediction, leveraging methods such as EMG–PPG fusion, EMG–FMG hybrid sensing, wavelet packet analysis, recurrence quantification analysis, and deep neural architectures to improve reliability and real-time adaptability. Collectively, these approaches provide a comprehensive foundation for understanding and forecasting neuromuscular decline, enabling more robust human–machine interaction, safer task execution, and performance-aware assistive technologies [42].

3.3 Detection muscle fatigue

Detecting muscle fatigue is essential for improving performance, preventing injury, and supporting rehabilitation across athletic, clinical, and occupational settings. sEMG serves as the primary non-invasive tool for monitoring neuromuscular activity, while advanced signal-processing and machine-learning methods significantly enhance the ability to identify fatigue-related patterns. Evidence from lower-limb isometric contraction studies shows that decomposing EMG signals using Improved Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) yields highly descriptive intrinsic mode functions, enabling the extraction of time-, frequency-, time-frequency, and nonlinear features. When combined with dimensionality reduction (t-SNE) and classifiers such as Support Vector Machines, fatigue detection accuracy can reach 99.8%, demonstrating superior sensitivity to subtle physiological changes.[75] Thus, multimodal approaches that integrate EMG and photoplethysmography (PPG) during dynamic shoulder movements further improve fatigue detection. After preprocessing, feature scaling, and class-imbalance correction using SMOTE-ENN, machine-learning models achieve robust performance, with optimized K-Nearest Neighbor classifiers reaching 95.14%–95.45% accuracy. SHAP-based explainability identifies median frequency shifts in upper trapezius EMG and PPG variability as the most influential fatigue markers [76].

Overall, all advanced EMG decomposition, multimodal physiological sensing, and explainable machine learning provide a powerful and reliable framework for detecting muscle fatigue in real time.

3.4 Muscle Fatigue Recognition

Muscle fatigue recognition is essential for improving safety, performance, and reliability across demanding human–machine environments. Recent studies consistently show that sEMG provides a sensitive, non-invasive window into neuromuscular fatigue, especially when paired with advanced signal-processing and machine-learning models. A multimodal EMG-FMG acquisition system demonstrated that combining electrical (EMG) and mechanical (FMG) muscle activity enhances robustness against noise and improves classification performance, with bimodal models outperforming EMG-only systems in gesture and force-related recognition tasks.[42]

A fatigue-recognition framework for special-equipment operators introduced a Partial-Attention Convolutional Neural Network (PAM-CNN), which uses sEMG signals and wavelet-packet features to classify fatigue into three levels. The method integrates a biomechanical fatigue-mechanism model with nonlinear Hidden Markov estimation and achieves **95.6% accuracy**, demonstrating strong potential for early fatigue warning in high-risk work environments [63]. Muscle fatigue can be accurately recognized using sEMG-based features enhanced by multimodal sensing, wavelet analysis, attention-based deep learning, and optimized machine-learning classifiers. This integrated approach provides a reliable foundation for real-time fatigue monitoring in prosthetics, industrial safety, rehabilitation, and human–machine interaction systems

3.5 Muscle Fatigue Prediction

Predicting muscle fatigue is essential for preventing performance decline and injury during both clinical and dynamic movement tasks. Recent work has advanced this goal by integrating sEMG with nonlinear and time–frequency analytical methods to forecast the onset and progression of fatigue. In minimally invasive surgery, where prolonged low-force activation imposes ergonomic strain, recurrence quantification analysis (RQA) applied to sEMG signals has been shown to identify early deterministic changes associated with fatigue, particularly in the deltoid and trapezius muscles, with fatigue onset occurring approximately 45–60 minutes into procedures.[77] Complementary research on dynamic contractions introduced a wavelet-based approach that decomposes sEMG into multi-scale energy features correlated with decreasing maximal voluntary isometric contraction (MVIC). Using optimized mother wavelets and motion-guided segmentation, this method accurately predicts a muscle's diminishing force-generation capacity through linear relationships between wavelet-level energy and fatigue progression [78]. Predictive fatigue modeling—whether through nonlinear recurrence metrics or wavelet-derived energy indices—can offer reliable, real-time indicators of neuromuscular decline, supporting safer surgical performance, improved training, and more adaptive human–machine interaction systems.

Table 1: Compare muscle fatigue detection, muscle fatigue recognition, and muscle fatigue prediction.

Aspect	Muscle Fatigue Detection	Muscle Fatigue Recognition	Muscle Fatigue Prediction
Primary Goal	Identify current fatigue state from physiological signals. [75]	Classify fatigue level or category based on learned patterns.[42]	Forecast future fatigue onset and progression. [77]
Typical Signals Used	sEMG (main), PPG in multimodal systems.[75]	sEMG + FMG (multimodal), wavelet-derived sEMG features.[63]	sEMG signals during sustained or dynamic tasks.
Key Techniques	ICEEMDAN signal decomposition; feature extraction (time, free, nonlinear); t-SNE; SVM; KNN; SMOTE-ENN; SHAP. [42]	EMG–FMG fusion; PAM-CNN; wavelet packet features; biomechanical modeling; Hidden Markov estimation. [42]	Recurrence Quantification Analysis (RQA); optimized wavelet mother functions; motion-guided segmentation.
Performance Reported	Up to 99.8% accuracy in ICEEMDAN-SVM systems; 95.14–95.45% with multimodal EMG–PPG + KNN. [76]	EMG–FMG fusion improves noise robustness; PAM-CNN achieves 95.6% accuracy. [63]	RQA identifies fatigue onset at 45–60 min; wavelet-energy models accurately predict MVIC decline. [77]
Strengths	Very high accuracy; captures subtle physiological changes; explainable AI (SHAP) highlights key biomarkers. [76]	Strong robustness against noise; multimodal improves reliability; suitable for classification in Realtime.[63]	Predictive insight before fatigue occurs; useful in surgery, sports, and high-risk tasks. [78]

Limitations	Mainly detects *existing* fatigue, not future onset.	Requires multimodal sensors and complex models.	Prediction depends on task duration, segmentation accuracy, and nonlinear modelling.
Applications	Real-time monitoring, rehabilitation, sports fatigue detection, and occupational safety [75].	Prosthetics, gesture recognition, robotics, industrial safety, human–machine interaction [42].	Surgery (M.I.S.), performance forecasting, long-duration tasks, adaptive control systems [77].

4. Discussion and research opportunities

The small amplitude of the underlying neuromuscular electrical activity. Raw EMG recordings commonly discuss in motion artifacts, power-line interference, baseline drift, electrode noise, and random environmental fluctuations, all of which distort the true muscle activity pattern and reduce the reliability of medical analysis and human–machine interaction. EMG signals in section 2.10 show that there is a big challenge related to noise, "seriously suffer from the addition of various noise sources and interferences, where more sophisticated and complex filtration is required before processing. Because noisy EMG signals impair diagnostic accuracy and degrade the performance of prosthetics, rehabilitation systems, and embedded biomedical devices, denoising is an essential preprocessing stage. Noise reduction can be achieved using either hardware improvements such as Arduino (high-quality amplifiers, instrumentation filters, stable power supply) or software methods (digital filtering, smoothing, artifact removal). While hardware-based enhancement is useful, "software improvement also participates in eliminating the negative effects that can impact signal quality," making digital denoising algorithms crucial for real-world low-cost systems . Arduino-based denoising algorithm, offering an efficient, low-cost solution suitable for portable healthcare devices. Where the implement a Moving Average Filter (MAF) to suppress high-frequency fluctuations, smooth signal variability, and recover the underlying muscle contraction waveform. And thus, the algorithm maintains a rolling window of recent samples.

The filter process is one of the most impressive aspects in pre- processing the signal of EMG is showed in figure 4, 5, 6, Figure 4 demonstrates strong fluctuations and irregular spikes in the raw EMG plot, representing both physiological activity and noise. while Figure 6 shows reduced high-frequency jitter, confirming the effectiveness of the moving-average approach for low-cost embedded systems. In the other hand denoising is common after the step waveform had been clean and smoothed. Finally, the conclusion emphasizes that EMG noise predominantly originates from instrumentation amplifiers, power-supply instability, and transistor switching inside analog front-end circuitry. Traditional nonlinear filters may distort the EMG waveform, while constant-gain filters only target specific noise frequencies. A solution proposed to significantly improve signal clarity is "hybrid hardware and software," which increases the applicability of electromyography (EMG) in immediate medical applications, prosthetic applications, and rehabilitation applications. De-noising methods are commonly applied in EMG preprocessing but may have successful or unsuccessful applications depending on the signal conditions and constraints from practical uses. Very simple filters including moving-average and linear smoothing at the receiver are computationally lightweight enough for applications on low-cost embedded systems, but they suffer from a trade-off between noise and physiological features of the signal. Advanced and flexible denoising techniques are able to improve noise reduction in such environments, but the higher computational load as well as their complexity make them not suited for low-power portable devices requiring real-time performance. In this respect, denoising tactics should be determined not just by the data noise pattern but also on system constraints and scenario of application. Of importance, denoising performance needs to be measured in fatigue detection accuracy and feature stability -not only in visual signal smoothness.

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