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Review Article

Deep Learning for Automated EMG Signal Quality Assessment in Intraoperative Neuromonitoring: A Systematic Review

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Abstract *- Intraoperative Neuromonitoring (IONM) plays a major role in preserving neural function during complex surgical procedures. Electromyography (EMG) is often used during real-time monitoring of motor pathways, and the reliability of the method is defined by the quality of signals, namely, measured in such parameters as Signal-to-Noise Ratio (SNR), accuracy of artifact detection, signal reliability, and processing latency, which can be influenced by noise and artifacts. This systematic review aims to assess the use of deep learning to assess the quality of the EMG signal in automated clinical and intraoperative neuromonitoring. The two principal research questions that guide the review are as follows: (1) How are different deep learning architectures compared to each other in real-time detection of EMG artifacts and signal quality classification? and (2) What are the current methodology limitations and future needs to implement it clinically? The systematic search of Google Scholar, PubMed, and IEEE databases has been performed with the help of such keywords as EMG, deep learning architecture (CNN, LSTM, GRU, transformer), and signal quality assessment. According to PRISMA guidelines, 3,150 preliminary records were found from the search. 90 of them were eligible according to the inclusion criteria. Hybrid architectures combining convolutional and recurrent networks demonstrate good accuracy for real-time detection and classification of artifacts and for real-time EMG signal quality assessment. Multimodal EMG can enhance signal quality, transfer learning techniques can aid the model to perform well, and the use of data augmentation can additionally support the models in their work. This leads to improved performance across patient groups. Models using temporal-spatial features and attention methods usually outperform traditional machine learning. Yet there are challenges to consider, such as differences between datasets, patient-to-patient variability, and also because of the complexity of computation required for intraoperative use. Automated analysis of EMG signal quality via deep learning shows strong potential for neuromonitoring. It can help ensure surgical safety, aid in real-time decisions during surgery, and minimize post-surgical complications. This supports safe, accurate, and timely assessments. Further research is needed on standardized data sets, model explainability, and the use of context-specific techniques-integration into clinical practice to facilitate wider uptake.*

Keywords *- Artifact detection, Deep Learning, Electromyography (EMG), Intraoperative Neuromonitoring (IONM), Signal quality assessment.*

1. Introduction

Intraoperative Neuromonitoring (IONM) has become an integral part of modern surgery across multiple disciplines including neurosurgery, orthopaedics, spinal surgery, and endocrine surgery. IONM allows for the assessment of the accuracy of a surgical intervention in real time and allows for the evaluation of the preservation of neural structures and their related functions [1-4]. During high-risk surgeries such as resection of brain tumors, repair of spinal deformities, and endocrine and peripheral surgeries, multimodal approaches of intraoperative monitoring that include somatosensory and motor evoked potentials, and Electromyography (EMG) are employed [5-8]. IONM has been shown to improve surgical functions and has been documented in consensus statements and practice guidelines for clinical care as an aid and an important tool in making intraoperative decisions [9, 10]. The

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indications for IONM are rapidly expanding beyond traditional neurosurgeries to include dorsal root ganglion stimulation, hip arthroplasties in severe dysplasia, and even more newly developed techniques such as minimally invasive spinal surgery [11-13].

Modern surgical techniques that are more intricate than older techniques are placing a greater reliance upon more advanced and more precise and dependable neuromonitoring systems. Within the context of such a high reliance upon an advanced monitoring system, the use of EMG is dependent upon the concept of "EMG signal quality." Within the context of this review, EMG signals are defined, and the quality is evaluated and assessed using objective measures and quantifiable definitions of performance, including assessment of Signal-to-Noise Ratio (SNR), detection of artifacts, evaluation of sensitivity and specificity, and evaluation of the reliability of classification and the latency of processing when EMG signals are utilized in a real-time operational system. It is important to establish these measures in order to appreciate the strength and advantages of an automated system in a highly variable and dynamic surgical operating room environment. Electromyography plays an important role in multimodal IONM. Free-run EMG can provide continuous recording of spontaneous neurotonic discharges of the irritation or traction of the nerves, whereas triggered EMG can also be used to map and identify neural structures during surgical manipulation functionality [14, 15]. EMG has been clinically applied in spinal surgery, repairing deformities in children, surgery on the thyroid and parathyroid, and skull base [16-19].

Although it is important, the interpretation of intraoperative EMG depends on the subjective experience of professional neurophysiologists to a great extent. Separating signal patterns into physiological discharges and artifacts is a challenging task that takes much experience and is prone to interobserver variability. Also, anesthetic agents and physiological processes may interfere with the EMG properties and make the interpretation even more complex [20, 21].

Several issues impact acquisition of electrophysiological signals in intraoperative settings. These include electrical contact, electrode motion, impedance change, mechanical vibrations at audio frequency, and fluctuations in the electrical noise [20, 22]. Artifacts affect the quality of neuromuscular signals and lessen the signals' interpretability. Filter-based noise reduction, thresholding, and custom feature extraction are the typical signal processing techniques that can be relied on to tackle noise in biomedical signals [23, 24]. Unfortunately, the typical constraints of an operating room limit the application of the aforementioned techniques. More advanced and flexible systems are needed to assess the quality of signals in the varying conditions of an intraoperative environment, coupled with variations in patient physiology and the available hardware. Deep Learning (DL) has redefined the approach to biomedical signal analysis by providing an opportunity to perform automatic feature extraction and recognize complex patterns directly on the raw data [25, 26]. In neurophysiology, deep neural networks have already been used to detect artifacts, denoise signals, and classify signals [27-29].

In the area of EMG, CNNs, LSTMs, and hybrids of the two have provided excellent results for the prediction of movements, the decoding of motor intentions, and the development of myoelectric control systems [30-33]. To some extent, transformer architectures and the attention mechanism have also been beneficial for extended coverage of the temporal sequences and the interchannel relationships [31, 34].

For Intraoperative Neuromonitoring (IONM), some researchers have proposed the application of ML (Machine Learning) methods for the automation of the interpretation of electrophysiological signals and for reducing the dependency on manual evaluations [35-37]. The continuous classification of EMG signals during surgery is possible with the deep learning model proposed by [38]. Real-time classification of waveforms is thus feasible. In EMG-based intraoperative monitoring, the use of advanced deep learning techniques has been studied [39, 40]. Musholt et al. [41] further automated the classification of EMG waveforms with the application of deep learning, focusing on thyroid and parathyroid surgery. Within the context of signal analysis during surgery, the application of Bayesian deep learning has been studied for its various advantages [42].

Regarding surface EMG, certain models of neural quality assessment have been developed and implemented in a non-invasive fashion [43]. These mark a clear tendency for automated signal quality modeling in neuromonitoring systems. For the purposes of this review, EMG signal quality is defined as the measurable capacity of a computational model to assess the integrity of electromyographic signals without interference from noise or technological constraints. Since signal quality is multidimensional, it needs to be operationalized in a number of complementary, objective measures.

The Signal-to-Noise Ratio (SNR) is used to quantify signal perturbation by noise. Many computational models are benchmarked on their ability to discriminate high-SNR signals from low-SNR signals. Another criterion is the performance of artifact identification, which is evaluated with metrics such as sensitivity, accuracy, precision, specificity, the F1-score, and the Area Under the ROC curve (AUROC). These metrics provide relative performance of a model in the context of signal integrity. In the context of real-time intraoperative systems, the performance in the temporal domain, which refers to the speed of processing, is vital. A low false alarm

rate is essential in maintaining the integrity of the clinical workflow. Finally, robustness to varying acquisition conditions (e.g., electrode impedance, motion artifact) should be evaluated in a cross-subject or external context. Together, the metrics provide a consolidated perspective on computational approaches for evaluating EMG signal integrity. Research on EMG signal quality assessment for Intraoperative Neuromonitoring (IMN) using deep learning is scant. Most literature focuses on the clinical utility of Intraoperative Neuromonitoring (IONM) [44] or provides some form of evidence for the use of Machine Learning (ML) [36]. However, none provide a thorough analysis of the significance of deep learning for quality assessment of EMG signals and its intraoperative applications. In addition, the deep learning literature in the field of EMG is mainly related to rehabilitation, human-machine interface, or gesture recognition rather than intraoperative signal reliability [45-47]. Research into artifact removal in related neurophysiological indicators, including EEG, provides methodological information but is not specifically dedicated to the limitations of intraoperative EMG [48, 49]. Therefore, it is unclear how these methods would be translationally ready for real-time clinical applications.

Given the increasing integration of AI-based surgical systems with embedded neuromonitoring devices [35, 50], there is a critical need for the consolidation of available methodologies and datasets, formal validation, and clinical outcomes. The goal of this systematic review is to assess the body of work involving deep learning applications for automated assessment of intraoperative EMG signal quality, in order to establish the strengths and weaknesses of the work, and provide recommendations for the development of real-time, clinically validated systems to support the routine integration of such systems in surgical practice. There is a notable discrepancy in the literature on the use of deep learning for EMG analysis and Intraoperative Neurophysiological Monitoring (INPM) despite the rapid development in this field.

Most reviews focus on the use of ML in neuromonitoring or rehabilitation-driven EMG analysis, and use of AI in biomedical signal processing at a more general level. There have been no systematic reviews on the application of deep learning for the assessment of EMG signal quality in the context of intraoperative neuromonitoring. Important methodological challenges still need solutions. Many factors differ among the available studies. They differ in the features of their datasets, signal acquisition, preprocessing, the architecture of the models, and the evaluation metrics. External validation and multicenter validation are limited, as is the study of the implementation of these models in a clinical setting. These issues affect the ability to implement these models in a surgical setting and affect the ability to evaluate these studies. This systematic review, therefore, attempts to evaluate available literature on automated EMG signal quality assessment in intraoperative neuromonitoring based on deep learning. In particular, this review aims at evaluating deep learning frameworks, synthesizing the methodologies, assessing the clinical relevance of the existing research, identifying the gaps in the literature, and recommending the next steps in the research towards the creation of clinically usable neuromonitoring systems.

In order to effectively tackle the existing landscape and technical issues of automated monitoring, the following two formal research questions are used in this review:

RQ1: What are the differences in the assessment of EMG signal quality and artifact detection in real-time intraoperative scenarios among the different deep learning frameworks?

RQ2: What are the main methodological difficulties in current deep learning models for neuromonitoring, and what developments are needed to support their broad, standardized clinical deployment?

2. Materials and Methods

2.1. Study Design and Reporting

This systematic review follows the PRISMA 2020 guidelines to ensure methodological rigour, transparency, and the ability to reproduce the study. In particular, the PRISMA framework guided systematic data collection and analysis of data relevant to the research questions (RQ1 and RQ2) developed for this study. The review synthesized evidence on the real-time quality assessment of EMG signals, focusing on the performance and clinical usefulness of the models used for intraoperative neuromonitoring.

2.2. Data Sources and Search Strategy

A comprehensive literature search was conducted in Google Scholar, PubMed, and IEEE Xplore. These databases were selected for their breadth in terms of clinical, biomedical, and computational study literature. The search terms in all three databases were as follows:

("electromyography" OR "EMG" OR "sEMG") AND ("deep neural network" OR "convolutional neural network" OR "CNN" OR "LSTM" OR "GRU" OR "transformer model") AND ("signal quality index" OR "quality assessment" OR "artifact detection" OR "noise classification" OR "signal reliability") AND ("real-time" OR "online monitoring" OR "intraoperative" OR "clinical monitoring")

The desired literature was published between January 2010 and December 2025. This range was selected to reflect the rapid progress in artificial intelligence, and in particular, the deep learning models used in the processing and assessment of the quality of EMG. Specifically, the focus was on the development of convolutional neural networks and the assessment of real-time signal processing.

2.3. Eligibility Criteria

The included studies had the following characteristics:

- Used deep learning models (such as CNNs, LSTMs, GRUs, or transformers) to analyze EMG or sEMG data;
- Offered solutions for the quality assessment of EMG signals, including detection of and removal of artifacts, classification of waveforms and noise, and assessment of signal reliability;
- Addressed Intraoperative Neuromonitoring (IONM), clinical neurophysiology, or other closely related fields that would help inform surgical or clinical monitoring;
- Provided assessment metrics;
- Appeared in peer-reviewed journals or in published conference proceedings written in English.

The following studies were excluded from consideration: those that were focused primarily on gestures, prosthetics, predictions of motor intention, rehabilitation, or Human-Machine Interfaces (HMI) that did not include any quality assessment of EMG signals nor offered any useful methods regarding EMG signal quality assessment. Any study that employed only traditional machine learning techniques (i.e., no deep learning) was excluded. Also, studies that were reviews, editorials, or commentaries, published abstracts that did not provide sufficient detail on the methods, and studies that did not provide sufficient details on model architecture, input, or performance were excluded. Although studies involving uses of EMG such as rehabilitation or motor control were mostly excluded from the main analysis, some of these studies were included in the Discussion in order to provide some context and inspiration for future studies involving automated EMG signal quality assessment in IONM. After screening, studies were classified as (i) main studies that discuss EMG signal quality assessment in intraoperative neuromonitoring and (ii) peripheral studies that discuss EMG signal quality assessment from other applications that are only used for methodological comparison. Only main studies were considered for quantitative analysis and for construction of tables. Table 1 provides a comparison of criteria for inclusion and exclusion.

Table 1. Inclusion and Exclusion criteria

Criteria Type	Inclusion Criteria	Exclusion Criteria
Signal Type	EMG or surface EMG (sEMG)	Non-EMG biosignals only (e.g., EEG-only, ECG-only)
Model Type	Deep learning architectures, including CNN, LSTM, GRU, Transformer, and hybrid networks	Traditional machine learning methods without deep learning components
Task Focus	EMG signal quality assessment, artifact detection, denoising, waveform classification, noise classification, or signal reliability evaluation	Gesture recognition, prosthetic control, motor intention prediction, rehabilitation, or human–machine interface applications without signal quality assessment
Clinical Context	Intraoperative Neuromonitoring (IONM), clinical neurophysiology, or applications with direct translational relevance to surgical or clinical monitoring	Offline laboratory studies lacking clinical or real-time relevance
Study Design	Peer-reviewed journal articles or conference proceedings published in English	Reviews, editorials, commentaries, abstracts without full methodological details
Reporting Quality	Adequate description of model architecture, input features, preprocessing methods, and quantitative performance metrics	Studies lacking sufficient information to extract model architecture, input representation, or quantitative evaluation metrics.

2.4. Study Selection and PRISMA Flow

Studies were selected based on PRISMA guidelines. A total of 2,130 records were screened based on titles and abstracts after removing duplicates. 1850 records were removed in this phase as they were irrelevant to studies based on gesture recognition, control of prosthesis, Non-EMG signals or traditional machine learning, and not deep learning. The remaining 280 articles were reviewed in full to check the appropriateness of the methods used, and if the studies were applicable in real-time or intraoperatively, and in what measure they were applicable. 181 articles were eliminated at this stage mainly for the following reasons: They did not assess the quality of EMG signals, were not applicable in a clinical setting or real time, did not include the model's architecture or evaluation criteria, and was not written in English. Thus, the qualitative synthesis addressed 90 studies that fulfilled the eligibility criteria as depicted in PRISMA (Figure 1). To first remove selection bias, the study screening was performed by two independent reviewers. Study titles and abstracts were the first to undergo the review, and the study's full text was garnered for the reviewers to check the inclusion and exclusion criteria. Impasses that arose were reconciled via inclusive discussion. When, after the discussion, it was still impossible to reach a conclusion, it was the responsibility of a third reviewer to make a decision. This was to promote and adhere to a firm and reproducible methodological environment for study selection.

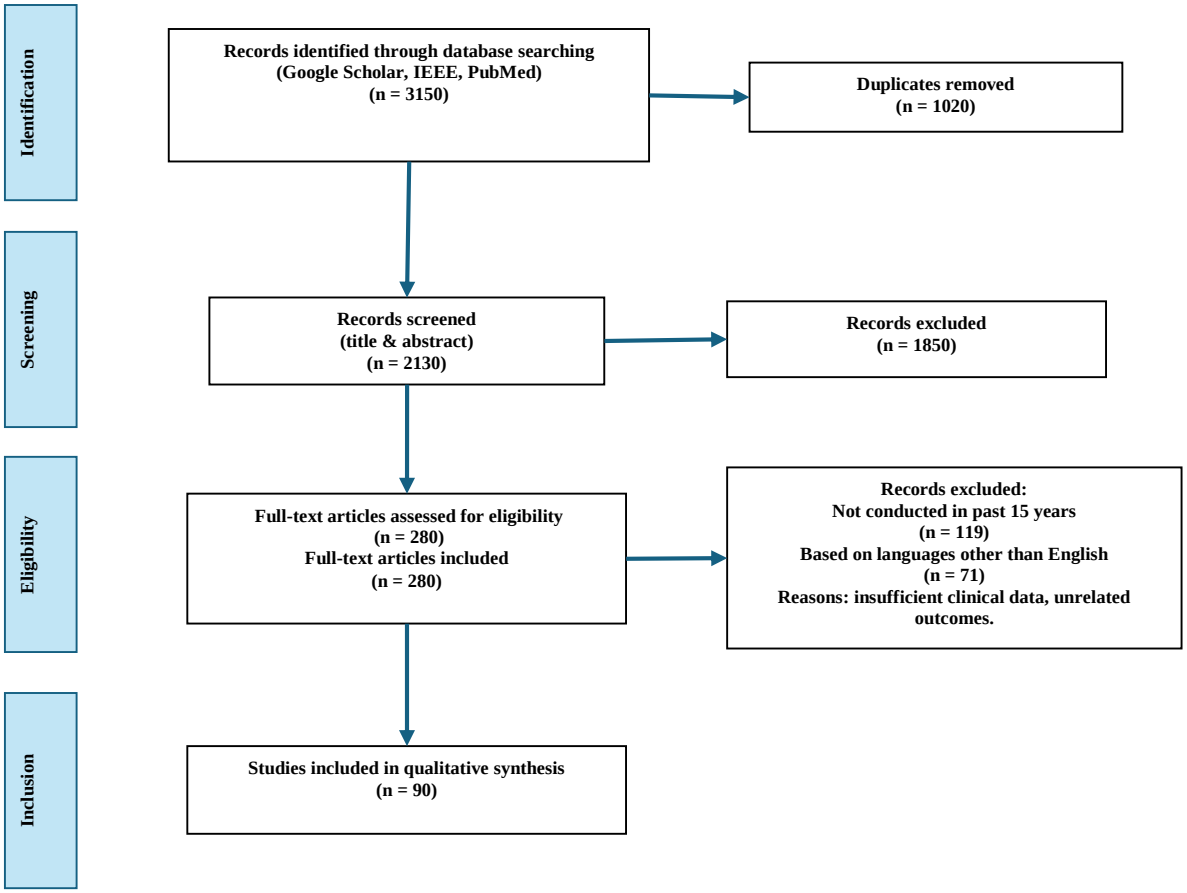

Fig. 1 PRISMA flow diagram for study selection in systematic reviews

2.5. Data Extraction and Synthesis

A typical framework was followed to extract data pertaining to study details, EMG modality, dataset details, deep learning, input features, target task, and metrics. Methodological trends, clinical applicability, and translational preparedness were compared in the syntheses. Due to high heterogeneity in datasets, architectures, and outcome measures, a quantitative meta-analysis was deemed unfeasible, and a constructive qualitative synthesis was adopted instead.

Risk of Bias Assessment The methodological quality of each study, together with its risk of bias, was appraised with the Prediction model Risk of Bias Assessment Tool (PROBAST). This tool was developed specifically for assessing diagnostic and prognostic models, including those built through machine learning and artificial intelligence. PROBAST assesses the risk of bias in the following four domains: participants, predictors, outcomes, and analysis. In the context of assessing artificial intelligence, machine learning, and other related technologies, main priority was given to the evaluation of the representativeness of the dataset, validation, clarity of the labels, transparency of the model, and reporting of relevant metrics. Based on these criteria, the studies were rated to be at low, high, or unclear risk of bias.

3. Results

3.1. Selection and Overview of the Study

The systematic review detected 3,150 records in Google Scholar, PubMed, and IEEE Xplore. Including studies after screening the abstract and full text brought the number of studies to 90. These studies included applications of Electromyography (EMG) in Intraoperative Neuromonitoring (IONM), rehabilitation, and in human-machine interfaces. The publications in these studies included a time span of 2010-2025. There was a jump in the number of studies that included the use of deep learning for the analysis of EMG signals in the last five years, showing a growing interest in automated signal quality analysis and real-time studies [1, 18, 51].

Surface EMG (EMG Signal Acquisition and Preprocessing Surface EMG) was used the most, although needle EMG and multi-channel recordings were also present, particularly in the case of intraoperative and high-precision applications [52]. Signals obtained were generally band-pass filtered, normalized and partitioned to improve readability and minimize noise. Methods of artifact removal included traditional signal processing and recent deep learning-based methods- like wavelet transforms and multimodal fusion- that have made major improvements in the quality and strength of the signals [40, 53, 54].

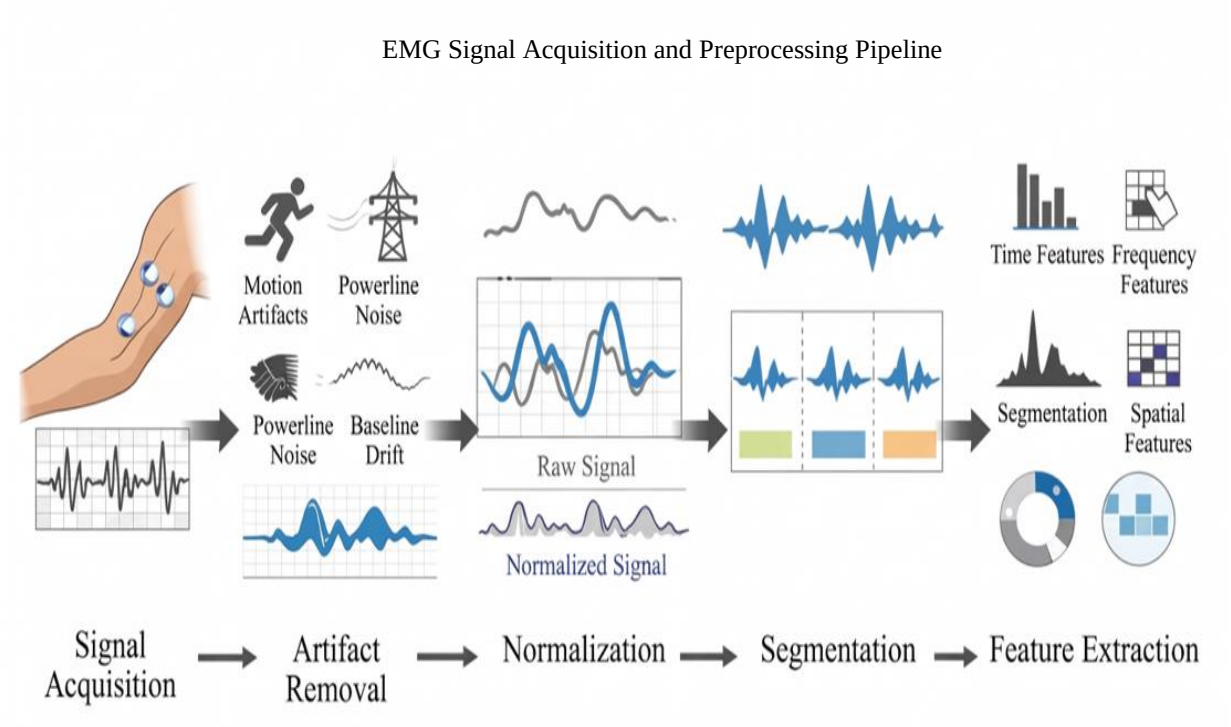

Fig. 2 EMG signal acquisition and preprocessing pipeline

Some of the studies focused on real-time monitoring and demonstrated the feasibility of automated artifact detection and quality measurement systems to be employed in neuromonitoring. These systems also award clinicians real-time (or near real-time) feedback, which enhances the trustworthiness of neuromonitoring [30, 44].

This is the signal processing pipeline of EMG activity shown in Figure 2. This includes the acquisition of raw signals through electrodes, artifact removal, normalization, partitioning, and feature extraction. The resulting signals are then routed to deep learning models for interpreting intraoperative neuromonitoring.

3.2. Deep Learning Architectures and Performance

Various deep learning models have been employed to assess the quality of EMG signals. To extract spatial and temporal features, Yurong Li et al. [55], Yao Wu et al. [56] applied CNNs to the raw EMG data. In terms of analyzing and predicting the temporal relationships essential for continuous intraoperative monitoring, the use of LSTMs and GRUs proved to be beneficial [30, 47].

Based on the recent literature, for the analysis of multi-channel EMG data and the prediction of joint kinematics, which facilitates highly advanced real-time applications, the use of transformers has shown great promise [31, 34].Hybrid algorithms that combine CNNs and LSTM layers or attention mechanisms have been popular as well, and they have proven to be very efficient in artifact detection and signal quality classification [48, 57].

As reported in the studied literature, the classification accuracy ranged from 85% to 98%. However, the authors suggest these should be interpreted with caution, as the considerable range illustrates an abundant amount of heterogeneity concerning the datasets, the respective data collection protocols, and the validation methods.

Regardless of the variability in the data, the reported results seem to generally indicate that deep learning approaches offer greater advantage and flexibility in complex intraoperative environments when compared to the conventional approaches [38, 41, 43].

As summarized in Table 2 [Appendix], CNN, LSTM, GRU, transformer, and hybrid architectures have been applied across various EMG applications, demonstrating considerable accuracy and robustness in both intraoperative and wearable settings.

Only studies related to gesture recognition, rehabilitation, projection of motor intent, or human-machine interaction cited in this section were considered. They were included in this section to provide a relevant methodological comparison. They have been explicitly excluded from the quantitative assessment as peripheral studies.

3.3. Clinical Applications

Automated quality assessment of surface Electromyography (sEMG) has been incorporated into several clinical applications. In neurosurgery, it has been used to enhance the safety and intraoperative control of spinal cord and cranial nerve stimulatory monitoring during tumor resection and spinal deformity correction [18, 44, 62].

Additionally, deep learning frameworks in thyroid and parathyroid surgery have also assisted the safe and intraoperative tracking of the recurrent laryngeal nerve and have helped decrease the probability of nerve damage [41]. sEMG-based models in rehabilitation and wearables have also shown the ability to predict motion and intention to move, and can potentially provide control of the prosthetic/human interface. This reveals the possibility of sEMG quality assessment automation beyond the operating theater [32, 47, 63]. Several studies have also targeted multimodal integration (combination of EMG with either EEG or inertial devices) to enhance detectability of artifacts and their robustness to varying conditions (i.e. patient fatigue, prolonged surgical procedures) [54, 57]. This is indicative of a growing interest in comprehensive and multi-sensor models of reliable and real-time monitoring.

4. Discussion

Xuefan et al. (2020) noted one substantial methodological advancement within Intraoperative Neurophysiological Monitoring (IONM) and clinical neuromonitoring: the use of Deep Learning (DL) models in predicting the quality of Electromyography (EMG) signals. The authors of this systematic review explore the use of DL in EMG signal processing from a technical perspective while evaluating the clinical relevance, consistency, and the application's constraints. The systematic review indicates that the application of deep learning in the assessment of EMG signal quality in IONM is a significant advancement. The body of literature on the application of deep learning in this context is relatively restricted; however, the existing studies indicate that deep learning can be successfully applied in detecting artifacts, classifying waveforms, performing denoising, and assessing the reliability of signals. In addition, the studies within other related EMG domains, such as rehabilitation and motor decoding, offer some methods which encourage further development of clinically operational systems for intraoperative use. The implementation of such automated systems would enhance the workflows of clinical procedures and increase patient safety, as well as improve the operational and overall surgical quality [1, 3, 23].

4.1. Interpretation of Findings

Based on the literature reviewed, there is a consensus that the use of deep learning models for assessing the quality of EMG signals provides numerous benefits. Many studies have evidenced the ability of these models to assess quality of EMG signals with high precision, in a robust manner, and in real time. Each of the models-CNN, LSTM, GRU, and the various transformer and hybrid architectures-possesses unique benefits and drawbacks for a specific context, either clinical or experimental. Considering the addition of automated quality assessment to intraoperative neuromonitoring, rehabilitation, and wearable systems, the overall quality and reliability of the signals is expected to grow, along with enhanced functional performance, thereby expanding the potential for wider clinical usage of these systems [36, 37, 41].

In order to understand the context of EMG-based and multimodal intraoperative neuromonitoring, Table 3 summarizes the additional studies incorporated in this review, including prospective and retrospective studies as well as the technical and methodological innovations that address EMG signal quality and machine learning-based monitoring. The modality of monitoring, the AI or EMG method used, the primary results, and the clinical significance of each reviewed study are provided in that table.

What this review provides is an overview of the various methods of enhancing the reliability and safety of intraoperative methods and the outcomes of different neurosurgical and orthopedic procedures.

Table 3. Summary of additional studies on Electromyography (EMG) and multimodal Intraoperative Neurophysiological Monitoring (IONM)

Ref.	Study Type	Monitoring Modality	Main Findings	Clinical Relevance
[64]	Prospective/Retrospective	Multimodal IONM	Optimized IONM protocols by comparing prospective vs. retrospective data	Supports standardization and improved IONM accuracy
[65]	Clinical study	BIS monitoring	Evaluated anesthetic depth during asleep-awake craniotomy	Guides intraoperative anesthetic management
[66]	Conference proceedings	IONM	Discussed advances presented at ACNS 2016	Captures emerging neuromonitoring standards
[67]	Conference proceedings	IONM	Presented ACNS 2024 guidelines	Updates clinical neuromonitoring practice
[68]	Prospective	Pelvic IONM	Risk factors for urogenital dysfunction post-TME	Highlights functional outcome prediction

[69]	Prospective	Pelvic IONM	Postoperative fecal incontinence analysis	Confirms predictive value of IONM
[70]	Review	Noninvasive IONM	Practical guidance for ICU neuromonitoring	Supports safety in intensive care settings
[71]	Case-control	Open TME surgery	Evaluated functional outcomes with vs. without IONM	Demonstrates clinical benefits of neuromonitoring
[72]	Review	ECG	Surveyed deep learning frameworks for IoT-based ECG	Relevant for real-time biomedical signal processing
[73]	Review	Spinal Cord Stimulation	Discussed neuromodulation techniques in IONM	Provides procedural guidance
[74]	Book chapter	IONM	Comprehensive overview of applications and limitations	Foundational reference for neurosurgical IONM
[75]	Review	Cranial and spinal IONM	Discussed essential vs. elective use	Provides critical evaluation of IONM necessity
[76]	Review	Spine surgery IONM	Overview of techniques and outcomes	Guides spine surgery monitoring
[77]	Review	EMG	Advances in EMG feature extraction	Enhances clinical EMG interpretation
[78]	Software description	EMG	EMGView8 software for nerve monitoring	Demonstrates practical software implementation
[79]	Clinical	Pediatric IONM	Evaluated neuromonitoring in surgical oncology	Confirms safety and efficacy in children
[80]	Framework	Epidural spinal cord electrodes	Supported electrode placement for paraplegia	Guides functional restoration procedures
[81]	Review	IONM	Role in cavernous malformation surgery	Provides surgical risk management guidance
[82]	Technical note	EMG	EMG technique for intradural spinal surgery	Ensures correct electrode placement
[83]	Prospective	External anal sphincter EMG	Evaluated sacral root monitoring	Confirms clinical utility in dorsal rhizotomy
[84]	Clinical	Anterior root muscle EMG	IONM during hip surgery under spinal anesthesia	Confirms intraoperative nerve monitoring feasibility
[85]	Technical	IONM	Design of intraoperative nerve monitoring system	Provides hardware design guidance

4.2. Clinical Significance of EMG Signal Quality

Assessment Relative to literature, signal quality determines the accuracy of automated artifact detection, in addition to the reliability of classification. In surgery with a high level of risk to the patient, such as surgery to remove the thyroid, repair deformities of the spine and surgery to the spinal and cranial nerves, observation of the pathway of the EMG signal can be critical [7, 14, 17, 86].

Signal quality can produce a number of consequences ranging from notifying the surgical team to stopping the surgery. These consequences can be just as dangerous as the unnoticed injuries that the EMG signal may inflict on the patient. Intraoperative high-fidelity EMG monitoring may reduce the number of postoperative neurological complications by as high as 78% for this population of complex neurosurgical patients [1]. In this population, the signal reliability of the monitor impacts the effectiveness of multimodal monitoring for spinal surgery, as it pertains to the monitoring of motor-evoked potentials during high-risk surgery [6]. In spite of these clinical benefits, the conventional approaches to measuring EMG signal quality are extremely dependent on the subjective experience of the neuromonitoring personnel and, therefore, prone to inter-observer errors and latency in detection [5, 16].

There is a way out of this limitation with the use of DL-based methods, which give objective, continuous and automated assessments of signal reliability. This solution has potential to reduce the level of human error and provide faster intraoperative decision-making [41, 42]. This kind of automation may especially come in handy when the risk of the surgery is high, e.g., the removal of an intramedullary tumor of the spinal cord where real-time feedback is necessary in order to avoid any motor dysfunction [18].

4.3. Deep Learning Architectures and Clinical Applicability

Numerous architectures including LSTMs, GRUs, CNNs, hybrid CNN-LSTM networks, and transformers have been explored in the context of EMG signal quality

assessment [31, 38, 48, 57]. Deep Convolutional Neural Networks (DCNNs) are advantageous in identifying noise and electrical artifacts among surface EMG (sEMG) signals. In fact, Cho-Yuan Lee et al. [43] indicated a CNN-based model artifact detection with a 92% accuracy in real-time EMG signal assessment, vastly improving the efficiency of artifact detection when compared to the laborious and time-consuming task of manual artifact evaluation. In comparison, LSTM, GRU networks, and their variants, capitalize on the temporal nature of EMG data for the purpose of modeling and predicting EMG-related motor responses to complicated and cognitively involved tasks [30, 47].

Temporal resolution is vital when there are fluctuations in neuromuscular excitability, for example, during the different levels of surgical anesthesia or varying depths of engagement with spinal and neuromuscular instrumentation [87, 88]. Multimodal data, including CNN-LSTM networks, have been found helpful to put together the spatial and temporal data to improve artifact and fatigue detection [54, 57].

The models can be observed to be very useful when working with intraoperative contexts where several signal sources, including EMG, EEG, and inertial sensors, have to be combined to produce actionable feedback [48, 89].

Intermediate models based on transformers with attention mechanisms and sequence-to-sequence learning have more recently shown the ability to use fine motor intent prediction on a variety of motor unit tasks, with a mean absolute error of 35 degrees in the prediction of joint angles [31, 34]. These methods are highly developed techniques in DL-enabled IONM, which can give better spatial and anatomical prediction features to make real-time surgical decisions.

4.4. Quantitative Performance and Artifact Reliability

The accuracy, sensitivity, and specificity of the investigated studies in detecting intraoperative EMG artifacts (e.g., due to electrocautery, patient movement, and electrode displacement) are generally high due to the usage of DL models [17, 19]. As an illustration, CNN-LSTM and transformers structures have shown strong continuous classification, and the F1 scores are often greater than 0.90 [38, 41, 48].

Moreover, it has been demonstrated that the combination of DL models with task-specific preprocessing (e.g., wavelet transforms) or multimodal data (e.g., EMG and EEG) is always able to positively affect signal-to-noise ratios and final noise resilience [27, 54]. Model generalizability can also be promoted by transfer learning when there is a changing signal-noise relationship between datasets [55, 90]. Finally, such predictive models assist in identifying unreliable signals and reducing the number of false-positive warnings, especially when using high-density sEMG arrays [43, 52].

4.5. Real-Time Implementation and Clinical Workflow Processing

Speed is important to intraoperative deployment. A variety of models are capable of processing latencies lower than the 100 ms mark, and certain architectures, such as certain CNN-LSTMs, EMG-SENet, and Set Transformers, have processing latencies lower still, which is under 50 ms [34, 41, 54,]. This high-rate processing makes it possible to perform automated landmark assessments in real time, which makes the neuromonitoring staff act instantly in response to declining signal quality or damaged electrode contacts. Fast response is particularly important in high-stakes procedures to avoid losses of function that cannot be reversed (spinal cord tumor resections and dorsal root ganglion stimulator placements) [3, 13].

Real-time automated feedback simplifies the clinical workflow by making the process of manually verifying the signal less demanding, thus enabling the staff to spend time on the interpretation of neurological data and not troubleshooting hardware [1, 50]. The operational principle of this continuous assessment mechanism is shown in Figure 3, which describes the automated pipeline of the raw signal as the input and the real-time clinician feedback as the output.4.6. Limitations and Technical Challenges

A number of methodological and validation limitations were found in the reviewed studies, which impact the reliability, generalizability, and clinical applicability of the present deep learning methods in the assessment of the EMG signal quality. One of the primary challenges associated with the studies is the limited availability of data. Many of the studies have used data from fewer than 100 subjects or a limited number of sessions. The use of small datasets can lead to artificial or overestimated model performance, especially when complex deep learning models are employed.

Another major weakness is the absence of multicenter validation. The majority of models were built and tested on single center data sets that had consistent acquisition protocols and hardware specifications. This restricts the possibility of evaluating the performance of models in a variety of clinical settings, patient groups, and neuromonitoring systems.

Dataset imbalance was common. In particular datasets, signals with artifacts made up small data portions. While this imbalance exists, the performance of models is likely to be imbalanced, and the artifacts are likely to overestimate model accuracy in the absence of real-world context. Furthermore, the majority of studies included in the literature review were retrospective in nature. There has been insufficient prospective validation of real-time intraoperative studies. The second significant issue is the absence of defined standards and metrics for the quality of EMG signals. They have identified a range of different criteria from classification accuracy and signal-to-noise ratio to performance in artifact

detection, but they have not invented a signal quality index. These unstandardized criteria reduce the degree of comparability between studies and inhibit the development of a benchmarking model. Also, there was minimal test on dissimilar hardware systems and acquisition configurations. The vast majority of studies assessed the model performance based on a single recording system, which can hardly account for the variability that is observed in clinical practice. Model performance and generalizability may be influenced by the signal properties which are hardware-dependent.

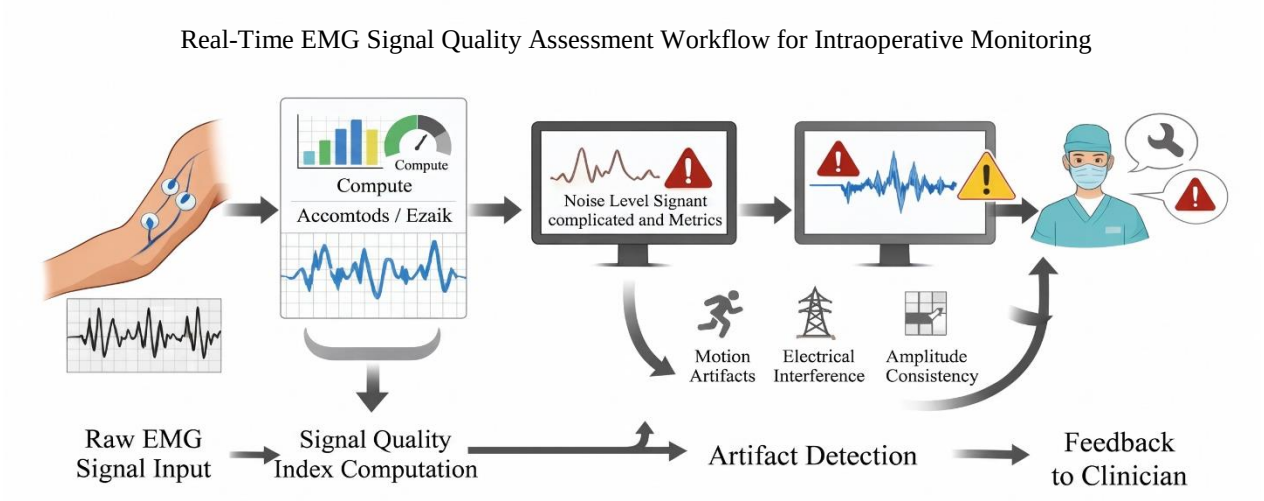

Fig. 3 Workflow for real-time assessment of EMG signal quality

Explainable AI systems, multimodal integration, and adaptive systems of this kind are the only foreseeable innovations for continuous use of IONM during surgery [33, 36]. These innovations should be within the boundaries of IONM standards, including ACNS. Lastly, possible real-time implementation and clinical integration have not been researched completely. While high performance has been seen in most of the studies used in offline analysis, fewer studies have investigated the reliability of models under real-time intraoperative conditions. This lack of knowledge limits what is known about the clinical applicability and dependability of operations.

One of the main findings from this review is that very few studies address EMG signal quality assessment for automated intraoperative neuromonitoring. There is an extensive amount of research in the wider EMG field, including gesture recognition, motor intention prediction, fatigue estimation, and rehabilitation. Still, few studies have focused on the evaluation and optimization of EMG signal quality within a surgical environment. This discrepancy indicates a significant research gap that is worth exploring.

Recordings of EMG taken during surgery carry their own distinctive difficulties, among them electrical interference, artifacts from motion, inconsistent placement of electrodes, and demanding real-time limits. As a result, a model built for non-surgical use will often fail to transfer to IONM conditions unless it is adapted considerably. Subsequent work ought to give priority to building standardized datasets, deep learning frameworks that are explainable, and validation studies spanning several centers that are purpose-built for use during surgery.

4.6. Research Gaps

Across this review, several pivotal shortcomings come to light that, at present, hold back both the maturation and the bedside translation of deep learning approaches aimed at the automated grading of EMG signal quality during intraoperative neuromonitoring. One prominent constraint is the scarcity of large, multi-institution datasets. The bulk of the work to date depends on modest collections drawn from a single center, offering little diversity across patient groups, types of operation, and the circumstances under which signals are captured. Such narrowness curtails how well a model generalizes and raises the likelihood that it will overfit.

A second salient gap concerns how difficult deep learning models are to interpret. Many are used as "black boxes" that reduce the confidence of clinicians and delay their adoption in situations where safety is critical, such as during surgery. Concurrently, there is a growing need for Explainable AI (XAI) techniques that can interpret the model's output in a clinically relevant way. Furthermore, there is no consensus in the field about a set of rules or a common understanding of EMG signal quality. As investigations use different criteria (e.g., accuracy, S/N ratio, degree of artifact detection), it is difficult to compare one study with another. For this reason, it is essential to have a single, comprehensive index of the quality of EMG signals. Similarly, most efforts focus on offline, retrospective analysis, with limited data to validate online, real-time use during surgery. Very few studies have

been conducted to measure the behavior of real patients in the operating room. Finally, there is a lack of external validation, generally, for the proposed models, limiting the extent to which they can be claimed to be reliable and widely applicable. Validating across hospitals, together with federated learning schemes, could offer encouraging ways to address this difficulty. Future studies should focus on developing standardized benchmarks, explainable deep learning frameworks, evaluation protocols designed for real-time application in the operating room, and multi-center datasets that would expedite translation into the clinic, overcoming the above-mentioned limitations.

Table 4. Research gaps and a forward agenda for Deep Learning-based assessment of EMG signal quality

Research Gap	Current Limitation	Proposed Direction
Dataset heterogeneity	Small single-center datasets with limited variability	Large-scale multicenter benchmark datasets
Lack of explainability	Black-box deep learning models with limited interpretability	Explainable AI (XAI) for clinically interpretable decisions
No standard EMG quality index	Heterogeneous metrics across studies	Development of a unified EMG signal quality framework
Limited real-time validation	Predominantly offline retrospective studies	Prospective intraoperative real-time validation
Poor external validation	Single-center evaluation only	Cross-institutional and federated learning approaches
Label inconsistency	Subjective artifact labeling across studies	Standardized annotation protocols and expert consensus labeling

4.7. Clinical Impact of Automated EMG Quality Assessment

The automated EMG quality assessment could significantly contribute to clinical practice by delivering fast and objective assessment of signal integrity during electrophysiological monitoring. Accurate quality assessment of EMG signal is useful to detect the deterioration of EMG signal due to noise, electrode displacement, motion artifact and technical fault, to avoid incorrect interpretation and increase confidence in clinical decision-making. During Intraoperative Neurophysiological Monitoring, quality assessment of EMG signals is important to ensure reliable and timely alerts that will help preserve neural function. Automated quality assurance systems can help differentiate between signal artifact and true neurophysiological changes to decrease false alarms and false missing alerts and provide surgical teams with a more appropriate response to clinically important events. In clinical practice, where professional neurophysiologists or electrophysiology clinicians are not always available, automated EMG quality assessment can prove to be of great value. AI-based systems can deliver standardized, up-to-the-minute quality assessment and decision support, minimize operator reliance and streamline the process. These features can enhance accuracy of diagnosis, optimize workflow, and result in safer patient care during intraoperative monitoring and during routine clinical EMG examinations.

4.8. Future Directions

It is important to be aware that future studies should aim for large and multicentric EMG databases and a standardized protocol for acquisition of EMG for maximum potential of a DL-based EMG monitoring system. The incorporation of EMG, EEG, and motion sensors would help to increase model robustness to artifacts and intersubject variability [46, 89]. Trust and clinical adoption will require clinicians to have explainable AI strategies [41, 42]. Lastly, real-time implementation studies of clinical outcomes and workflow efficiency in the clinic are required to provide evidence on routine use in the operating room [34, 50, 54].

4.9. Implementation and Deployment Considerations

The deep learning-based method for EMG signal quality measurement must be implemented in a clinical environment, which requires adequate computing resources and system integration. While it's typical for many models to run on high-powered GPUs, models that need to be used in real time during surgery can rely on either embedded hardware or edge-computing units with limited compute capabilities. The tuning of the model is therefore needed to satisfy the real-time requirements. These models need to be used in conjunction with the intra-operative neuro-monitoring equipment already available, such as Electromyography (EMG) recorders and the interfaces employed for signal processing. The system should also be able to accept signals without interfering with the existing clinical tasks of the staff. In most scenarios, the processing delay that may be acceptable for normal functioning during surgery is $\leq$ 100 milliseconds, and any deterioration in the signal should be detected immediately. These should be implemented in the clinic by first being regulatorily approved, e.g. FDA cleared up or CE-marked. This is done by showing safety, reliability, and external validation on different datasets. Information privacy and protection of patient data require the use of secure data storage as well as high levels of cybersecurity. Furthermore, if successful, results in a format that can be used clinically are crucial.

5. Conclusion

One important point to note from this review is that there has been comparatively less research that focuses on automated quality assessment of EMG signals during intraoperative neuromonitoring. Most deep learning research is conducted in the broader EMG space; however, reemphasizes a significant gap and highlights the need for clinically validated and purpose-built approaches designed for surgical neuromonitoring. This review focused on the methodological approaches for the development of deep learning techniques to assess the quality of Electromyography (EMG) signals, the performance metrics associated with these techniques, and their potential application in clinical and intraoperative neuromonitoring. The surveyed articles show that these models can accurately detect signal artifacts, predict signal integrity, and facilitate automated assessment of the quality of signals. These models have been shown to be able to recognize signal degradation with measurable reliability in controlled experimental conditions, as reported by metrics like accuracy, F1-score, and AUROC. These findings, however, must be interpreted with caution because the studies are very heterogeneous. The size of the dataset varies widely, as do the methods used to acquire the signals, the design of the electrodes, the pipelines used for preprocessing, the type of models, and how they are assessed. Such methodological differences make it difficult to compare and make it impossible to draw any definitive conclusions about the superiority of any of the practices or the clinical superiority of any of the models.

Further, some studies relied on data from a single centre, on a simulated environment, or on limited numbers of subjects, making translation to a real intraoperative or clinical situation less straightforward. The need for substantiated external, cross-center checking is a weakness that is common in the literature. Models can be overfitted on their own and often do not perform well on other patients or in other clinical settings. Attaining true reliability and reproducibility will require putting these models through rigorous external testing on independent datasets gathered at a range of institutions. Furthermore, the quality of EMG signals is not well defined, nor are there evaluation criteria against which to gauge the quality of EMG signals, one of the major developmental problems. The definitions, measurement, and reporting of signal quality are not standard and can be challenging to compare across studies and to set a universally agreed-upon set of benchmarks. Standardization of methodological rules, such as standardized metrics of performance, validation processes, and reporting are necessary in the further development of the field. There are also implementation challenges, which need to be addressed. Clinical applications that are for real-time, it is important to have a computationally efficient model that can be executed within a tight latency constraint and is not influenced by dynamic changes in the signals. Other key factors that can have a significant impact on the successful implementation include integration with current neuromonitoring systems, hardware considerations, and integration with clinical workflows. Overall, deep learning is definitely a valuable source of tools for automated evaluation of EMG signal quality, albeit limited by a lack of methodological uniformity, external validation, and standardization.

Future research should maintain cross-center validation, agreed evaluation protocols, and prospective testing in real time within the clinic as the main focus so that the reliability, reproducibility, and clinical applicability of models can finally be determined. The final role that deep learning can play in the quality grading of EMG signals will be greatly influenced by how these issues will be addressed. Combined, these results suggest that the field is impeded most by the lack of standardization of the datasets, standardization of how to evaluate the performance of the algorithm, and clinically validated benchmarks for assessing the quality of EMG signals in the operating room.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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References

[1] Liaquat Ali et al., “Emerging Super-Specialty of Neurology: Intraoperative Neurophysiological Monitoring (IONM) and Experience in Various Neurosurgeries at a Tertiary care Hospital in Doha, Qatar,” *Cureus*, vol. 13, no. 12, pp. 1-6, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Francesca Bianchi, and Ubaldo Del Carro, *Intraoperative Neurophysiological Monitoring in Neurosurgery*, Springer, pp. 33-48, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Giusy Guzzi et al., “Intraoperative Neurophysiological Monitoring in Neurosurgery,” *Journal of Clinical Medicine*, vol. 13, no. 10, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[4] Andrew K. Wong, "Intraoperative Neuromonitoring," *Neurologic Clinics*, vol. 40, no. 2, pp. 375-389, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Sema BRANDMEIER et al., "Multimodal Intraoperative Neurophysiological Monitoring in Neurosurgical Oncology," *Turk Neurosurg*, vol. 28, no. 2, pp. 204-210, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[6] Fabio Cofano et al., "Intraoperative Neurophysiological Monitoring during Spinal Surgery: Technical Review in Open and Minimally Invasive Approaches," *Neurosurgical Review*, vol. 42, no. 2, pp. 297-307, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[7] Ji-Yoon Jung, "Intraoperative Nerve Monitoring in Thyroid Surgery: A Comprehensive Review of Technical Principles, Anesthetic Considerations, and Clinical Applications," *Journal of Clinical Medicine*, vol. 14, no. 9, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] Lorena Vega-Zelaya, Rafael G. Sola, and Jesús Pastor, "Intraoperative Neurophysiological Monitoring in Neuro-Oncology," *Neurooncology*, pp. 207-249, 2016. [Publisher Link]

[9] Keewon Kim et al., "Intraoperative Neurophysiological Monitoring: A Review of Techniques used for Brain Tumor Surgery in Children," *Journal of Korean Neurosurgical Society*, vol. 61, no. 3, pp. 363-375, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[10] JayL. Shils, and Tod B. Sloan, "Intraoperative Neuromonitoring," *International Anesthesiology Clinics*, vol. 53, no. 1, pp. 53-73, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[11] Tim T.C.R. de Mees et al., "Multimodal Intraoperative Neuromonitoring during Total Hip Arthroplasty in Severe Hip Deformities: How do we do it and when do the Alerts Occur?," *Archives of Orthopaedic and Trauma Surgery*, vol. 145, no. 1, pp. 1-9, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Steven M. Falowski, and Alexander Benison, "Prospective Analysis Utilizing Intraoperative Neuromonitoring for the Evaluation of Inter-Burst Frequencies," *Journal of Pain Research*, vol. 14, pp. 703-710, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] Lei Lu et al., "Intraoperative Neurophysiological Monitoring during Lead Placement for Dorsal Root Ganglion Stimulation: A Literature Review and Case Series," *Neuromodulation: Technology at the Neural Interface*, vol. 27, no. 1, pp. 160-171, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Francis X. Dillon, "Electromyographic (EMG) Neuromonitoring in Otolaryngology-Head and Neck Surgery," *Anesthesiology Clinics*, vol. 28, no. 3, pp. 423-442, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[15] Pierre Pandin, Isabel Estruch-Pons, and Maelle Parvais, *Intraoperative Neurophysiological Monitoring (IONM) during Anaesthesia: Evoked Potentials (EP) and Electromyography (EMG)*, Springer, pp. 113-173, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[16] James Drake et al., "Intraoperative Neurophysiological Monitoring during Complex Spinal Deformity Cases in Pediatric Patients: Methodology, Utility, Prognostication, and Outcome," *Child's Nervous System*, vol. 26, no. 4, pp. 523-544, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[17] Daisuke Fujimoto, Keizo Taniguchi, and Hirotoshi Kobayashi, "Intraoperative Neuromonitoring during Prone Thoracoscopic Esophagectomy for Esophageal Cancer Reduces the Incidence of Recurrent Laryngeal Nerve Palsy: A Single-Center Study," *Updates in Surgery*, vol. 73, no. 2, pp. 587-595, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Kai Liu et al., "The Role of Intraoperative Neurophysiological Monitoring in Intramedullary Spinal Cord Tumor Surgery," *Chinese Neurosurgical Journal*, vol. 9, no. 1, pp. 57-66, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Nattawut Niljianskul, I-Sorn Phoominaonin, and Alongkorn Jaiimsin, "Intraoperative Monitoring of the Recurrent Laryngeal Nerve with Electromyography Endotracheal Tube in Anterior Cervical Discectomy and Fusion," *World Neurosurgery: X*, vol. 17, pp. 1-8, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Brett Sanders, Santiago Catania, and Astri M.V. Luoma, "Principles of Intraoperative Neurophysiological Monitoring and Anaesthetic Considerations," *Anaesthesia and Intensive Care Medicine*, vol. 21, no. 1, pp. 39-44, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Dohyung Kim et al., "Intelligent Soft Wearable Bioelectronics for Neurological Disorders," *Materials Horizons*, vol. 12, no. 14, pp. 4970-4997, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[22] G. Krishna Kumar et al., "Intraoperative Electrophysiological Principles in Neurooncological Practice," *International Journal of Neurooncology*, vol. 4, no. 1, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Almir Badnjević, and Lemana Spahić, *Biomedical Signal Acquisition and Processing*, Springer, pp. 47-130, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[24] Hui Yu et al., "Technical System of Electroencephalography-based Brain-Computer Interface: Advances, Applications, and Challenges," *Neural Regeneration Research*, vol. 21, no. 9, pp. 3885-3907, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[25] Shuo Gao et al., "Use of Advanced Materials and Artificial Intelligence in Electromyography Signal Detection and Interpretation," *Advanced Intelligent Systems*, vol. 4, no. 10, pp. 1-30, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[26] Michele Introna, John George Karippacheril, and Carla Carozzi, "Artificial Intelligence and EEG during Anesthesia: Ideal Match or Fleeting Bond?," *Artificial Intelligence Surgery*, vol. 6, no. 1, pp. 1-17, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[27] Pravin V. Dhole et al., "A Review of EEG Artifact Removal Techniques for Brain-Computer Interface," *SN Computer Science*, vol. 6, no. 8, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[28] Miguel Fernandez-de-Retana et al., "A Deep Learning Approach to Artifact Removal in Transcranial Electrical Stimulation: From Shallow Methods to deep Neural Networks and State Space Models," *Neuroscience*, vol. 588, pp. 152-159, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[29] Banghua Yang et al., "Automatic Ocular Artifacts Removal in EEG using deep Learning," *Biomedical Signal Processing and Control*, vol. 43, pp. 148-158, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[30] Shuai Huang et al., "Prediction of Self-Care Behaviors in Patients using High-Density Surface Electromyography Signals and an Improved Whale Optimization Algorithm-Based LSTM Model," *Journal of Bionic Engineering*, vol. 22, no. 4, pp. 1963-1984, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[31] Zijun Wei, Zhiqiang Zhang, and Sheng Quan Xie, "A Transformer Framework Informed by Muscle Anatomy and Sequence-to-Sequence Translation for Continuous Joint Kinematics Prediction using sEMG," *IEEE Journal of Biomedical and Health Informatics*, vol. 30, no. 2, pp. 1140-1152, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[32] Meng Zhu et al., "sEMG-based Lower Limb Motion Prediction using CNN-LSTM with Improved PCA Optimization Algorithm," *Journal of Bionic Engineering*, vol. 20, no. 2, pp. 612-627, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[33] Tala Zaim et al., "Machine Learning-and Deep Learning-based Myoelectric Control System for Upper Limb Rehabilitation Utilizing EEG and EMG Signals: A Systematic Review," *Bioengineering*, vol. 12, no. 2, pp. 1-27, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[34] Dongfang Li et al., "Real-time Decoding Fine Motor Intentions from a Set of Motor Unit Activities using Set Transformer," *Biomedical Signal Processing and Control*, vol. 117, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[35] Fabio Montagna et al., "A Machine Learning Approach for Automated Wide-Range Frequency Tagging Analysis in Embedded Neuromonitoring Systems," *Methods*, vol. 129, pp. 96-107, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[36] Dougho Park, and Injung Kim, "Application of Machine Learning in the Field of Intraoperative Neurophysiological Monitoring: A Narrative Review," *Applied Sciences*, vol. 12, no. 15, pp. 1-15, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[37] John P. Wilson Jr et al., "Proposed Applications of Machine Learning to Intraoperative Neuromonitoring During Spine Surgeries," *Neuroscience Informatics*, vol. 3, no. 4, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[38] Xuefan Zha et al., "A Deep Learning Model for Automated Classification of Intraoperative Continuous EMG," *IEEE Transactions on Medical Robotics and Bionics*, vol. 3, no. 1, pp. 44-52, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[39] Abdalla Nabil Elsharkawy, and Nourhan Zayed, "EMG-based Intraoperative Neuromonitoring using Advanced Machine Learning Approaches," *2024 International Conference on Computer and Applications (ICCA)*, Cairo, Egypt, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[40] Abdalla Nabil Elsharkawy, and Nourhan Zayed, "Exploring the Effects of Wavelet Types and Windowing on EMG-based IONM Through Deep Learning Architectures," *Neuroscience Informatics*, vol. 6, no. 1, pp. 1-11, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[41] Thomas J. Musholt, Petra B. Musholt, and Tobias Kortus, "Application of Deep Learning towards Automated Electromyographic wave Classification for Neuromonitoring in Thyroid and Parathyroid Surgery," *BJS open*, vol. 10, no. 1, pp. 1-8, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[42] Tobias Kortus et al., "Automated Robust Interpretation of Intraoperative Electrophysiological Signals-A Bayesian Deep Learning Approach," *Current Directions in Biomedical Engineering*, vol. 7, no. 2, pp. 69-72, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[43] Cho-Yuan Lee et al., "A Non-Intrusive Neural Quality Assessment Model for Surface Electromyography Signals," *2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando, FL, USA, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[44] Luca Zanin et al., "Intraoperative Neurophysiological Monitoring in Contemporary Spinal Surgery: A Systematic Review of Clinical Outcomes and Cost-Effectiveness," *Brain Sciences*, vol. 15, no. 7, pp. 1-23, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[45] Zixun He, Zixuan Qin, and Yasuharu Koike, "Continuous Estimation of Finger and Wrist Joint Angles using a Muscle Synergy based Musculoskeletal Model," *Applied Sciences*, vol. 12, no. 8, pp. 1-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[46] Qin Hu et al., "X-MyoNET: Biometric Identification using deep Processing of Dynamic Surface Electromyography," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1-13, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[47] Longbin Zhang et al., "Estimation of Joint Torque by EMG-Driven Neuromusculoskeletal Models and LSTM Networks," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 3722-3731, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[48] Marcin Kołodziej et al., "A Hybrid CNN-LSTM Approach for Muscle Artifact Removal from EEG using Additional EMG Signal Recording," *Applied Sciences*, vol. 15, no. 9, pp. 1-28, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[49] Huan Wang et al., "BiModule-ECA Network: A Dual-Module Fusion Strategy for Robust EEG Denoising using Efficient Channel Attention," *2025 44th Chinese Control Conference (CCC)*, pp. 8640-8645, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[50] Qendresa Parduzi et al., "Safety through Automation: Advancing Intraoperative Neurophysiological Monitoring to Preserve Motor Function," *At-Automatisierungstechnik*, vol. 73, no. 12, pp. 911-921, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[51] Umme Rumman et al., "FORS-EMG: A Novel sEMG Dataset for Hand Gesture Recognition across Multiple Forearm Orientations," *arXiv preprint arXiv*, 1-13, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[52] Wanting Ma et al., "A Multichannel Electromyography Dataset for Continuous Intraoperative Neurophysiological Monitoring of Cranial Nerve," *Data in Brief*, vol. 53, pp. 1-10, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[53] Marcos Fabietti, Mufti Mahmud, and Ahmad Lotfi, "Effectiveness of Employing Multimodal Signals in Removing Artifacts from Neuronal Signals: An Empirical Analysis," *International Conference on Brain Informatics*, Padua, Italy, pp. 183-193, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[54] Fuyuan Feng et al., "EMG-SENet: Multi-Modal Speech Enhancement with Electromyography Signals," *IEEE Transactions on Audio, Speech and Language Processing*, vol. 33, pp. 3111-3123, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[55] Yurong Li, et al., "Transfer Learning-based Muscle Activity Decoding Scheme by Low-Frequency sEMG for Wearable low-cost Application," *IEEE Access*, vol. 9, pp. 22804-22815, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[56] Yao Wu et al., "Spinal Posture Recognition Device using Cloud Storage and BP Neural Network Approach based on Surface Electromyographic Signal," *International Conference on Big Data and Security*, Xiamen, China, pp. 507-517, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[57] Soree Hwang et al., "A Multimodal Fatigue Detection System using sEMG and IMU Signals with a Hybrid CNN-LSTM-Attention Model," *Sensors*, vol. 25, no. 11, pp. 1-18, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[58] Rosanna Manzo, "Real-Time Detection of Skin-Electrode Adhesion based on Embedded Neural Networks for Bioimpedance Spectroscopy," *IEEE Access*, vol. 13, pp. 155385-155398, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[59] Mohamed Taha et al., "Electromyography Signal Classification with Artificial Intelligence for Detection of Neuromuscular Disorders Using a Large Clinically-Acquired Database," *Muscle and Nerve*, vol. 73, no. 2, pp. 319-328, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[60] Nina Pilehvar and M. Rezaei, "Focus on Utility Intraoperative Neuro-Monitoring in Neurosurgery: Scoping Review," *Eurasian Journal of Chemical, Medicinal and Petroleum Research*, vol. 3, no. 1, pp. 99-110, 2024. [Google Scholar] [Publisher Link]

[61] Tian-Yu Bai et al., "Application of Intraoperative Neurophysiological Monitoring in Unilateral Biportal Endoscopic Lumbar Spine Surgery," *Journal of Orthopaedic Surgery and Research*, vol. 20, no. 1, pp. 1-7, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[62] Junwei Li et al., "Bioelectronic Sensors for Neuromuscular Perception in Human-Machine Interfaces," *Advanced Robotics Research*, vol. 1, no. 3, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[63] Ans Claesen, "Prospective and Retrospective Data Collection to Optimize the use of Multimodal Intraoperative Neuromonitoring," 2018. [Google Scholar]

[64] Valeria Conte et al., "Bispectral Index during Asleep-Awake Craniotomies," *Journal of Neurosurgical Anesthesiology*, vol. 25, no. 3, pp. 279-284, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[65] Priya Dhawan, and Brent Goodman, "2016 ACNS Annual Meeting and Courses February 10-14, 2016, Hilton Orlando Lake Buena Vista, Orlando, Florida," *Journal of Clinical Neurophysiology*, vol. 33, no. 3, pp. 276-298, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[66] During, and Global Cerebral Hypoperfusion, "American Clinical Neurophysiology Society (ACNS) 2024 Annual Meeting and Courses," *Journal of Clinical Neurophysiology*, vol. 41, no. 6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[67] Daniel W. Kauff, Hauke Lang, and Werner Kneist, "Risk Factor Analysis for Newly Developed Urogenital Dysfunction after Total Mesorectal Excision and Impact of Pelvic Intraoperative Neuromonitoring-a Prospective 2-year Follow-up Study," *Journal of Gastrointestinal Surgery*, vol. 21, no. 6, pp. 1038-1047, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[68] Daniel W. Kauff et al., "Fecal Incontinence after Total Mesorectal Excision for Rectal Cancer-Impact of Potential risk Factors and Pelvic Intraoperative Neuromonitoring," *World Journal of Surgical Oncology*, vol. 18, no. 1, pp. 1-8, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[69] Yorinde S. Kishna et al., "Practicalities of Noninvasive Neuromonitoring in Intensive Care," *Neurocritical Care*, vol. 44, no. 2, pp. 456-472, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[70] Werner Kneist et al., "Is Intraoperative Neuromonitoring Associated with Better Functional Outcome in Patients Undergoing Open TME?: Results of a Case-Control Study," *European Journal of Surgical Oncology (EJSO)*, vol. 39, no. 9, pp. 994-999, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[71] Subramanyam Shashi Kumar, and Prakash Ramachandran, "Review on Compressive Sensing Algorithms for ECG Signal for IoT based deep Learning Framework," *Applied Sciences*, vol. 12, no. 16, pp. 1-37, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[72] Rohan J. Kurian, and Steven Falowski, "Spinal Cord Stimulation: Neuromodulation for Intraoperative Neuromonitoring Personnel," *The Neurodiagnostic Journal*, vol. 65, no. 4, pp. 264-286, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[73] David MacDonald, Barbara Bischoff, and Josef Zentner, *Application of Intraoperative Neuromonitoring*, Springer, pp. 159-189, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[74] Nitin Manohara, Krishna Kumar, and Rajesh Boyina Jagadeeshwar, "Intraoperative Neurophysiological Monitoring in Cranial and Spinal Surgery-Essential or Luxury," *Current Practice in Neurosciences, Neurological Society of India*, Agra, India, 2024. [Google Scholar]

[75] Keith W. Michael, and Scott D. Boden, "Intraoperative Neuromonitoring in Spine Surgery," *Contemporary Spine Surgery*, vol. 13, no. 8, pp. 1-7, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[76] Lasitha Piyathilaka et al., "Advances in EMG Signal Processing and Pattern Recognition: Techniques, Challenges, and Emerging Applications," *Electronics*, vol. 15, no. 3, pp. 1-40, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[77] Marco Gazzoni, and Paolo Bardella, "*EMGView8: a Software for Intraoperative Nerve Monitoring*," Master Thesis, Polytechnic University of Turin, 2020. [Google Scholar] [Publisher Link]

[78] Barrie S. Rich et al., "The Utility of Intraoperative Neuromonitoring in Pediatric Surgical Oncology," *Journal of Pediatric Surgery*, vol. 58, no. 9, pp. 1708-1714, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[79] Schöfer Patrick et al., "A Neuromonitoring Framework Supporting the Intraoperative Placement of an Epidural Spinal Cord Electrode Array for Functional Restoration in People with Paraplegia," *Current Directions in Biomedical Engineering*, vol. 7, no. 2, pp. 65-68, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[80] Mei Shao et al., "The Role of Intraoperative Neurophysiological Monitoring in Intracranial Cavernous Malformation Surgery: A Narrative Review," *Iranian Journal of Medical Sciences*, vol. 50, no. 10, pp. 661-671, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[81] Maamoun Abu Shousha, Mostafa Elmaghraby, and Othman M. Othman, "Emg Monitoring Technique during Intra-Dural Spinal Surgery," *Turkish Journal of Physiotherapy and Rehabilitation*, vol. 32, no. 3, 2021. [Google Scholar]

[82] Marc Sindou, Anthony Joud, and George Georgoulis, "Usefulness of External Anal Sphincter EMG Recording for Intraoperative Neuromonitoring of the Sacral Roots-a Prospective Study in Dorsal Rhizotomy," *Acta Neurochirurgica*, vol. 163, no. 2, pp. 479-487, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[83] Pınar Yalınay Dikmen et al., "Intraoperative Neuromonitoring of Anterior Root Muscle Response during Hip Surgery under Spinal Anesthesia," *Journal of Clinical Monitoring and Computing*, vol. 33, no. 4, pp. 695-702, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[84] Yantong Yuan et al., "Design of Intraoperative Nerve Monitor," *ECITech 2022; The 2022 International Conference on Electrical, Control and Information Technology*, Kunming, China, pp. 1-4, 2022. [Google Scholar] [Publisher Link]

[85] Neil R. Malhotra, and Christopher I. Shaffrey, "Intraoperative Electrophysiological Monitoring in Spine Surgery," *Spine*, vol. 35, no. 25, pp. 2167-2179, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[86] Soniya Biswas, "Comparison of Effects of Propofol and Dexmedetomidine on Motor Evoked Potentials in Neurosurgery: A Prospective Randomised Single Blinded Interventional Study," *SCTIMST*, pp. 1-149, 2019. [Google Scholar]

[87] Steven M. Falowski et al., "Multicenter Retrospective Analysis of Dorsal Root Ganglion Stimulator Placement using Intraoperative Neuromonitoring in Asleep Patients During Early Periods of Adoption," *Neuromodulation: Technology at the Neural Interface*, vol. 24, no. 4, pp. 753-757, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[88] Lichy Han et al., "Deep Learning Models using Intracranial and Scalp EEG for Predicting Sedation Level During Emergence from Anaesthesia," *BJA open*, vol. 12, pp. 1-9, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[89] Milou ter Braak, "Transfer Learning for Multi-Class Artefact Classification in Dry EEG using Convolutional Neural Networks," 2024. [Google Scholar]

[90] Jong-Hwa Park, and Seung-Jae Hyun, "Intraoperative Neurophysiological Monitoring in Spinal Surgery," *World Journal of Clinical Cases: WJCC*, vol. 3, no. 9, 2015. [CrossRef] [Google Scholar] [Publisher Link]

Appendix

Table 2. Synthesis of deep learning models for assessment of EMG signals and associated applications

Author	Dataset Size	Clinical Setting	EMG Type	Model	Validation Method	Key Performance Metrics	Real-Time Testing	External Validation
[38]	8,000+ EMG segments	Thyroid surgery (IONM)	Continuous intraoperative EMG	CNN-LSTM	Train/test split, cross-validation	Accuracy, Sensitivity, Specificity	No	No
[41]	16,305 EMG waveforms	Thyroid and parathyroid IONM	Evoked EMG	1D CNN	Random train/test split	Accuracy, AUC, Precision, Recall	No	No
[40]	12,000 EMG samples	Simulated intraoperative EMG	Surface EMG	CNN, Transformer	k-fold cross-validation	Accuracy, F1-score, AUC	No	No
[39]	9,500 EMG samples	Neuromonitoring simulation	Surface EMG	CNN-LSTM hybrid	Train/test split	Accuracy, Sensitivity	No	No
[43]	5,200 EMG recordings	Orthopedic surgery IONM	Intraoperative EMG	Deep CNN	Cross-validation	Accuracy, Precision, Recall	No	No
[42]	4,800 EMG signals	Neurosurgery IONM	Continuous EMG	Bayesian Deep Neural Network	Cross-validation	Accuracy, Confidence estimation	Partial	No
[35]	3,500 EMG recordings	Intraoperative neuromonitoring	Continuous EMG	Embedded Neural Network	Real-time system validation	Accuracy, Latency	Yes	No
[58]	7,200 EMG signals	Thyroid surgery IONM	Surface EMG	CNN	Prospective validation	Accuracy, Sensitivity	Yes	No
[59]	18,000 EMG samples	Neuromonitoring and motor decoding	High-density EMG	Deep CNN	Cross-validation and real-time test	Accuracy, Latency, AUC	Yes	Limited
[60]	22,000 EMG signals	Clinical neuromonitoring database	Surface EMG	CNN-LSTM	External dataset validation	Accuracy, F1-score, AUC	No	Yes
[61]	6,800 EMG samples	Neuromonitoring simulation	Surface EMG	CNN-LSTM	Train/test split	Accuracy, RMSE	No	No
[28]	10,200 EMG recordings	Clinical EMG artifact removal	Surface EMG	Deep CNN	Cross-validation	Accuracy, Signal-to-Noise Ratio	No	No
[57]	5,900 EMG signals	Neuromuscular monitoring	Surface EMG	LSTM	Real-time validation	Accuracy, F1-score	Yes	No
[57]	8,400 EMG samples	Neuromonitoring research	Surface EMG	LSTM	Cross-validation	Accuracy, RMSE	No	No
[31]	11,000 EMG samples	Continuous EMG monitoring	Surface EMG	Transformer	Cross-validation and real-time simulation	Accuracy, AUC	Partial	No