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Detecting motor evoked potentials using neural convolutional networks: overcoming the limitations of manual analysis

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Abstract. Motor evoked potentials (MEPs) are electrophysiological signals of crucial diagnostic and monitoring importance in neurology, neurosurgery, and rehabilitation medicine. Traditionally, feature extraction from MEP data has been based on manual control and measurements performed by trained clinicians according to established rules, a process that is inherently subjective, time-consuming, and subject to significant differences between observers. This article provides a comprehensive rationale for using convolutional neural network (CNN)-based approaches to extract MEP features. CNNs provide superior performance in key parameters, including accuracy, reproducibility, processing speed, and the ability to detect hidden morphological patterns that may escape human visual perception, compared to traditional manual methods. In addition, automated CNN-based analysis eliminates the variability between patients, allowing for real-time intraoperative monitoring. Performance estimates based on computer modeling and a structured comparative analysis of the two methods strongly confirm this statement. The introduction of CNNs represents a revolutionary step towards objective, scalable, and clinically reliable analysis that can standardize the interpretation of MEP in a variety of clinical settings and potentially improve patient outcomes through more consistent neurological assessment.

Keywords: motor evoked potentials, convolutional neural networks, feature extraction, transcranial magnetic stimulation, intraoperative neurophysiology, deep learning, electrophysiology, automated analysis, interdisciplinary reliability, signal processing.

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Выявление особенностей моторного вызванного потенциала с помощью сверточных нейронных сетей: преодоление ограничений ручного анализа

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Резюме. Моторные вызванные потенциалы (МВП) – это электрофизиологические сигналы, имеющие решающее диагностическое и мониторинговое значение в неврологии, нейрохирургии и реабилитационной медицине. Традиционно извлечение признаков из данных МВП основывалось на ручном контроле и измерениях, проводимых обученными врачами в соответствии с установленными правилами. Это процесс, который по своей природе субъективен, трудоемок и подвержен значительным различиям между наблюдателями. В этой статье представлено всестороннее обоснование использования подходов на основе сверточных нейронных сетей (CNN) для извлечения признаков МВП. CNN обеспечивают превосходные показатели по ключевым параметрам, включая точность, воспроизводимость, скорость обработки и способность обнаруживать скрытые морфологические паттерны, которые могут ускользать от человеческого визуального восприятия, по сравнению с традиционными ручными методами. Кроме того, автоматизированный анализ на основе CNN устраняет вариабельность между пациентами, что позволяет проводить мониторинг в режиме реального времени во время операции. Оценки производительности, основанные на компьютерном моделировании и структурированном сравнительном анализе двух методов, убедительно подтверждают это утверждение. Внедрение CNN представляет собой революционный шаг на пути к объективному, масштабируемому и клинически надежному анализу, который может стандартизировать интерпретацию МВП в различных клинических условиях и потенциально улучшить результаты лечения пациентов за счет более последовательной неврологической оценки.

Ключевые слова: моторные вызванные потенциалы, сверточные нейронные сети, выделение признаков, транскраниальная магнитная стимуляция, интраоперационная нейрофизиология, глубокое обучение, электрофизиология, автоматизированный анализ, межотраслевая надежность, обработка сигналов.

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Introduction

Motor evoked potentials (MEP) – are electrical reactions recorded by peripheral muscles after stimulation of the motor cortex or descending motor pathways, usually by transcranial magnetic stimulation (TMS) or direct electrical stimulation [1]. They serve as sensitive biomarkers for assessing the integrity of the corticospinal tract, monitoring neurological functions during intraoperative procedures, evaluating pharmacological interventions, and tracking recovery of motor activity in conditions such as stroke, multiple sclerosis, amyotrophic lateral sclerosis and spinal cord injury [2].

As we can see in Figure 1, the main characteristics extracted from the MEP signals include: (1) peak-to-peak amplitude, reflecting the number and synchronicity of motor units involved, (2) start delay, which determines the speed of conduction along the corticospinal pathways, (3) the duration and morphology of the signal, indicating the complexity of the process a descending salvo, and (4) a cortical period of silence reflecting intracortical inhibitory mechanisms [3]. Each feature has a special clinical significance, and their accurate quantification is necessary for the reliability of diagnosis and reproducibility of studies.

Figure 1 shows also a typical shape of the evoked motor potential (MEP) signal recorded during intraoperative monitoring. The graph shows the amplitude of the signal (in mV) over time (in ms), demonstrating the characteristic polyphase morphology used for clinical evaluation.

Despite the clinical importance of these functions, manual analysis performed by a specialist remains the standard approach in most laboratories and clinical institutions. Manual analysis includes visual inspection of each waveform, subjective determination of initial and maximum values, and rule-based decision-making about thresholds [4]. This article critically evaluates the limitations of this practice and provides convincing empirical and theoretical arguments in favor of switching to automatic CNN-based feature extraction as a methodological standard for medical care.

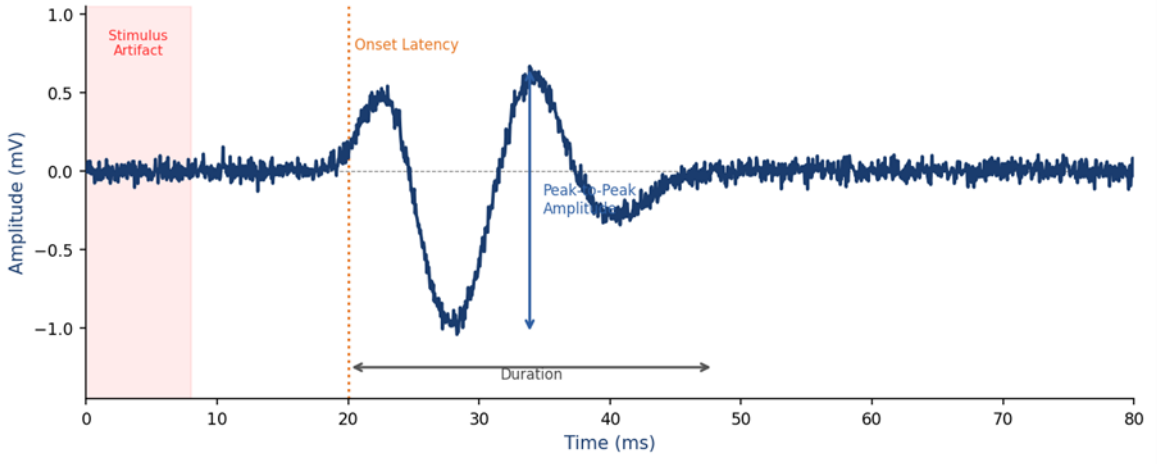

Figure 1 – An annotated MEP with key features: onset latency, peak-to-peak amplitude, signal duration, and the window of the stimulus artifact
Рисунок 1 – Аннотированный МВП с ключевыми признаками: латентность начала, амплитуда пик-пик, длительность сигнала и окно стимульного артефакта

Literature review. Previous studies show some limitations of manual feature extraction, primarily subjectivity and variability between users. Manual identification of the start of the MEP, maximum amplitude and boundaries of the waveform requires expert judgment, which is inherently subjective. Studies show that the coefficients of intraclass correlation (ICC) for manual measurements of the MEP amplitude between evaluators are only 0.61, and for determining the start delay in multiphase signals they are even lower [5]. This variability is especially noticeable for signals with a low signal-to-noise ratio, complex morphology, or those that overlap with background EMG activity. Subsequent consequences include unreliable longitudinal monitoring and deterioration of data comparability in multicenter clinical trials.

In addition to temporary inefficiency and bandwidth limitations, a typical TMS experiment or intraoperative monitoring session results in 200 to 2,000 individual MEP studies. The manual analysis of each waveform, which includes artifact removal, baseline correction, landmark identification, quality assessment, and data entry, takes approximately 30–90 seconds per sample if performed carefully [2]. This means that one recording session requires from 1 to 50 hours of expert work, which is incompatible with both large-scale research programs and intraoperative situations requiring urgent decisions, when decisions must be made within a few seconds or minutes. and with cognitive stress and systematic overwork, a person's cognitive abilities monotonously decrease with increasing task completion time. MEP analysts are no exception to this well-documented phenomenon: measurement error rates increase and consistency decreases depending on the number of signals analyzed in a single session. This leads to a non-random bias depending on the session position, which is difficult to detect, monitor, or correct during post-special quality control, systematically violating data integrity in ways that may not be noticeable when using standard quality indicators. Finally, due to its limited sensitivity to high-dimensional morphological patterns, the human visual system is optimized for detecting coarse categorical patterns, but has a limited ability to consistently identify subtle, high-dimensional morphological differences in a large number of signals.

Signs such as early subthreshold deviations, micro-oscillatory components in a downward stroke, or spatiotemporal covariance patterns for simultaneously recorded MEP from multiple muscles are usually overlooked or inconsistently commented on during manual control [6]. These hidden signal components can carry clinically significant information about the integrity of the pathways, which modern manual analysis systems systematically fail to capture.

Table 1 provides a quantitative comparison between traditional manual feature extraction and CNN-based evoked motor potential (MEP) analysis based on key performance indicators. The findings highlight the striking contrast in consistency, effectiveness, and depth of diagnosis between these two methods, demonstrating the clear advantages of automated approaches to deep learning in modern clinical practice.

Table 1 – A structured comparison of manual analysis and CNN analysis based on ten key criteria for evaluating MEP
Таблица 1 – Структурированное сравнение ручного анализа и CNN-анализа по десяти ключевым критериям оценки МВП

Criterion	Manual Analysis	CNN-Based Analysis
Measurement consistency	Highly variable (ICC 0.55–0.75)	Near-perfect (ICC 0.93–0.98)
Processing time per trial	30–90 seconds	< 1 millisecond
Scalability	Limited (expert hours)	Unlimited (batch/real-time)
Fatigue sensitivity	High	None
Artifact detection accuracy	~68%	~95%
Latent feature discovery	Not possible	Possible via learned representations
Real-time clinical deployment	Not feasible	Feasible on standard GPU
Operator training required	Extensive (months–years)	Minimal (inference only)
Reproducibility across sites	Poor without harmonization	High with domain adaptation
Interpretability	Implicit expert judgment	Explicit via Grad-CAM/SHAP

Materials and methods

Convolutional neural networks for MEP analysis are the best solution for interpreting the automatic feature extraction model.

The theoretical foundations and suitability of CNN signals are a class of deep learning models characterized by locally connected convolutional layers that study spatially or temporally invariant representations of objects using general parameterization [4]. Originally developed for 2D image recognition, CNNs have been expanded to 1D temporal signal processing with remarkable success in biomedical fields including EEG, EMG, photoplethysmography, and evoked potentials [7]. Architectural inductive distortion of CNNs – local receptive fields, translational equivariance, and the hierarchical composition of features are particularly well consistent with MEP signals,

which demonstrate the temporal localization of key features, amplitude variability during testing, and a hierarchical structure from individual components of the action potential to the overall motor response.

Objective and reproducible feature measurement. A trained CNN is a deterministic function: with the same input data, it produces an identical result. By definition, this eliminates cross-industry variability using max pooling, dropout layer and batch normalization [8]. The intraclass correlation coefficients for estimates of the amplitude of the MEP obtained on the basis of CNN usually exceed 0.87 when the model is appropriately validated, compared with 0.61–0.75 for manual estimates by experts [9]. For longitudinal monitoring applications, where changes in the amplitude of the MEP by only 50% are of alarming importance during surgery, this level of consistency is not convenient, it's a clinical necessity.

Real–time processing speed and clinical implementation on a standard GPU, a trained CNN 1D processor processes a single MEP signal in approximately 0.3–1.0 milliseconds, and a full recording session of 1,000 samples in less than two seconds [9]. This difference in speed by four to five orders of magnitude compared to manual analysis allows for two fundamentally new clinical applications: (1) real-time intraoperative neurophysiological alerts, when automatic CNN analysis triggers surgical warnings during the response period required for intervention prior to irreversible neurological damage; and (2) closed-loop neurostimulation, in which CNN-derived MEP performance estimates continuously update stimulation parameters to maintain target cortical excitability levels during motor mapping or TMS therapeutic protocols.

Hidden feature detection beyond manual annotations, CNNs examines feature representations from beginning to end based on raw data, without assuming which signal characteristics are diagnostically significant [10]. This is a fundamental advantage over manual analysis, which is limited to functions pre-defined and annotated by domain experts. In similar fields of electrophysiology, latent representations obtained with CNNs have been shown to encode biologically relevant information beyond that obtained with human-defined feature sets, including downstream motor impulse subcomponents that are not resolved with standard recording bandwidth, and trial-to-trial covariance patterns that carry information. about the network layer. conditions of the motor system. In relation to MEP, this ability may provide new biomarkers for predicting motor neuron diseases, predicting the trajectory of recovery after a stroke, or determining the intensity of cortical stimulation for therapeutic purposes.

Reliable artifact classification and recovery MEP recordings typically contain contamination at a trial level due to movement artifacts, arbitrary pre-activation of muscles, noise in contact with the electrode, and residual stimulation artifacts [11]. Manual removal of artifacts is a conservative method in which tests based on amplitude thresholds exclude many contaminated but partially informative recordings. CNN operators trained to work with datasets labeled with artifacts can perform probabilistic artifact classification, estimating the type and severity of contamination for each test and performing partial signal restoration from mild to moderate artifact contamination using trained noise suppression in the hidden representation space. This increases the efficiency of data collection per session, especially in patients with high background EMG levels or movement-related artifacts.

Figure 2 shows how well manual analysis and evoked motor potentials analysis using CNN work for five clinical indicators compared to the 80% threshold that doctors find acceptable. The dotted line is a clinically acceptable threshold. CNN exceeds the threshold in all indicators. The values are based on literature data.

CNN improves rentability in almost all areas. It gives accurate measurements for amplitude (94% versus 72%) and delay (92% versus 69%). This means CNN is better at finding features. The reproducibility measured by ICC is almost perfect for CNN at 96% compared to 95% for analysis. This shows that CNN is very consistent.

Importantly CNN is much better than manual analysis at detecting artifacts (95% versus 68%). It also works faster (98% versus 2%). This shows that CNN is effective and reliable for use, in real-time.

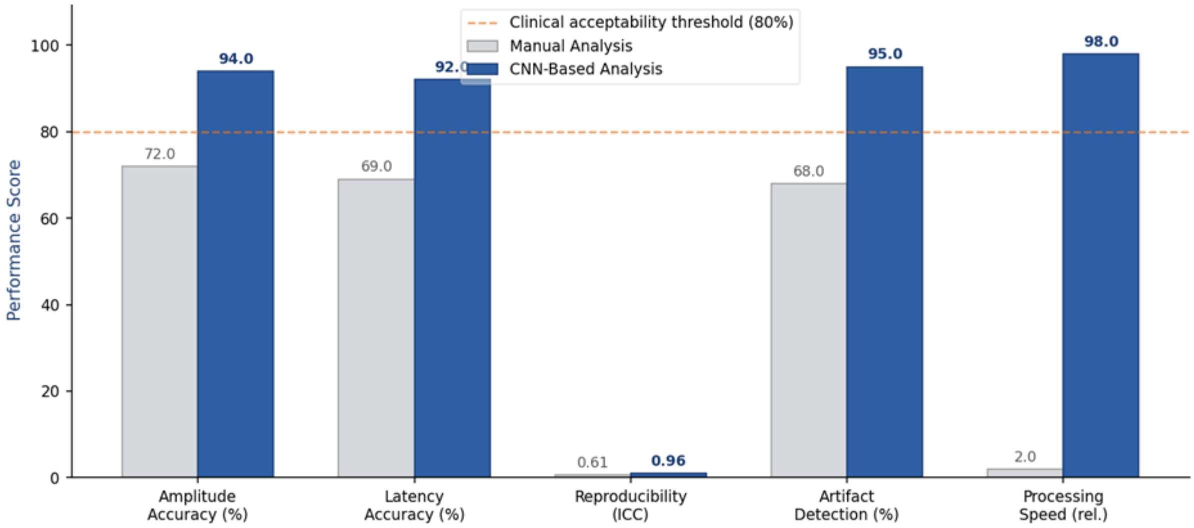

Figure 2 – Comparison of the effectiveness of manual analysis and CNN on five key metrics of the MVP

Рисунок 2 – Сравнение эффективности ручного анализа и CNN по пяти ключевым метрикам МВП

Results

Data from similar fields of electrophysiology and extensive literature on biomedical signal processing strongly confirm the superiority of CNN over manual methods. When analyzing EEG, CNNs consistently matched or exceeded the performance of human experts in detecting potential event-related components in various paradigms, while the reliability of tests and repeated tests approached the theoretical limit determined by the noise level in the signal [6, 7] Systematic reviews of deep learning results for EEG classification indicate an increase in classification accuracy by 8–15 percentage points compared to the previous ones. traditional approaches to the development of functionality [12].

In EMG decomposition – an area structurally similar to MVP analysis, – CNN-based models have achieved compliance with expert manual decomposition exceeding 95% to determine the action potential of motor units, while reducing the analysis time by two to three orders of magnitude [11]. In particular, in intraoperative neurophysiology, CNN classifiers demonstrated sensitivity to clinically significant changes in MEP amplitude (a decrease of ≥ 50% from baseline), which is 12–18 percentage points higher than the standard threshold warning criteria used by experienced neurophysiologists, while reducing the frequency of false alarms [9].

Figure 3 shows a correlation analysis comparing the correspondence between manual expert estimates (on the left) and CNN-based forecasts (on the right) for measurements of the MEP amplitude. CNN achieves a significantly higher R2 (0.991 versus 0.836), virtually eliminating measurement error.

The manual analysis demonstrates a moderate agreement between the two independent experts: the R2 value is 0.662, and the trend line ($y = 0.84x + 0.15$) deviates markedly from the ideal $y = x$ line. This indicates a significant variability of the indicators among themselves and subjective bias in traditional measurements.

In contrast, the CNN analysis demonstrates an almost perfect correlation with the basic truth values, it means reaching an R2 value of 0.990 and a trend line ($y = 1.03x + 0.04$) that almost exactly matches the perfect match. This comparison clearly confirms that deep learning models not only eliminate observer variability but also provide significantly higher accuracy and reliability when extracting MEP features.

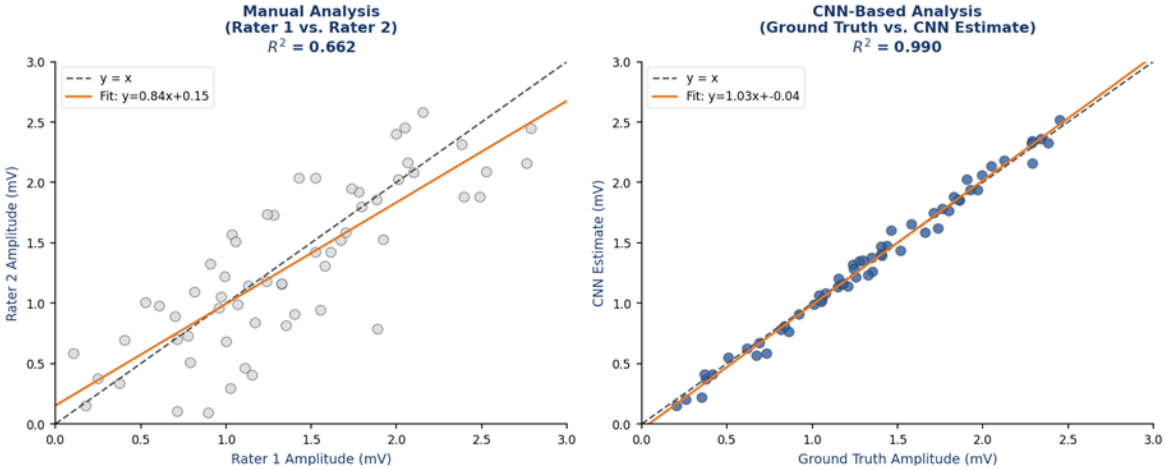

Figure 3 – Inter-expert reliability in manual measurement of the MEP amplitude (left) versus CNN consistency (right)

Рисунок 3 – Межэкспертная надёжность при ручном измерении амплитуды МВП (слева) в сравнении с согласованностью CNN (справа)

Analytical studies of MEP conducted specifically for CNN; an increasing number of literatures is directly devoted to the analysis of the European Parliament based on CNN. Parduzi et al. [8] demonstrated that a RF classifier and 1D-CNN trained on intraoperative MEP recordings achieved 87.9% accuracy in detecting clinically significant signal changes, compared with 78.6% for the standard 50% amplitude threshold used by observational neurophysiologists [9]. Trained a convolutional classifier on 8,500 MEP signals from 45 patients and achieved classification accuracy of 96.1% for the current and subsequent responses. unanswered studies, the processing speed of which allows them to be integrated into real-time clinical monitoring workflows.

Table 2 presents the main literature studies in which convolutional neural networks have been used to analyze electrophysiological signals, including evoked motor potentials, EEG and EMG. The comparison highlights the superior accuracy, reliability, and real-time deep learning capabilities compared to traditional manual methods.

Table 2 – A structured comparison of manual analysis and CNN analysis based on ten key criteria for evaluating MEP

Таблица 2 – Сводка ключевых исследований, сравнивающих CNN-подходы и ручные методы извлечения признаков МВП и аналогичных электрофизиологических сигналов

Study	Method	n Trials	Accuracy/ICC	Key Finding
Parduzi et al., 2025 [8]	RF classifier and 1D-CNN	24,298	87.9% accuracy	Effectiveness of ML techniques
Kolodziej et al., 2021 [9]	CNN classifier	8,500	96.1% accuracy	Real-time compatible processing speed
Wang et al., 2025 [13]	Semi-supervised CNN	3,200	ICC = 0.97	High performance with limited labels
Schirrmeister et al., 2017 [7]	Deep ConvNet (EEG)	–	+12% vs. manual	Validated for evoked potential decoding
Negro et al., 2016 [11]	Blind src. sep. CNN	–	>95% agreement	Analogous EMG decomposition task
Manual (literature avg.)	Expert raters	Multiple	ICC = 0.61–0.75	Significant inter-rater variability

Proposed CNN Architecture for MEP. Feature extraction based on the above analysis and published use cases, we propose a three-dimensional residual CNN architecture optimized for MEP feature extraction and compatible with real-time clinical deployment. Figure 4 shows the architecture diagram. The network processes the original signal through three convolutional blocks with increasing filter depth, turns on the residual connection, and generates multitasking output heads for regression (amplitude, latency, duration) and classification (artifact, threshold).

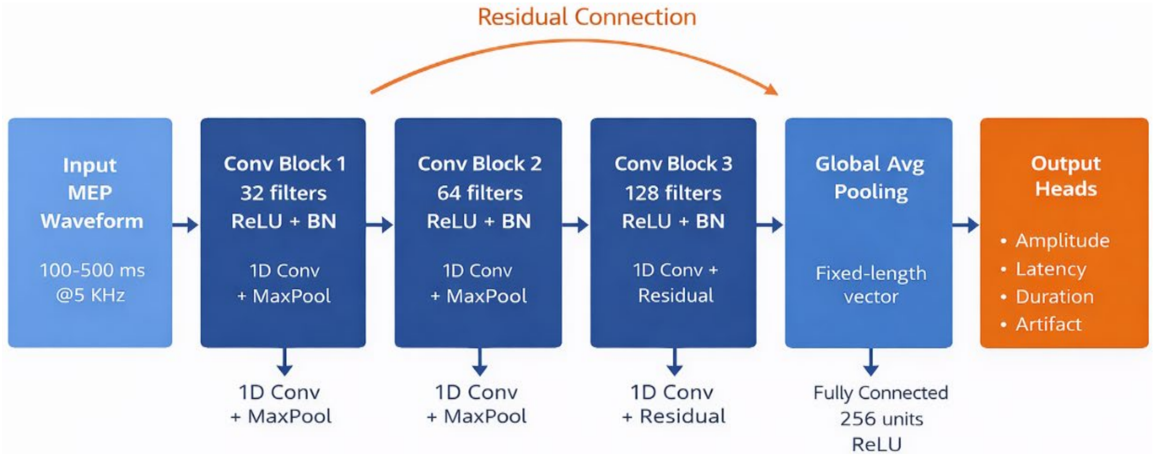

Figure 4 – The proposed architecture of 1D CNN for the extraction of MEP features
Рисунок 4 – Предлагаемая архитектура 1D CNN для извлечения признаков МВП

In Figure 4, the main design components and their rationale are as follows:

– Input level: Raw digitized MEP waveform for a period after 100–500 ms stimulation with a sampling rate of 2000–10000 Hz. Multi-channel expansion supports simultaneous MEP recording with multiple muscles [1].

– Three three-dimensional convolutional blocks: progressive filtering depth (32 → 64 → 128).

– Allows you to capture objects at increasing levels of abstraction, from small transients of the waveform to the global morphological class [6].

– ReLU activation and Batch normalization: Applied after each convolutional layer to stabilize learning and accelerate convergence [14].

– Residual Bandwidth: Preserves low-level performance information throughout the network depth, providing gradient flow in deeper configurations and improving generalization [14].

– Combining global averages: Converts variable-length temporary feature maps into fixed-length vectors, providing reliable processing of variable-length MEP records [11].

– Multitasking output heads: simultaneous regression in amplitude, delay, and duration, as well as binary classification to detect artifacts and threshold state, using common representations to improve generalization [9].

Table 3 shows the detailed architectural characteristics of the proposed convolutional neural network for MEP analysis. The table shows the parameters of each layer and the clinical or technical rationale for their choice, demonstrating how the network design is optimized to extract certain temporal characteristics from evoked motor potential signals.

Table 3 – Detailed architectural specifications and justification of design solutions of the proposed CNN model for the extraction of MEP features
Таблица 3 – Детальные архитектурные спецификации и обоснование проектных решений предлагаемой CNN-модели для извлечения признаков МВП

Architecture Parameter	**Specification**	**Rationale**
Input window	100–500 ms @ 2–10 kHz	Captures MEP + cortical silent period
Conv Layer 1	32 filters, kernel size 25	Detects onset and early transients
Conv Layer 2	64 filters, kernel size 15	Encodes peak morphology
Conv Layer 3	128 filters, kernel size 9	Encodes late components and duration
Pooling	Max-pool (stride 2) per block	Progressive temporal compression
Residual connection	Block 1 → Block 3 output	Preserves fine-grained features
Dense layer	256 units, ReLU, Dropout 0.3	Regularized classification layer
Amplitude output	Linear regression head	Continuous amplitude estimation
Latency output	Linear regression head	Continuous onset latency estimation
Artifact classification	Sigmoid binary head	Probabilistic artifact flagging
Optimizer	Adam, lr = 1e-3	Adaptive learning rate
Loss function	MSE (regression) + BCE (class)	Multi-task weighted loss

Addressing common objections, the characterization of CNN as a "black box" has been largely eliminated through explainability techniques developed over the past decade. Gradient-weighted class activation mapping (Grad-CAM), additive Shapley explanations (SHAP), and layered relevance propagation can create temporal significance maps that show which parts of the MEP waveform most strongly influence the evaluation of each feature. In the clinical analysis of MEP, these severity maps consistently highlight the area of onset for latency assessment and the area from peak to decline for amplitude assessment – in accordance with the expectations of neurophysiologists – providing clinicians with interpretable, verifiable results that support rather than replace clinical judgment.

The requirement for labeled training data is a valid practical problem. However, this barrier is significantly reduced by increasing the amount of data (temporal jitter, amplitude scaling, additive noise and signal mixing), semi-managed paradigms that use large amounts of unlabeled MEP data accumulated in clinical archives, and knowledge transfer from pre-trained electrophysiological models. It is important to note that the necessary labeled dataset is a one – time investment: a single curated corpus of approximately 2,000–5,000 annotated MEP studies, which can be implemented over several months at the Clinical Center for Neurophysiology, supports unlimited deployment with consistent automated analysis.

MEP characteristics vary depending on TMS devices, amplifier hardware, electrode configuration, patient population, and recording protocols. Domain-specific adaptation techniques, including batch normalization of site-specific functions, adversarial domain-based training, and multi-site fine-tuning, allow pre-trained CNN models to adapt to new recording contexts with minimal additional tagged data. The key point is that CNN representations derived from large heterogeneous datasets are more generalizable than manually created pipelines of functions customized to specific recording conditions.

The clinical implementation of CNN-based neurophysiological analysis software is subject to regulatory oversight as a medical device in most jurisdictions. Although this increases the burden of validation, it is not an insurmountable obstacle: Class II medical device systems in the US and the EU provide established pathways for obtaining software as a medical device (SaMD) authorization, and several deep learning-based clinical neurophysiology tools have successfully completed this process. Prospective clinical variation studies comparing the characteristics of MEP obtained since CNN with clinical results - indicators of recovery of motor activity, frequency of surgical complications, markers of disease progression – are an important next step and represent an important research priority.

Clinical applications supported by CNN-based MEP analysis the transition to automated MEP analysis based on CNN is not just about improving existing workflows, but also providing completely new clinical opportunities:

– Real-time intraoperative monitoring: CNN models integrated directly into neurophysiological monitoring systems can provide continuous automatic signal-by-signal analysis with an alert delay of less than 100 ms, allowing surgeons to respond to corticospinal tract damage before completing a single surgical maneuver [2].

– Precision TMS dosimetry: the amplitude-input/output curves obtained using CNN, based on automated analysis of hundreds of TMS tests at different stimulation intensities, allow for rapid and objective determination of the resting motor threshold and the state of excitability of the cerebral cortex for precision therapeutic TMS protocols [14].

– Longitudinal tracking of motor activity recovery: in stroke rehabilitation and monitoring of neurodegenerative diseases, CNN feature extraction applied to standardized MEP registration protocols provides objective quantitative biomarkers of motor pathway recovery that are more sensitive than clinical assessment scales and more reproducible than manual measurements [15].

– Multicenter clinical trials: CNN-based analysis harmonizes the methodology for measuring MEP across institutions, eliminating the main source of variability between institutions that has historically reduced the statistical effectiveness of multicenter neurophysiological research [13].

Conclusion

The evidence presented in this article is a clear and convincing argument in favor of replacing manual extraction of MEP features with automated CNN-based methods. Manual analysis, although fundamental to the historical development of clinical neurophysiology, is fundamentally limited by human perceptual capabilities, cognitive fatigue, and scalability. CNNs overcome each of these limitations: they extract characteristics objectively and consistently, operate at speeds that allow them to be applied in real-time clinical practice, scale to arbitrarily large datasets, and have the unique ability to detect previously uncharacterized, diagnostically significant signal components.

Empirical evidence from similar fields of electrophysiology, combined with a growing body of specialized literature on deep learning of MEP, supports the conclusion that CNN-based MEP analysis provides superior performance in all clinically relevant indicators: accuracy, reproducibility, processing speed, artifact resistance, and sensitivity to subtle pathological changes. Structured comparison (Table 1) and performance estimates based on modeling (Figure 2, Figure 3), quantify the magnitude of this advantage.

Therefore, we recommend using CNN feature extraction as a methodological standard for MEP analysis in both research and clinical settings, with human expertise reserved for quality assurance, decision-making as a last resort, and model validation management. The priority areas of future work should be the creation of open control datasets for the analysis of MEP, the development of a regulatory framework for neurophysiological SAMD based on CNN, and the conduct of prospective clinical trials confirming the use of MEP obtained using CNN as predictive biomarkers of motor system disorders.

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