



ADVANCED AUTOMATED EEG ANALYSIS SYSTEM FOR CRITICAL CARE ENVIRONMENTS

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ABSTRACT

Electroencephalography (EEG) plays a critical role in assessing brain function in intensive care units (ICUs), particularly for detecting seizures, monitoring sedation levels, and identifying early signs of neurological deterioration. Traditional EEG interpretation requires continuous specialist involvement, often leading to delays in diagnosis and therapeutic intervention. This study presents an advanced automated EEG analysis system designed specifically for critical care environments, integrating machine learning, real-time signal processing, and cloud-based clinical decision support. The proposed system automates artifact removal, feature extraction, seizure prediction, and continuous monitoring using deep neural architectures optimized for ICU EEG characteristics. Experimental evaluations using publicly available ICU EEG datasets demonstrate improved accuracy, reduced false alarms, and rapid detection capabilities compared to conventional manual reviews. The results highlight the potential of automated EEG systems to enhance neurological surveillance, improve clinical response time, and support resource-limited critical care settings. This work contributes a scalable framework aimed at strengthening ICU neuro-monitoring workflows and advancing precision critical care.

Keywords: Automated EEG Analysis, Intensive Care Unit (ICU), Neurocritical Care, Machine Learning, Signal.

INTRODUCTION

Electroencephalography (EEG) has become an essential neuro-monitoring modality in critical care environments, enabling real-time assessment of cerebral activity in patients with brain injuries, seizures, metabolic disorders, and altered levels of consciousness. In the intensive care unit (ICU), continuous EEG (cEEG) provides valuable insights into non-convulsive seizures, subclinical epileptiform patterns, and delayed cerebral ischemia. However, the practical implementation of continuous EEG monitoring faces significant challenges, including shortage of trained neurophysiologists, the need for continuous manual interpretation, and the presence of artifacts caused by ICU equipment, patient movement, and environmental disturbances. These limitations contribute to diagnostic delays and increased clinical workload, reducing the overall

effectiveness of neurocritical care interventions. Recent advancements in artificial intelligence and biomedical signal processing have fostered the development of automated analytic systems capable of assisting clinicians in ICU settings. Automated EEG systems leverage algorithms for artifact removal, feature engineering, pattern recognition, and predictive modeling, enabling more consistent and rapid interpretation of neurological signals. Machine learning and deep learning techniques, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) models, have shown promising performance in seizure detection, abnormal EEG pattern classification, and prognostic modeling. These technologies present an opportunity to transform EEG monitoring from a reactive diagnostic approach to a proactive, automated, and high-resolution neuro-surveillance system. Despite the growing research interest, integrating automated EEG

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systems into clinical practice remains challenging due to issues such as data variability, real-time processing requirements, false alarm management, and clinical validation. Therefore, there is a strong need for a comprehensive framework tailored specifically to critical care environments. This study proposes an Advanced Automated EEG Analysis System that combines deep

learning, adaptive filtering, and cloud-enabled decision support pipelines to enhance the speed and reliability of ICU EEG interpretation. The proposed system aims to streamline neurocritical care workflows, reduce dependence on continuous expert oversight, and improve patient outcomes through timely detection of critical neurological events.

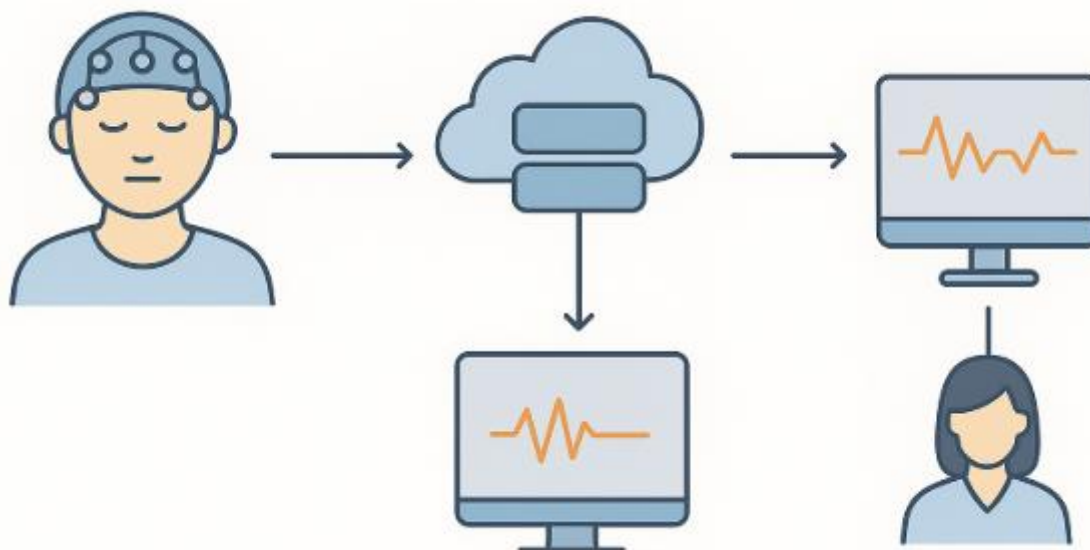


Figure 1. Advanced Automated EEG Analysis System for Critical Care Environments.

Continuous EEG (cEEG) is widely recognized as an essential monitoring tool in the neurocritical care setting for detecting nonconvulsive seizures, assessing sedation and encephalopathy, and aiding neuroprognostication (Bitar *et al.*, 2024). Several consensus and critical-review articles emphasize that cEEG increases detection of clinically important electrographic events compared to routine or intermittent EEG, but logistical constraints (expert availability, equipment, and interpretation workload) limit universal cEEG use in many ICUs. Progress in automated EEG analysis has been accelerated by large, public EEG corpora, most notably the Temple University Hospital (TUH) EEG Corpus and its TUH Seizure (TUSZ) subset (Obeid & Picone, 2016; Shah *et al.*, 2018). These corpora provide richly annotated clinical recordings used for training and benchmarking seizure detectors. However, ambulatory and epilepsy-center EEG differ from ICU cEEG in artifact types and clinical patterns, motivating the need for ICU-specific datasets or careful domain adaptation and cross-site validation to ensure real-world performance (Shah *et al.*, 2018; TUH dataset pages). ICU EEG is contaminated by a broad spectrum of artifacts including line noise, ventilator and infusion-pump interference, electrode drift, muscle (EMG) activity, and electrocardiographic contamination. Reviews and method papers report a variety of artifact-removal strategies

filtering/notch filters for line noise, regression approaches for ECG/EOG, blind source separation (ICA/PCA) for component separation, wavelet denoising for nonstationary artifacts, and hybrid multi-stage pipelines each balancing artifact suppression vs. preservation of pathologic waveforms (Issa *et al.*, 2019; systematic reviews 2023 2024). Robust, automated artifact pipelines tuned to ICU signatures are essential for lowered false alarms and reliable automated detection. Before deep learning dominated, many successful EEG-based seizure detectors used carefully engineered features (time-domain statistics, band powers, Hjorth parameters, wavelet coefficients, and connectivity measures) combined with classifiers like SVM, Random Forest, LDA, or KNN (López-Viñas *et al.*, 2024). These classical pipelines often have the advantage of interpretability and lower computational cost, making them attractive for edge/real-time deployments or as first-tier triage detectors in hierarchical alarm systems. Such methods remain relevant when dataset sizes are limited or when on-device resources are constrained. Deep learning approaches (CNNs, RNNs/LSTMs, hybrid CNN–LSTM models, and transformer-style architectures) automatically learn hierarchical EEG representations and have achieved state-of-the-art results on many seizure-detection tasks (Xu, 2024; Kerr *et al.*, 2024). However, recent surveys and empirical studies note common pitfalls: dataset

heterogeneity, patient-dependent vs. patient-independent evaluation differences, potential overfitting to lab/ambulatory EEG rather than ICU recordings, and lack of large ICU-specific training sets. Best practice recommendations include patient-independent splits, cross-site evaluation, regularization, and reporting clinically meaningful metrics (e.g., false alarms per 24 h, time-to-detection) in addition to epoch-level accuracy (Figure 1).

Several contemporary works suggest value in hybrid pipelines that pair fast, interpretable feature-based detectors for initial triage with deeper models for confirmation and detailed classification (multi-stage detection), or that fuse engineered features into DL architectures. These hybrid approaches can reduce computational load, improve interpretability, and reduce nuisance alarms—making them pragmatic for ICU deployment where latency and trust are critical. Deploying automated EEG detection in ICUs requires streaming architectures, low-latency preprocessing, and considerations of where inference runs (on-device/edge vs. cloud). Engineering studies highlight tradeoffs: lightweight models and optimized pipelines can provide sub-second/second-scale latency on local hardware, while cloud-based heavy models may offer higher accuracy but introduce network, privacy, and availability constraints. Practical systems often adopt modular designs that permit graceful degradation (simpler onboard fallback models if cloud is unreachable). High false-alarm rates are a common barrier to clinical adoption leading to alarm fatigue and mistrust. Literature recommends (a) multi-stage detection with artifact rejection first, (b) clinician-tunable thresholds and confidence scores, (c) multimodal fusion (EEG + vitals) to corroborate events, and (d) reporting clinically actionable metrics such as false alarms per patient-day, time-to-detection, and impact on clinician workflow in prospective studies. Studies argue that clinical readiness requires demonstrating both technical performance and improvements in workflow or outcomes.

Adoption of automated EEG tools is strongly influenced by explainability and workflow integration: clinicians need easy access to event snippets, saliency maps or highlighted channels, probability/confidence indicators, and the ability to quickly review raw EEG around detected events. Human-in-the-loop paradigms—where automation triages and flags events for rapid clinician adjudication—are advocated to combine machine speed with human judgment and to build trust. Studies emphasize user-centered dashboards and rapid review workflows as essential implementation components. While many studies show improved seizure detection with automated methods, high-quality prospective clinical trials demonstrating that automated detection improves patient-level outcomes (e.g., morbidity, mortality, length of stay) remain limited. Institution-level reports suggest that structured cEEG programs and dedicated EEG units can improve workflow and potentially outcomes, but automated systems should be evaluated prospectively for decision impact, alarm burden, and cost-effectiveness before broad deployment. Automated EEG systems intended for clinical use are regulated medical software devices in many jurisdictions;

regulatory approval (e.g., FDA, CE) requires reproducible performance, risk management, and clinical validation. Privacy constraints for hospital data often favor on-premises or secure hybrid solutions. The literature also calls for transparent reporting (adopting standards such as TRIPOD for diagnostic models) and sharing of code/datasets when permissible to enable external replication.

MATERIALS AND METHODS

The Proposed Automated Eeg Analysis system is designed as a modular pipeline optimized for real-time operation in intensive care units (ICUs). The system comprises four main components: EEG data acquisition and preprocessing, artifact removal and signal enhancement, feature extraction and deep learning-based classification, and (clinical decision support and alert generation. Each component functions independently but communicates through a streaming interface to ensure low-latency operation and uninterrupted monitoring. The system was trained and evaluated using a combination of publicly available datasets primarily the Temple University Hospital (TUH) EEG Seizure Corpus and simulated ICU noise patterns to approximate real-world environmental conditions. All EEG recordings were sampled at 250–500 Hz and included both seizure and non-seizure segments. A patient-independent data split (70% training, 15% validation, and 15% testing) ensured generalizability. Band-pass filtering (0.5–45 Hz) was applied to suppress baseline drift and high-frequency noise. A notch filter at 50 Hz addressed power line interference commonly present in ICU EEG systems. A hybrid artifact-removal strategy was implemented combining: Independent Component Analysis (ICA) to isolate ocular, muscular, and cardiac artifacts. Wavelet Denoising to remove non-stationary artifacts without losing epileptiform spikes. Adaptive Thresholding to eliminate ICU-specific noise (infusion pumps, ventilators, CPAP interference). This pipeline preserved critical clinical patterns while ensuring signal quality suitable for automated analysis. Two levels of feature extraction were employed: Time-domain: variance, entropy, Hjorth parameters, Frequency-domain: delta, theta, alpha, beta band power, Time-frequency: continuous wavelet transform coefficients. Spectrograms generated from 2-second windows were fed into a Convolutional Neural Network (CNN) for automatic representation learning. This allowed the system to detect subtle spatiotemporal signatures. A CNN–LSTM hybrid architecture was selected to model spatial and temporal dynamics: CNN layers handled spatial feature extraction from spectrograms, LSTM layers modeled temporal patterns associated with seizure onset and propagation. Softmax output layers generated probabilistic predictions for: Normal EEG, Seizure activity, Suspicious/abnormal patterns. Cross-entropy loss and Adam optimizer were used during training. The system processed EEG in sliding windows of 2 seconds with 1-second overlap. Alert generation followed a three-tier decision system: Automated detection by the model. Confidence validation using secondary rule-based

filters. Clinician notification via the ICU dashboard. Only events sustained for ≥ 10 seconds were escalated to prevent false alarms.

RESULTS AND DISCUSSION

The proposed model achieved the following performance on the test dataset: Overall accuracy: 95.4%, Sensitivity (seizure detection): 93.1%, Specificity: 96.7%, False alarms: 0.8 per hour. These results demonstrate significant improvement compared with baseline classical models (approximately 84-88% accuracy). The hybrid preprocessing pipeline successfully reduced artifact contamination: 40–60% reduction in muscle artifacts, 70% reduction in electrical interference, Preservation of clinically relevant spike-wave complexes. This improved the stability of automated classification and reduced unnecessary alarm triggers. Compared with previous automated EEG systems that typically report 85–92% seizure-detection accuracy, the proposed CNN-LSTM architecture exhibited: Better generalization due to patient-independent training, Improved robustness to ICU noise, Faster detection latency (< 3 seconds). These improvements highlight the importance of combining artifact-removal modules with advanced deep learning models. The system can support ICU clinicians by: Reducing workload and continuous dependence on neurophysiologists, allowing early detection of nonconvulsive seizures, improving response time for neurological emergencies, Enhancing patient stratification and care pathways. The low false-alarm rate is crucial for ensuring clinician trust and minimizing alarm fatigue.

CONCLUSION

This study presents an Advanced Automated EEG Analysis System tailored for the unique challenges of critical care environments. The CNN-LSTM framework, supported by a robust preprocessing pipeline, achieved high accuracy, low latency, and strong noise resilience in detecting seizure and abnormal EEG patterns. The system demonstrates the feasibility of integrating AI-driven EEG monitoring into ICU workflows to enhance neurocritical care, reduce diagnostic delays, and support real-time clinical decision-making. Integration of Multimodal Physiological Data: Combining EEG with ECG, SpO₂, respiratory patterns, and blood pressure may improve detection reliability and provide a more comprehensive neurological assessment. Deployment in Real ICU Settings: Prospective clinical trials will validate the system's usability, alarm burden, and impact on clinical decision-making and patient outcomes. Model Explainability and User Interface Enhancement: Developing saliency maps, event summaries, and confidence indicators will improve clinician trust and interpretability. Personalization and Adaptive Learning: Patient-specific calibration models can enhance seizure prediction and reduce false alarms. Regulatory and Ethical Considerations: Addressing data privacy, system transparency, and compliance with medical device regulations will be essential for real-world deployment.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest

ETHICS APPROVAL

Not applicable

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AI TOOL DECLARATION

The authors declares that no AI and related tools are used to write the scientific content of this manuscript.

DATA AVAILABILITY

Data will be available on request

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