ALEKSANDRE TSERETELI [1,2], TAMAR SAKVARELIDZE [1,2], TAMTA CHILACHAVA [2], NIKOLOZ MALASHKHIA [2], NATELA OKUJAVA [1,2]

AI-BASED ALGORITHM ENCEVIS PERFORMANCE IN THE EPILEPSY MONITORING UNIT: A MULTIFACTORIAL ANALYSIS

[1]Tbilisi State Medical University (TSMU); [2]S. Khechinashvili University Hospital (SKUH); Tbilisi, Georgia

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ალექსანდრე წერეთელი [1,2], თამარ საყვარელიძე [1,2], თამთა ჩილაჩავა [2], ნიკოლოზ მალაშხია [2], ნათელა ოკუჯავა [1,2]

ხელოვნურ ინტელექტზე დაფუძნებული ალგორითმის ENCEVIS ეფექტურობა ეპილეფსიის მონიტორინგის განყოფილებაში: მულტიფაქტორული ანალიზი

[1]თბილისის სახელმწიფო სამედიცინო უნივერსიტეტი; [2]სიმონ ხეჩინაშვილის სახელობის საუნივერსიტეტო კლინიკა; თბილისი, საქართველო

რეზიუმე

კვლევის მიზანი: ელექტროენცეფალოგრამის ანალიზის ხელოვნურ ინტელექტზე დაფუძნებული ალგორითმის ENCEVIaS ეფექტურობის შესწავლა გულყრების ამოცნობაში. ასევე გულყრების ამოცნობის მგრძნობელობაზე ისეთი მახასიათებლების გავლენა, როგორიცაა ეპილეპტოგენური ზონა, რითმულობა და ხანგრძლივობა.

მეთოდი: ჩვენი პროსპექტული კვლევა ჩატარდა ს. ხეჩინაშვილის სახელობის საუნივერსიტეტო კლინიკაში 2019 წლიდან 2023 წლამდე. კვლევაში ჩაერთო 267 ხანგრძლივი ეეგ ჩანაწერი. ნეიროფიზიოლოგების მიერ ენცეფალოგრამის ტრადიციული ვიზუალური შეფასებით განისაზღვრა ეპილეპტოგენური ზონა, შეტევების ხანგრძლივობა და ეპილეპტიფორმული აქტივობის რითმულობა. ჭეშმარიტ დადებითად ჩაითვალა ალგორითმის მიერ გულყრის ამოცნობა შემდეგი დროის ფანჯარაში: ეპილეფსიურ გულყრის დაწყებამდე 30 წმ და შეტევის დასრულების შემდეგ 60 წამი. მულტივარიანტული რეგრესიის მეთოდით შეფასდა ალგორითმის ჭეშმარიტად დადებით დეტექციაზე ისეთი ფაქტორების გავლენა, როგორიცაა ლოკალიზაცია, რითმულობა, ხანგრძლივობა, ასევე ვარიანტები რითმულობა ხანგრძლივობასთან ერთად და ლოკალიზაცია რითმულობასთან ერთად.

შედეგები: კვლევის პერიოდში ჯამში დაფიქსირდა 114 ეპილეფსიური გულყრა. ENCEVIS-მა სწორად ამოიცნო 65 (მგრძნობელობა 57%). საფეთქლის წილში ეპილეპტოგენური ზონის ლოკალიზაციის დროს ალგორითმის მიერ გულყრების ამოცნობა იყო (71%, <0.05), გენერალიზებული ტონური გულყრებისთვის (35.1%). ალგორითმი სარწმუნოდ უკეთ ამოიცნობდა შეტევებს რითმული პატერნებით, არითმულ პატერნებთან შედარებით (71.4% vs 22.7%, $p<0.05$). ალგორითმი ყველაზე კარგად ამოიცნობდა 38-68 წმ ხანგრძლივობის შეტევებს. ლოგიკური რეგრესიის მეთოდით შეტევების ამოცნობაზე ყველაზე დიდ გავლენას ახდენდა რითმულობა (OR = 2.13), ამოცნობასთან ასევე პოზიტიურად კორელირებდა ვარიანტი - რითმულობა ხანგრძლივობასთან ერთად (OR = 1.61). დამოუკიდებლად ლოკალიზაცია და/ან ხანგრძლივობა გულყრის დეტექციისთვის მნიშვნელოვან ფაქტორს არ წარმოადგენდა.

დასკვნა: ENCEVIS კარგად ამოიცნობს რითმულ და საშუალო ხანგრძლივობის (38-68წმ) საფეთქლის ლოკალიზაციის შეტევებს. არითმული ხანმოკლე ტონური შეტევების შემთხვევაში ალგორითმის სენსიტიურობა დაბალია. ალგორითმში გულყრების მულტიფაქტორული მახასიათებლების ჩართვა გაზრდის მის მგრძნობელობას სხვადასხვა ტიპის შეტევების ამოცნობაში და გაამარტივებს იმპლემენტაციას კლინიკურ საქმიანობაში.

Introduction: Long-term video-EEG monitoring (LTM), particularly in specialized epilepsy monitoring units (EMUs), increases the likelihood of capturing epileptic seizures and relevant EEG abnormalities [1]. Accurate EEG interpretation requires highly trained specialists, and misinterpretation remains a major cause of epilepsy misdiagnosis. The extensive data generated by long-term monitoring (LTM) places a significant burden on clinical neurophysiology services [2,3].

To assist in EEG interpretation, automated seizure detection algorithms have recently been developed. One such algorithm is ENCEVIS, created by the Austrian Institute of Technology (AIT). While commercial systems demonstrate acceptable overall sensitivity, their performance can vary significantly. For example, in a comparative study by Reus et al., ENCEVIS achieved 88% sensitivity with 5.5 false positives per 24 hours, compared to Persyst's 93% sensitivity and 1.7 false positives [4]. Similarly, Kural et al. reported that ENCEVIS demonstrated high specificity but lower sensitivity relative to other tools [5].

Despite substantial advances, few studies have systematically evaluated seizure-specific factors that affect algorithmic detection performance, particularly features such as seizure localization, duration, and rhythmicity. In this study, we conducted a multifactorial analysis of ENCEVIS detection performance across these dimensions to identify key predictors of successful detection and define directions for future algorithmic refinements.

Method: This prospective study was conducted between 2019 and 2023 at Khechinashvili University Hospital, Tbilisi, to evaluate the performance of the ENCEVIS artificial intelligence (AI)-based seizure detection algorithm and to identify seizure-specific factors influencing detection sensitivity. The study protocol was approved by the SKUH Ethics Review Board. Written informed consent was obtained from all participants or their legal guardians.

This study focused on prolonged EEG recordings; therefore, only recordings exceeding three hours were included. Standard short-duration EEGs (typically 30–40 minutes) were excluded from the final analysis. Additionally, as ENCEVIS is limited to detecting electrographic activity, recordings containing EEG-negative epileptic seizures were excluded.

Seizure onset was defined as the first visually identifiable electrographic change associated with a clinical event. EEG recordings were stored in two independent databases without preprocessing. Blinded visual analyses were conducted independently by two clinical neurophysiologists, with discrepancies resolved by consensus with a third expert reviewer. Reviewers of raw EEG data were blinded to ENCEVIS outputs, whereas reviewers assessing ENCEVIS annotations were blinded to video-EEG findings. Human expert annotations were subsequently compared with ENCEVIS detections.

ENCEVIS applies a multimodal detection framework. EEG data are first subjected to automated preprocessing and artifact reduction. Features including rhythmic activity, amplitude, muscle artifact, and cardiac-related signals (e.g., ictal tachycardia) are then extracted. These features are analyzed across time and presented in the "Trends and Seizures" output module, from which all algorithm detections were extracted [6].

Seizure detections were classified as true positives (TP) when an ENCEVIS annotation occurred within a window from 30 seconds before electrographic onset to 60 seconds after seizure termination. False negatives (FN) were defined as expert-confirmed seizures not detected by ENCEVIS, whereas false positives (FP) referred to algorithm detections not corresponding to verified seizure activity. Sensitivity was computed as TP / (TP + FN).

To examine variability in detection performance, seizures were stratified by anatomical localization (temporal, frontal, generalized, and parietal/occipital), rhythmicity (rhythmic vs. arrhythmic), and duration (seconds). Seizure rhythmicity was determined by visual inspection. Rhythmic patterns included seizures characterized by rhythmic theta, delta, alpha, sharp-wave, or spike–wave activity, whereas arrhythmic patterns included fast activity, EEG attenuation, or artifact-dominated segments without observable rhythmic organization.

Multivariate logistic regression was applied to identify independent predictors of seizure detection. The model incorporated seizure duration, rhythmicity, and localization as covariates.

Interaction terms—**rhythmicity × duration** and **localization × rhythmicity**—were also evaluated. Statistical significance was defined as $p < 0.05$.

Result: During the study period, 868 EEG recordings were collected. After applying predefined inclusion and exclusion criteria, 267 recordings were included in the final analysis. The final cohort comprised 140 females and 127 males, with a median age of 27 years (range: 2–75 years). The median EEG recording duration was 12.0 hours (mean: 10.9 ± 8.3 hours).

Clinical events were observed in 54 patients (20.2%). Among these, 43 patients (16.1%) experienced at least one clinical epileptic seizure, while 11 patients (4.1%) had non-epileptic events. Notably, two patients had both epileptic and non-epileptic episodes.

A total of 114 seizures were recorded, of which 65 were correctly identified by the ENCEVIS detection algorithm, corresponding to an overall detection rate of 57.0% ($p > 0.05$). Detection sensitivity per recording ranged from 0% to 100%.

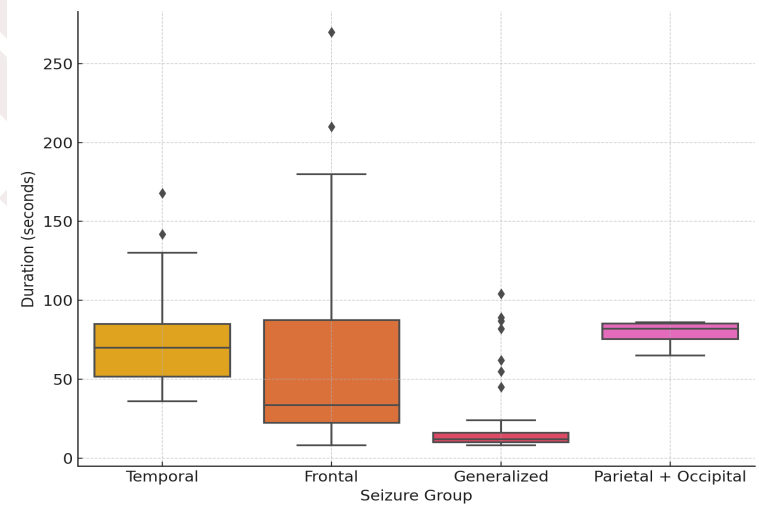
Temporal lobe seizures had the highest detection rate at 71.0%, which was statistically significant ($p < 0.05$). Generalized seizures had the lowest detection rate at 35.1%. Frontal seizures demonstrated moderate detection performance. Parietal and occipital seizures showed promising detection trends but lacked statistical significance due to small sample sizes (Table 1).

Table 1. Seizure Sensitivity by Localization

Region	Sensitivity (%)	True Positives	False Negatives	P-Value
Frontal	52.4	22	20	1.0
Temporal	71.0	22	9	0.0289
Generalized	35.1	13	24	0.0167
Parietal/Occipital	75.0	3	1	0.6874

Seizure durations varied across regions. Frontal seizures showed high variability, with some exceeding 250 seconds. Temporal seizures showed moderate durations, aligning with higher detection rates. Generalized tonic seizures were the shortest (approximately 10–20 seconds), correlating with lower detection rates. Parietal and occipital seizures were relatively consistent in duration, ranging from 75 to 85 seconds (Figure 1).

Figure 1: Seizure Duration by Onset



A sliding-window analysis (20-second window, 10-second step) was used to assess the relationship between seizure duration and detection sensitivity. A statistically significant peak in sensitivity was found within the 38–68 second duration range ($p < 0.05$). Seizures shorter than 20 seconds or longer than 180 seconds had reduced detection sensitivity (Figure 2).

Figure 2. Seizure duration and detection sensitivity

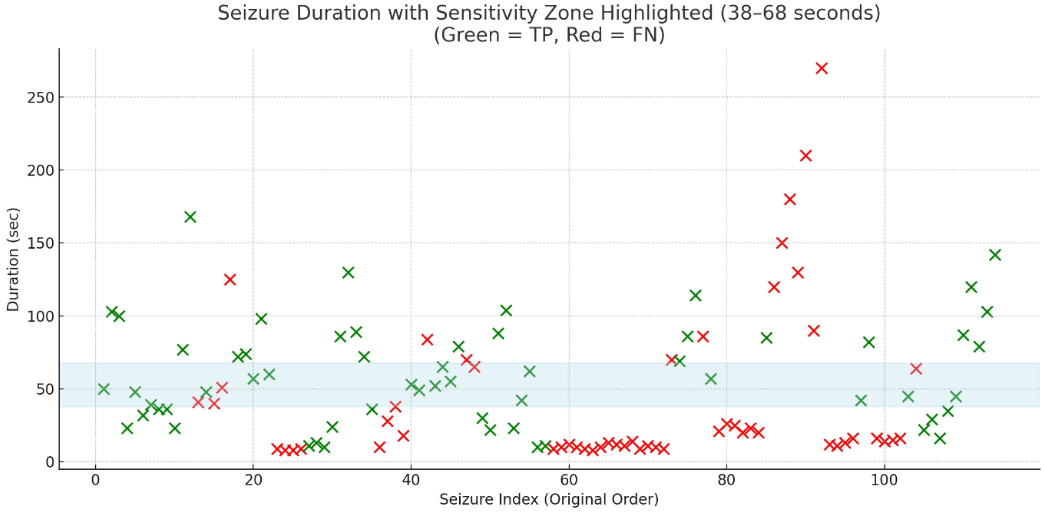
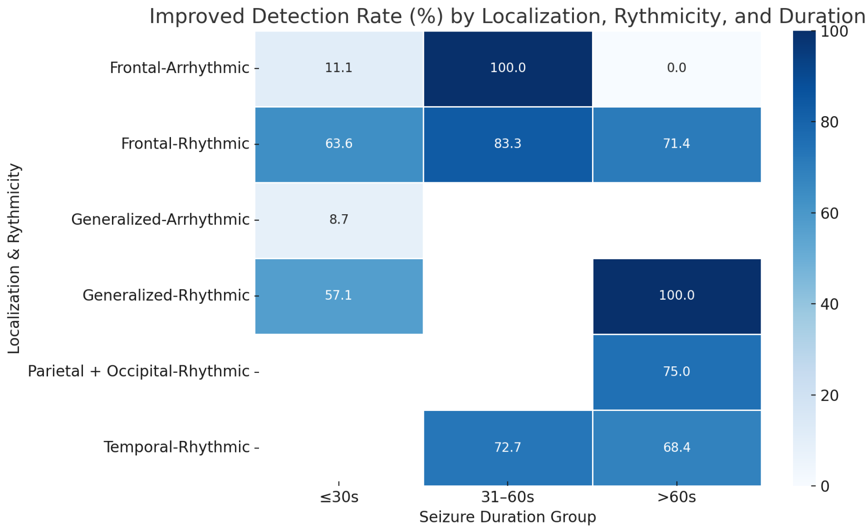


Figure 2 - Seizures that were correctly identified by the ENCEVIS algorithm (true positives) are shown in green, while undetected seizures (false negatives) are in red. The shaded light blue region (38–68 seconds) denotes the seizure duration range where detection sensitivity was significantly higher ($p < 0.05$). This range corresponds to the optimal duration interval for algorithmic detection in the current dataset.

Seizure rhythmicity had a strong, statistically significant factor for true positive detection. Rhythmic seizures showed a detection rate of 71.4% (50 true positives, 20 false negatives), while arrhythmic seizures had a detection rate of 22.7% (10 true positives, 34 false negatives). The difference between rhythmic and arrhythmic seizure detection was significant ($p < 0.0001$).

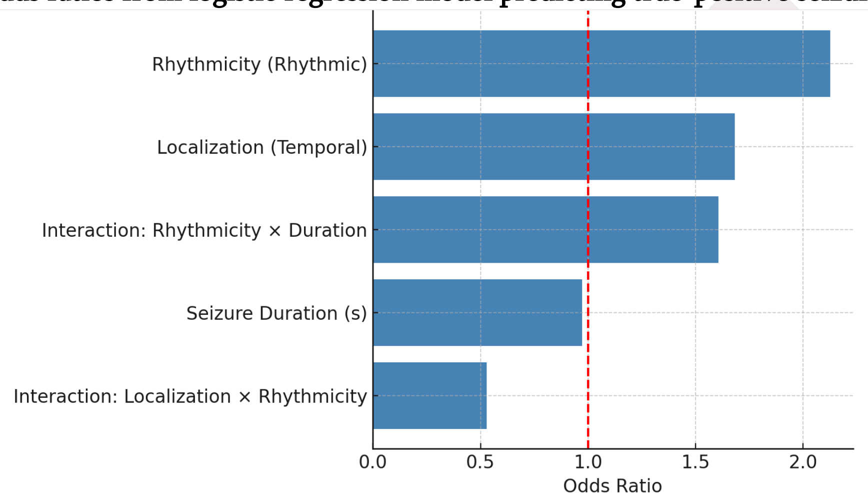
Stratified analysis showed substantial variation in detection based on seizure characteristics. Arrhythmic, short-duration seizures, especially those with frontal or generalized localization, had poor detection rates. For example, arrhythmic tonic seizures lasting 30 seconds or less had a detection rate of only 11.1% (n = 9), while rhythmic frontal seizures lasting 31–60 seconds achieved an 83.3% detection rate (n = 6). Temporal seizures had consistently higher detection rates, particularly when rhythmic (Figure 3).

Figure 3: Heatmap of detection rate (%) by seizure localization, rhythmicity, and duration (N ≥ 3 included)



A logistic regression model was used to identify independent predictors of true-positive seizure detection. Rhythmicity was the strongest predictor, with rhythmic seizures being more than twice as likely to be detected (OR = 2.13). A positive interaction between rhythmicity and duration was also observed (OR = 1.61), indicating that longer rhythmic seizures were more likely to be detected. Temporal localization showed a mild, non-significant increase in detection probability (OR = 1.68). Seizure duration alone had a minimal negative effect (OR = 0.97), and the interaction between localization and rhythmicity was not a significant predictor (Figure 4).

Figure 4: Odds ratios from logistic regression model predicting true-positive seizure detection



Discussion: In this study, we assessed the performance of the ENCEVIS automated seizure detection system across a heterogeneous cohort of EEG recordings, focusing on the influence of seizure localization, duration, and rhythmicity. Our findings demonstrate that seizure rhythmicity and duration exert a significant and synergistic effect on detection sensitivity, with implications for optimizing algorithm design and deployment in clinical practice.

Rhythmicity emerged as the strongest predictor of detection performance. Rhythmic seizures were detected with significantly greater sensitivity than arrhythmic seizures (71.4% vs. 22.7%, $p < 0.05$), and multivariate analysis confirmed rhythmicity as an independent predictor of true-positive detection. Furthermore, a positive interaction between rhythmicity and seizure duration was observed, indicating that longer rhythmic seizures are detected especially well. These findings support previous observations [7,8].

Seizure duration alone was only a weak predictor of detection in multivariate models. However, a duration window of 38–68 seconds was associated with significantly increased detection rates. Seizures shorter than 20 seconds and longer than 180 seconds were less reliably detected. Notably, the combination of intermediate duration and rhythmicity resulted in the highest detection rate, emphasizing the importance of modeling seizure features in combination rather than isolation.

Seizure localization significantly affected detection performance. Temporal lobe seizures demonstrated the highest sensitivity (71.0%, $p < 0.05$), whereas generalized seizures exhibited the lowest (35.1%). Frontal seizures showed intermediate sensitivity without a significant difference from the overall mean. Although parietal and occipital seizures displayed favorable detection trends, the small sample sizes in these groups preclude definitive interpretation. These findings align with previous reports demonstrating higher detection rates for focal rhythmic ictal discharges originating from the temporal lobe compared with generalized arrhythmic ictal patterns [7,8,9].

The stratified analysis underscored substantial heterogeneity in detection rates across seizure subtypes. Arrhythmic and short-duration seizures were particularly challenging to detect, especially in frontal and generalized onset. For instance, arrhythmic frontal seizures lasting ≤30 seconds were detected in only 11.1% of cases, whereas rhythmic seizures in the same region and lasting 31–60 seconds reached 83.3% sensitivity. These findings highlight potential detection weaknesses that may have clinical significance, particularly in patients with less stereotypical seizure patterns.

While temporal localization and seizure duration were not significant predictors on their own, their interaction with rhythmicity influenced detection likelihood. This suggests that multifactorial approaches to algorithm design—accounting for rhythmicity, duration, and localization together—may be more effective than models relying on single-feature detection thresholds.

This study has several limitations. The relatively small number of seizures in certain subgroups, particularly parietal and occipital localizations, limited our ability to draw statistically robust conclusions for these regions. Clinical annotations served as the reference standard, which may be subject to inter-rater variability despite standardized review.

Conclusion: Our findings demonstrate that seizure detection by the ENCEVIS algorithm is significantly influenced by seizure rhythmicity, duration, and localization. Rhythmic and moderately long seizures with temporal localization are detected with the highest sensitivity. In contrast, arrhythmic, short, and generalized seizures are detected less reliably, representing a key limitation. These results highlight the importance of integrating multidimensional seizure characteristics into future algorithm development. Enhancing detection performance for underrepresented seizure types will be essential for AI Seizure detection model implementation in clinical practice.

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ALEKSANDRE TSERETELI [1,2], TAMAR SAKVARELIDZE [2], TAMTA CHILACHAVA [2], NIKOLOZ MALASHKHIA [2], NATELA OKUJAVA [1,2]

AI-BASED ALGORITHM ENCEVIS PERFORMANCE IN THE EPILEPSY MONITORING UNIT: A MULTIFACTORIAL ANALYSIS

[1]Tbilisi State Medical University (TSMU); [2]S. Khechinashvili University Hospital (SKUH); Tbilisi, Georgia

SUMMARY

Objective: To evaluate the performance of the ENCEVIS AI-based seizure detection algorithm in long-term EEG recordings and to identify seizure characteristics - specifically localization, rhythmicity, and duration - that influence detection sensitivity.

Methods: This prospective study included 267 prolonged EEG recordings (>3 hours) collected from 2019 to 2023 at Khechinashvili University Hospital. Seizures were visually evaluated by experts, and onset zone, rhythmicity, and duration were defined. ENCEVIS detections were considered true positives if they occurred within 30 seconds before to 60 seconds after expert-defined seizure boundaries. Detection sensitivity was calculated and analyzed using multivariate logistic regression with interaction terms for rhythmicity × duration and localization × rhythmicity.

Results: A total of 114 seizures were identified, of which 65 were correctly detected by ENCEVIS (overall sensitivity: 57.0%). Temporal lobe seizures were detected with the highest sensitivity (71.0%, $p < 0.05$), while generalized tonic seizures showed the lowest (35.1%). Rhythmic seizures had significantly better detection than arrhythmic seizures (71.4% vs. 22.7%, $p < 0.0001$). Peak sensitivity was observed for seizures lasting 38–68 seconds. In logistic regression, rhythmicity was the strongest independent predictor of detection (OR = 2.13), with a positive interaction observed between rhythmicity and seizure duration (OR = 1.61). Duration alone and localization alone showed limited predictive value.

Significance: Seizure detection by ENCEVIS is primarily driven by rhythmicity and moderately long duration, particularly in temporal lobe seizures. Arrhythmic, short, and generalized tonic seizures remain underdetected, underscoring the need for algorithmic refinement. Enhancing detection performance for underrepresented seizure types will be essential for AI seizure detection model implementation in clinical practice.

Keywords: EEG, Automated seizure detection, Seizure duration, Seizure localization, AI