Epilepsy & Behavior Reports 26 (2024) 100656

Contents lists available at ScienceDirect

Epilepsy & Behavior Reports

journal homepage: www.elsevier.com/locate/ebcr

The ENCEVIS algorithm in the EMU and the factors affecting its performance: Our experience

Aleksandre Tsereteli [a,*,1], Natela Okujava [a,b], Nikoloz Malashkhia [a], Konstantine Liluashvili [c], Al de Weerd [d]

[a] Epilepsy and Sleep Centre, S. Khechinashvili University Hospital (SKUH), Georgia
[b] Department of Clinical Neurology, Tbilisi State Medical University (TSMU), Georgia
[c] Department of Internal Medicine, Tbilisi State Medical University (TSMU), Georgia
[d] Stichting Epilepsie Instellingen Nederland (SEIN), Zwolle, Netherland

ARTICLE INFO

Keywords:
Automatic seizure detection
Long term video EEG monitoring
Epilepsy
Seizure

ABSTRACT

The study's purpose was to assess the seizure detection performance of ENCEVIS 1.7, identify factors that may influence algorithm performance, and explore its potential for implementation and application in long-term video EEG monitoring units. The study included video-EEG recordings containing at least one epileptic seizure. Forty-three recordings, encompassing 112 seizures, were included in the analysis. True positive, false negative, and false positive seizure detections were defined. Factors that may influence algorithm performance were studied. ENCEVIS demonstrated an overall sensitivity of 71.2%, significantly higher (75.1%) in focal compared to generalized seizures (62%). Ictal patterns rhythmicity (rhythmic 59.4 %, arrhythmic 41.7 %), seizure duration (<10 sec 6.3 %, >60 sec. 63.9 % ($p < 0.05$)) and patient age (<18 years 39.5 %, >18 years 58.1 % ($P < 0.05$)) influenced ENCEVIS sensitivity. The coexistence of extracerebral signal changes did not influence sensitivity. ENCEVIS with 79.1% accuracy annotates at least one seizure in those recordings containing epileptic seizures. ENCEVIS seizure detection performance was reasonable for generalized/focal to bilateral tonic-clonic seizures and seizures with temporal lobe onset. Rhythmic ictal patterns, longer seizure duration, and adult age positively influenced algorithm performance. ENCEVIS can be a valuable tool for identifying recordings containing seizures and can potentially reduce the workload of neurophysiologists.

1. Introduction

The diagnosis of epilepsy is primarily based on the patient's medical history and the clinical presentation of seizures. Long-term monitoring (LTM) is the most effective method for detecting seizures in patients with epilepsy. This involves recording video-electroencephalography (vEEG) for an extended duration, usually ranging from several hours to 1–2 weeks. Long-term EEG is commonly used to capture epileptic seizures, diagnose epilepsy and its syndromes, differentiate epilepsy from other conditions, and perform presurgical evaluation [1,2].

Long-term video-electroencephalogram (vEEG) recordings generate vast data that requires EEG experts to assess it visually. This process is both time-consuming and expensive. Automatic seizure detection (ASD) and automatic detection of interictal epileptiform patterns have been long-standing interests in epilepsy departments, particularly those centres involved in epilepsy surgery. Over the past three decades, several ASD algorithms have been developed to assist in generating reviews of long-term EEG data. To implement ASD in epilepsy monitoring units (EMUs) during long-term EEG monitoring, a reasonably high sensitivity (i.e., high seizure-detection rate), high specificity (i.e., low false alarm rate), and short detection delays are required [3,4]. Although several studies have demonstrated the high sensitivity and specificity of various ASD algorithms, they often contain only a small number of patients or cannot be replicated [3,5,6].

There are a number of automatic seizure detection systems based on scalp EEG available. One such system is the ENCEVIS system, which was developed by the Austrian Institute of Technology (AIT) [7]. Promising results were obtained from studies conducted in the EMU. According to a study by Koren et al., commercially available seizure-detection software packages showed similar and reasonable sensitivities when using the

* Corresponding author at: 0186 Ana Politkovskaia st. 12 a., App. 99, Tbilisi, Georgia.
E-mail address: tseretelialex@gmail.com (A. Tsereteli).
[1] S. Khechinashvili University Hospital, Tbilisi, Georgia.

https://doi.org/10.1016/j.ebr.2024.100656
Received 27 December 2023; Received in revised form 26 February 2024; Accepted 3 March 2024
Available online 5 March 2024

same data set. In this study three algorithms were compared to each other Besa 2.0, Persyst 13 and ENCEVIS 1.7. Besa showed a mean sensitivity of 67.6 %, mean false alarm rate (FAR) of 0.7/h. Encevis had a mean sensitivity 77.8 % FAR of 0.2/h. Persyst showed a sensitivity of 81 %, FAR of 0.9/h. Thus, ENCEVIS 1.7 had slightly lower sensitivity but the highest specificity [8]. In the study by Reus et al. same algorithms were compared. Sensitivity for the combination of live monitoring and seizure detection by Persyst was 93 %, by ENCEVIS 88 %, and by BESA 84 %. False positive rate for Persyst was 1.7 per 24 h, for ENCEVIS 5.5 per 24 h and for BESA 2.4 per 24 h. In this study Persyst showed slightly better performance [9].

2. Aim

This study aimed to evaluate ENCEVIS 1.7′s seizure detection performance, identify factors influencing algorithm performance, and explore its potential for use in long-term video EEG monitoring units (EMU).

3. Study design

This study compared the accuracy of seizure detection between ENCEVIS version 1.7 and classical visual EEG analysis. The study was carried out at the SEIN-SKUH Epilepsy and Sleep Centre, S. Khechinashvili University Hospital (SKUH), in Tbilisi, Georgia. The SKUH Ethics Review Board approved the study protocol, and the inclusion of participants required informed consent either from the patient or their caregiver.

4. Methods

In the initial assessment, all EEG recordings that were recorded between 2018 and 2021 at the SEIN-SKUH Epilepsy and Sleep Centre, and were longer than 4 h, were included. The study focused on patients who underwent vEEG for paroxysmal event classification and seizure localization. Patients who required treatment in the intensive care unit were excluded from the study. The ages of the patients ranged from 4 to 67 years. The study selected recordings that included at least one electroclinical epileptic seizure, which was identified by gold standard analysis. However, recordings of patients with non-epileptic paroxysmal events such as psychogenic non-epileptic events, syncope, and parasomnia were not included. Additionally, only electroclinical seizures lasting more than 5 s were considered for the final analysis.

Micromed EEG system (System PLUS Evolution 1.04.215, Micromed S.p.A., Veneto, Italy) was used to record EEG. The sampling rate was set at 1024 Hz. A total of 25 electrodes were placed following the International 10–10 system, with additional inferior temporal electrodes (F9, F10, FT11, FT12, T9, T10). Polygraphic electrodes, including EOG, chin EMG, and ECG were also utilized. ENCEVIS, a seizure detection system, was running online with the Video-EEG monitoring (VEM) process.

ENCEVIS employs a multimodal approach to seizure detection. The data undergoes initial automatic pre-processing and artifact reduction before being sent to modules where EEG features are calculated and specific patterns are identified. Rhythmic patterns are detected, amplitude values are extracted, and features that help detect vigorous muscle activity and ictal tachycardia are calculated. All these extracted features were compared to a baseline and combined to achieve final seizure detection (as shown in Fig. 1). [7,10].

ENCEVIS 1.7 was running online with video-EEG monitoring. The recordings were copied into two separate databases without any processing. Later, two independent EEG experts performed a visual analysis and assessment of ENCEVIS. The experts who analyzed the EEG data did not have access to ENCEVIS annotations. On the other hand, the experts who assessed the detection results of the seizure-detection software were blind to the video-EEG reports of visual analysis. All experts involved in the study had over ten years of experience in epileptology and were certified as clinical neurophysiologists by the Ministry of Health in Georgia.

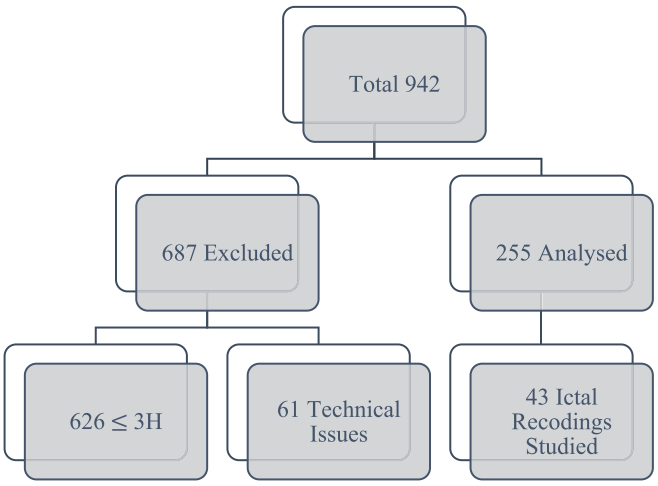

Fig. 1. Chart Flow: EEG Recordings Included in the Study.

EEG experts used the first observable electrographic change of clinical seizures to determine the onset of seizures for study purposes. Seizures without electrical signal changes were excluded. The experts identified markers for seizure onset and termination, which were extracted for each seizure in all patients. These markers were accepted as the reference standard, and annotations made by ENCEVIS 1.7 were compared to them.

During the evaluation of ENCEVIS performance, a seizure detection was considered true positive (TP) if it was detected by ENCEVIS within 30 s before the seizure onset and 60 s after the seizure termination. False negatives (FN) were identified when the experts detected seizures, but ENCEVIS missed them. False positives (FPs) were identified when ENCEVIS incorrectly annotated EEG as seizures. The sensitivity was calculated as the TP/(TP + FN) ratio, and the specificity was measured as the number of false positives per hour (FP/h).

In order to identify factors that might influence the algorithm's performance, we compared seizure detection according to several characteristics, including seizure duration, seizure onset zone, rhythmicity, and extracerebral signal changes (surface EMG and ECG signals).

We also studied ENCEVIS seizure detection sensitivity per recording, calculated for each recording separately, including all seizures of this individual patient.

In this study, we focused on recordings that captured at least one electroclinical seizure, as they are crucial for diagnosing epilepsy and its syndrome. To determine whether ENCEVIS has potential as a screening tool for seizure detection, we compared the number of recordings marked by EEG experts as containing seizures and those annotated by ENCEVIS. In this case, correct ENCEVIS annotations of at least one epileptic seizure were considered a positive finding.

5. Statistical analysis

The statistical analysis, which was performed using the standard SPSS 27 software, involved calculating the mean values and standard deviations (mean ± SD) of the variables for the patients in the study group. To compare the values of parametric variables and independent variable data between different patient groups, one- or two-sample t-tests were used. The tests were performed with a 95 % confidence interval.

One-way Analysis of Variance (ANOVA) was employed to evaluate the differences in the distribution of parametric indicators based on various criteria. These criteria included the types of seizures (generalized vs. focal with different localisations), other EEG indicators detected

or calculated by ENCEVIS and visual analysis, and the indicators of test sensitivity (True Positive or False Negative).

Furthermore, analysis of covariance was utilized to evaluate changes in seizure detection rates according to seizure duration (<10 s, 11–60 s, >60 s). The differences between calculated values were considered reliable if the statistical confidence coefficient p was less than 0.05 with a 95 % confidence interval.

6. Results

A total of 942 vEEGs were recorded during the study period using the ENCEVIS system. After applying inclusion and exclusion criteria (e.g., technical problems, duration shorter than four hours), 255 recordings were selected for the primary assessment. The mean duration was 11.06 h (ranging from 4 to 48 h), resulting in a total 2690 h of analysed data. Out of the 255 analyzed recordings, 43 contained at least one electro-clinical seizure identified through visual analysis and were included in the study. These 43 recordings accounted for 112 visually documented seizures (Fig. 1).

The characteristics of patients included in the study are shown in Table 1: 19 (44.2 %) were female, 24 (55.8 %) were male, the mean age at VEM was 27.1 years (range 4–67), and the mean duration of the VEMs was 11.06 h (range 4-48 h). During the study, we detected a total of 112 seizures with the help of visual analysis. The median seizure count was 2.6 per recording (range 1–17). Out of these, 76 seizures had a focal onset (average 2.3 per recording), and 36 seizures had a generalized

Table 1
Recordings' characteristics.

N	Age	Sex	Recording Duration (min)	Diagnosis	EpiSE	EpiSV	TP	TP%	FP	FP/h	FN	FN_PR	TP_PR	Etiology
1	27	M	720	FLE	6	3	3	100	3	0.25	0	N	Y	Unknown
2	33	M	720	FLE	6	6	6	100	0	0	0	N	Y	Unknown
3	8	M	1440	EECSWS	48	1	1	100	47	1.95	0	N	Y	Unknown
4	23	F	720	MTLE	7	1	1	100	6	0.5	0	N	Y	Unknown
5	44	M	720	MTLE	2	1	1	100	1	0.08	0	N	Y	HS
6	64	M	240	MTLE	2	6	2	33.33	0	0	4	N	Y	Unknown
7	38	M	720	MTLE	7	3	3	100	4	0.33	0	N	Y	HS
8	34	M	720	FLE	9	5	1	20	8	0.66	4	N	Y	Unknown
9	16	F	1440	LGS	23	4	4	100	19	0.79	0	N	Y	GA
10	27	M	1440	LGS	2	1	1	100	1	0.04	0	N	Y	Unknown
11	22	M	1440	MTLE	41	1	1	100	40	1.67	0	N	Y	HS
12	12	F	1440	JME	13	1	1	100	12	0.5	0	N	Y	Unknown
13	58	M	1440	MTLE	3	2	2	100	1	0.04	0	N	Y	HS
14	24	M	1440	LGS	1	1	0	0	0	0	1	Y	N	Unknown
15	40	M	1440	FLE	0	3	0	0	0	0	3	Y	N	FCD
16	47	M	1440	FLE	7	3	2	66.66	4	0.17	1	N	Y	FCD
17	39	M	240	MTLE	1	1	1	100	0	0	0	N	Y	HS
18	44	F	720	PLE	2	1	1	100	1	0.08	0	N	Y	HI
19	21	F	720	EWEM	1	1	1	100	0	0	0	N	Y	GA
20	72	F	1440	MTLE	3	3	1	33.33	2	0.08	2	N	Y	GT
21	15	F	720	FLE	8	3	3	100	5	0.42	0	N	Y	Unknown
22	32	M	720	JAE	1	1	1	100	0	0	0	N	Y	Unknown
23	35	M	720	FLE	10	1	1	100	9	0.75	0	N	Y	Unknown
24	4	M	240	ACECTS	1	1	1	100	0	0	0	N	Y	Unknown
25	24	F	720	JME	6	1	1	100	5	0.42	0	N	Y	GA
26	5	F	1440	LGS	10	17	2	11.76	8	0.33	15	N	Y	HI
27	35	F	720	MTLE	4	1	0	0	4	0.33	1	Y	N	Unknown
28	20	M	1440	MTLE	3	3	3	100	0	0	0	N	Y	HS
29	28	M	720	OLE	3	1	0	0	3	0.25	1	Y	N	Unknown
30	48	F	720	MTLE	1	1	1	100	0	0	0	N	Y	HS
31	22	F	240	FLE	1	6	0	0	1	0.33	6	Y	N	Unknown
32	7	M	1440	PLE	9	1	1	100	8	0.33	0	N	Y	TBI
33	18	F	1440	LGS	6	7	0	0	6	0.25	7	Y	N	not Established
34	10	F	1440	LGS	10	4	0	0	10	0.42	4	Y	N	LIS
35	30	F	720	MTLE	6	1	1	100	5	0.42	0	N	Y	Unknown
36	16	M	1440	JAE	7	1	1	100	6	0.25	0	N	Y	GA
37	2	M	1440	LGS	52	4	0	0	52	2.2	4	Y	N	Unknown
38	5	M	720	FLE	10	1	1	100	9	0.75	0	N	Y	Unknown
39	28	M	240	MTLE	3	1	0	0	2	0.67	1	Y	N	DNET
40	48	M	720	FLE	5	5	5	100	0	0	0	N	Y	Unknown
41	18	F	720	EGTCSA	1	1	1	100	0	0	0	N	Y	GA
42	3	F	720	FLE	2	1	1	100	1	0.08	0	N	Y	Unknown
43	24	M	240	OLE	1	1	1	100	0	0	0	N	Y	Unknown

Note. Diagnosis: EWEM = Epilepsy with Eyelid Myoclonia, LGS = Lennox-Gastaut Syndrome, ACECTS = Atypical Childhood Epilepsy with Centrotemporal Spikes, EECSWS = Epileptic Encephalopathy with Continuous Spike-Wave during Slow-Wave Sleep, JAE = Juvenile Absence Epilepsy, JME = Juvenile Myoclonic Epilepsy, EGTCSA = Epilepsy with Generalised Tonic-Clonic Seizures Alone, FLE = Frontal Lobe Epilepsy, PLE = Parietal Lobe Epilepsy, OLE = Occipital Lobe Epilepsy, MTLE = Medial Temporal Lobe Epilepsy, EpiS = Number of Identified Epileptic Seizures Detected by ENCEVIS calculated as the product of the number of visually identified seizures (E) and the number of recordings (V), Diagnosis epilepsy overall per recording: TP-PR = True Positive Per Recordings (marked by ENCEVIS as recording containing Seizures), FN-PR False negative Per Recordings (marked by ENCEVIS as recording containing Seizures), TP%= Percentage of all visually seen seizures, detected by ENCEVIS.

Aetiology: GA = Gene Abnormality, FCD = Focal Cortical Dysplasia, LIS = Lissencephaly, HS = Hippocampal Sclerosis, HI = Hypoxic-Ischemic, TBI = Traumatic Brain Injury, DNET = Dysembryoplastic Neuroepithelial Tumour, GT = Glial Tumours, Unknown.

Example: Patient 8 in Table 1 had 5 visually detected seizures and 9 seizures detected by ENCEVIS. Only one of those seizures was detected both visually and by ENCEVIS at the same time. This is the true positive (TP). The interpretation is as follows: TP = 1, False positive (FP) = 8 and False Negative (FN) = 4 and sensitivity (TP / (TP + FN) = 1/ (1 + 4) = 20 %).

onset (average 3.4 per recording), as shown in Table 1.

In the study population, the distribution of epilepsy based on seizure onset was as follows: 30 patients (69.7 %) had focal epilepsy, out of which 12 (27.9 %) had frontal lobe epilepsy (FLE), 14 (32.55 %) had temporal lobe epilepsy (TLE), and 4 (9.3 %) had parietal/occipital lobe epilepsy (P/OLE). Additionally, 13 patients (30.25 %) had generalized epilepsy syndromes. MRI scans were performed on 37 patients (86 %), out of which 15 (34.8 %) had MRI-documented structural changes in the brain. Among these 15 patients, 13 had focal epilepsy, and two had generalized epilepsy (as shown in Table 1).

6.1. ENCEVIS performance analysis per recording

ENCEVIS true positive seizure detections per recording varied from 0 % to 100 %, with a mean of 71.2 %. For focal epileptic seizures, the average sensitivity was 75.1 % (frontal lobe onset – 73.8 %, temporal lobe onset – 76.2 %, and occipital/parietal lobe onset – 75 %). The mean sensitivity in the generalized seizure onset subgroup was 62 % (as shown in Table 2). The patients in the study who had generalized epilepsy were quite diverse, covering nearly all seizure types with generalized onset, including absences, tonic, and GTCS. The sensitivity in detecting these seizures varied based on the seizure type. The sensitivity was highest (100 %) for generalised tonic-clonic seizures (GTCS), while it was lowest (18.4 %) for brief, subtle tonic seizures in patients with Lennox-Gastaut Syndrome (LGS). In our opinion, the overall lower sensitivity in the detection of generalized epileptic seizures could be attributed to this variability in sensitivity.

ENCEVIS had a mean false positive (FP) detection rate of 6.3 per recording. The mean false negative (FN) detection rate was 1.4 per recording. The rate of false positive detections per hour varied from 0/hour to 2.2/hour, with a mean of 0.35/hour (0.35 ± 0.50).

ENCEVIS was tested as a screening tool to identify those recordings that contained at least one electroclinical seizure. Results showed that ENCEVIS accurately identified at least one seizure in 34 out of 43 recordings, or 79.1 % of the time. Moreover, ENCEVIS did not make any FP or FN annotations in one of the recordings.

6.2. ENCEVIS performance analysis per seizure

6.2.1. Descriptive analysis

The total number of seizures detected by ENCEVIS was 344, while the gold standard visual analysis identified 112 electroclinical seizures. Out of the 112 visually detected seizures, ENCEVIS correctly marked 58 of them, resulting in a true positive (TP) detection rate of 51.8 %.

The comparison of the seizure detection rates between ENCEVIS and visual analysis overall (as shown in Table 2) demonstrated that the mean rate of events annotated as a seizure by ENCEVIS was 8.0 seizures per recording. Specifically, the mean rate for generalized seizures was 10.2 per recording, while for focal seizures, it was 7.1 per recording. On the other hand, the mean rate of visually marked seizures was 2.6 per recording, with 3.4 for generalized seizures and 2.3 for focal seizures.

In the analysis of children and adolescents (age < 18 years), the TP detection rate for individual seizures was 39.5 %. For adults (age > 18 years), the TP detection rate was higher at 58.1 %, with significantly higher detection in adults $P < 0.05$.

6.2.2. Influence of seizure duration on the ENCEVIS

Our study revealed a positive correlation between ENCEVIS sensitivity and seizure duration. The total number of seizures analyzed was 112, with a TP detection rate of 51.8 % and a FN rate of 48.2 %. For short seizures lasting below 10 s, the sensitivity was 6.3 %; for seizures ranging from 10 to 60 s, the sensitivity was 55.7 %; seizures longer than 60 s had the highest sensitivity at 63.9 % ($p < 0.005$). Thus, detection performance by ENCEVIS improved as the seizure duration increased. (as shown in Table 3).

6.2.3. Influence of seizure onset zone on the ENCEVIS

Localization of the epileptogenic zone is indeed a crucial aspect of epilepsy diagnosis. In our analysis, we compared ENCEVIS detection sensitivity based on the localization of seizure onset (as presented in Table 4). The sensitivity for seizures with frontal lobe onset was 53.5 %. The sensitivity for seizures with parietal/occipital lobe onset was 75 %, although this result is based on a small sample size of only four seizures, making it less reliable and insignificant. For seizures with temporal lobe onset, the sensitivity was 69 %, and for seizures with generalized onset, the sensitivity was lower at 33.3 %.

The comparison of the true positive (TP) and false negative (FN) rates demonstrated that seizures of temporal lobe onset was statistically reliable with a p-value of less than 0.005 ($p < 0.005$). That suggests that ENCEVIS demonstrated more consistent and accurate performance in detecting temporal lobe seizures than seizures from other localization.

6.2.4. Influence of ictal EEG patterns and extracerebral activity on the ENCEVIS sensitivity

In our analysis, we categorized the ictal EEG patterns into two groups based on visual observation: a) rhythmic patterns and b) arrhythmic patterns. Rhythmic patterns included seizures with rhythmic theta, delta, alpha activity, sharp wave, and spike-wave rhythmic patterns. On the other hand, arrhythmic patterns included seizures where

Table 2
ENCEVIS Performance vs. Gold Standard.

		All recordings	Generalised seizure onset	Focal seizure onset
Number of the patients with detected seizures	*N*	43	13	30
	%	100	30.2	69.8
Seizure detected by ENCEVIS	*Mean*	8.0	10.2	7.1
		8.05 ± 11.9	10.2 ± 13.5	7.1 ± 10.7
Seizure detected by GOLD STANDARD	*Mean*	2.6	3.4	2.3
		2.6 ± 2.86	3.4 ± 4.3	2.3 ± 1.7
ENCEVIS False Positive seizure detection	*Mean*	6.63	9.1	6.5
		6.63 ± 11.99	9.1 ± 13	5.5 ± 10.8
ENCEVIS False Negative seizure detection	*Mean*	1.25	2.4	0.8
		1.25 ± 2.78	2.4 ± 4.2	0.8 ± 1.5
ENCEVIS True positives seizure detection	*Mean*	1.34	1	1.5
		1.34 ± 1.3	1 ± 1.03	1.5 ± 1.38

Table 3
Influence of Seizure Duration on the ENCEVIS per Seizure Sensitivity.

Seizure Duration		True Positive	False Negative
Number of Ictal Events analyzed	*n*	58	54
	%	51.8 ± 50.2	48.2 ± 50.2
Seizure duration in seconds (sec)	*mean*	58.2 ± 33.9	44.1 ± 56.6
	median	52.5	16
	min	10	8
	max	168	270
Onset of ≤ 10sec duration Seizures	*n*	1	12
	%	6.3 ± 25.0	93.7 ± 25.0
Onset of 11-60sec duration Seizures	*n*	34	27
	%	55.7 ± 50.1	44.3 ± 50.1
Onset of > 60sec duration Seizures	*n*	23	12
	%	63.9 ± 48.7	36.1 ± 48.7
Correlation with Seizure duration	*Pearson's coeff.*	0.152	−0.152

Table 4
Influence of Seizure Onset Zone on the ENCEVIS per Seizure Sensitivity.

Seizure Onset		Total	ENCEVIS True Positive	ENCEVIS False Negative
Total	*n*	112	58	54
	%	100	51.8 ± 50.2	48.2 ± 50.2
Frontal Lobe	*n*	43	23	20
	%	38.39	53.5 ± 50.4	46.5 ± 50.2
Parietal/Occipital	*n*	4	3	1
Lobe	%	3.57	75 ± 46.3	25 ± 46.3
Temporal Lobe	*n*	29	20	9
	%	25.89	69 ± 47.1	31 + 47.1
Generalised	*n*	36	12	24
	%	32.15	33.3 ± 47.81	66.7 + 47.81

rhythmicity was not observed (focal or generalized fast activity, EEG attenuation, or high amplitude muscle artifacts with only marginal rhythmic activity) (as presented in Table 5).

According to the study, the ENCEVIS exhibited a detection sensitivity of 59.4 % (P = 0.034) for seizures with rhythmic patterns, whereas for seizures with arrhythmic patterns, the sensitivity was 41.7 % (P = 0.10). These findings indicate that the ENCEVIS was more effective in detecting seizures with well-defined rhythmic patterns than seizures with less distinct or absent rhythmicity.

Our study investigated how extracerebral signal changes affect ENCEVIS seizure detection sensitivity, specifically regarding ECG and EMG (see Table 5).

The study found that with EEG signal changes alone, the sensitivity of ENCEVIS was 52.68 %. In cases where EMG changes were presented alongside EEG changes, the sensitivity increased slightly to 54.7 % (P = 0.56). When ECG changes were presented with EEG changes, the sensitivity improved to 57.7 % (P = 0.31). Interestingly, combining all three signals (EEG, EMG, and ECG) did not significantly improve sensitivity, which remained at 55.3 % (P = 0.52). Therefore, the study suggests that extracerebral signal changes do not significantly affect ENCEVIS sensitivity.

7. Discussion

In our study, we covered a wide range of epilepsy syndromes, providing excellent insight into the sensitivity of ENCEVIS across various forms of epilepsy commonly seen in clinical practice. That is particularly significant because previous studies have mainly focused on adult patients with focal epilepsy. Our findings have shown that ENCEVIS has the potential to be used in epilepsy monitoring units due to its ability to cover a broad spectrum of epileptic seizures.

The seizures were classified into two groups based on the location of the ictal activity. These groups are the generalized seizure onset group and the focal seizure group, which includes patients with temporal lobe epilepsy (TLE), frontal lobe epilepsy (FLE), and parietal/occipital lobe epilepsy (P/OLE). The ENCEVIS had an average sensitivity of 71.2 % per recording, with the highest sensitivity observed for temporal lobe onset seizures (76.2 %). However, the recordings from patients with generalized epilepsy had significantly lower sensitivity (62 %). These findings are consistent with previously published data [8,10].

We have observed a significant variation in ENCEVIS's ability to detect seizures among different recordings. The sensitivity of the algorithm ranges from 0 % to 100 %. To identify the factors affecting the algorithm's performance, we analyzed the sensitivity based on the location of the ictal activity, rhythmicity, duration, and extracerebral signal changes.

Our study found that the sensitivity of ENCEVIS was significantly higher in seizures with rhythmic ictal patterns compared to those with arrhythmic patterns (59.4 % vs. 41.7 %). Additionally, the seizure duration was found to affect the performance of ENCEVIS, with sensitivity increasing with a longer seizure duration. However, the coexistence of extracerebral signal changes had only a minor impact on sensitivity, which is consistent with other studies. Fürbass et al. have also reported similar findings [7,10].

ENCEVIS had the highest sensitivity (100 %) in detecting seizures with generalized tonic-clonic seizures (GTCS) and focal to bilateral tonic-clonic seizures (FB-TCS). The lowest sensitivity (18.4 %) was observed in detecting brief tonic seizures with arrhythmic EEG patterns. Although the sample size was limited, it is noteworthy that brief seizures with arrhythmic patterns, accompanied by significant muscle tone changes and ECG tachycardia, were detected better than those without extracerebral signal changes. The study showed that seizure type could affect the sensitivity of ENCEVIS. Brief tonic seizures and those with extratemporal onset had the lowest seizure detection sensitivity, whereas seizures with temporal lobe onset and GTCS/FB-TCS had significantly higher detection rates. Our study covered only 112 seizures from 43 patients, and the number of specific seizure types was insufficient to allow for statistically significant comparisons. More seizure recordings are required for this comparison. The prevalence of rhythmic seizure patterns and longer seizure durations in temporal lobe seizures could explain the difference in detection rates compared to extratemporal seizures.

The results show that false positives occur at a rate of 0.35 per hour, consistent with previous studies [7,8,9,10]. The background EEG activity may influence the detection of false positives by ENCEVIS. Therefore, additional studies are needed to identify factors affecting the FP detection rate.

Our study found that the ENCEVIS sensitivity was significantly higher in adults (above 18 years) than in children (below 18 years), with a detection rate of 58.1 % and 39.5 %, respectively (P < 0.05). Similar observations were reported by Fürbass et al. An explanation for the difference in seizure detection sensitivity between pediatric and adult populations is that seizures with the lowest detection rates, such as brief generalized tonic seizures and seizures with extratemporal onset, were observed more commonly in the pediatric than in the adult population.

Our study evaluated the effectiveness of ENCEVIS as a screening tool for identifying electroclinical seizures in recordings. Our findings indicate that ENCEVIS made a true positive (TP) annotation of at least one seizure in 79.1 % of recordings that contained seizures. That is a significant result as it suggests that ENCEVIS 1.7 can help neurophysiologists select recordings with epileptic seizures from a large dataset and reduce their workload. However, the current false seizure detection rate of 0.35/h is relatively high, which raises questions about the feasibility of implementing ENCEVIS in long-term EEG monitoring units to reduce the workload of clinical neurophysiologists.

Our research indicates that extracerebral signal changes may not significantly impact the sensitivity of ENCEVIS. However, it is essential to conduct further analysis and research to confirm these results and investigate any potential factors that could affect the algorithm's performance in specific situations.

Future multicentre studies and data sharing initiatives are crucial to

Table 5
Influence of Cerebral Plus Extracerebral Signal Changes on the ENCEVIS Sensitivity.

		Total	True Positive	False Negative
Rhythmic Ictal Pattern	N	64	38	26
	%	57.1	59.4	41.6
Arrhythmic Ictal EEG Pattern	N	48	20	28
	%	42.9	41.7	58.3
EEG + EMG	*N*	64	35	26
	%	100	54.7	45.3
EEG + ECG	*N*	80	46	34
	%	100	57.5	42.5
EEG + EMG + ECG	*N*	56	31	25
	%	100	55.3	44.7

EEG – electroencephalography, EMG – electromyography, ECG – electrocardiography.

establish statistically robust comparisons and identify factors that may impact ENCEVIS performance. Additionally, continued algorithm improvements will facilitate successful clinical implementation.

6. Conclusion

ENCEVIS has the potential to be a valuable tool for neurophysiologists. Our research indicates that the performance of the algorithm is influenced by the rhythmicity of the ictal pattern, seizure duration, seizure onset localization, and patient age. In particular, it has been observed to be highly effective in identifying seizures in adult patients with rhythmic ictal EEG patterns and in cases where the seizures last for more than 60 s.

ENCEVIS can annotate at least one seizure in the ictal EEG recordings with 79.1 % sensitivity making it a valuable tool for automated screening to identify such recordings. This can potentially save time and reduce the workload of neurophysiologists.

Ethical statement

The study was carried out at S. Khechinashvili University Hospital (SKUH), Tbilisi, Georgia and was approved by the ethical committee of ethical board.

Our study processes EEG data of patients, EEGs were included in the study based on informed contest.

CRediT authorship contribution statement

Aleksandre Tsereteli: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Natela Okujava:** Writing – review & editing, Supervision, Formal analysis, Data curation, Conceptualization. **Nikoloz Malashkhia:** Investigation, Formal analysis. **Konstantine Liluashvili:** Formal analysis, Data curation. **Al de Weerd:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

We thank SEIN (Stichting Epilepsie Instellingen Nederland) for its collaborative partnership and support in this study.

Tilmann Kluge from Center for Health & Bioresources, Austrian Institute of Technology GmbH, Vienna, Austria, for his relentless support in solving technical issues during the project.

Author contribution

Authors Aleksandre Tsereteli, Natela Okujava, and Al de Weerd participated in (a) conception and design, analysis, and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

Authors Alerksandre Tsereteli and Nikoloz Malashkia participated in patient inclusion, video-EEG data acquisition, and processing.

Author Konstantine Liluashvili participated in statistical analysis and interpretation of data.

References

[1] Baumgartner C, Pirker S. Video-EEG. Handb Clin Neurol 2019;160:171–83. https://doi.org/10.1016/B978-0-444-64032-1.00011-4.
[2] Rosenow F, Luders H. Presurgical evaluation of epilepsy. Brain 2001;124(Pt 9): 1683–700. https://doi.org/10.1093/brain/124.9.1683.
[3] Baumgartner C, Koren JP, Rothmayer M. Automatic computer-based detection of epileptic seizures. Front Neurol 2018;9:639. https://doi.org/10.3389/fneur.2018.00639.
[4] Beniczky S, Karoly P, Nurse E, Ryvlin P, Cook M. Machine learning and wearable devices of the future. Epilepsia 2021;62(Suppl 2):S116–24. https://doi.org/10.1111/epi.16555.
[5] Da Silva Lourenço C, Tjepkema-Cloostermans MC, van Putten MJAM. Machine learning for detection of interictal epileptiform discharges. Clin Neurophysiol 2021;132(7):1433–43. https://doi.org/10.1016/j.clinph.2021.02.403.
[6] Rubboli G, Beniczky S, Claus S, et al. A European survey on current practices in epilepsy monitoring units and implications for patients' safety. Epilepsy Behav 2015;44:179–84. https://doi.org/10.1016/j.yebeh.2015.02.004.
[7] Fürbass F, Ossenblok P, Hartmann M, Perko H, Skupch AM, Lindinger G, et al. Prospective multi-center study of an automatic online seizure detection system for epilepsy monitoring units. Clin Neurophysiol 2015;126(6):1124–31. https://doi.org/10.1016/j.clinph.2014.09.023.
[8] Koren J, Hafner S, Feigl M, Baumgartner C. Systematic analysis and comparison of commercial seizure-detection software. Epilepsia 2021;62:426–38. https://doi.org/10.1111/epi.16812.
[9] Reus EEM, Visser GH, van Dijk JG, Cox FME. Automated seizure detection in an EMU setting: are software packages ready for implementation? Seizure 2022;96: 13–7. https://doi.org/10.1016/j.seizure.2022.01.009.
[10] Fürbass F, Kampusch S, Kaniusas E, Koren J, Pirker S, Hopfengärtner R, et al. Automatic multimodal detection for long-term seizure documentation in epilepsy. Clin Neurophysiol 2017;128:1466–72. https://doi.org/10.1016/j.clinph.2017.05.013.