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Tagging EEG features within exam reports to quickly generate databases for research purposes

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ABSTRACT

Objective: assess the effectiveness of a new method for classifying EEG recording features through the use of tags within reports. We present feature prevalence in a sample of patients with toxic-metabolic encephalopathy and discuss the advantages of this approach over existing classification systems.
Methods: during EEG report creation, tags reflecting background activity, epileptiform features and periodic discharges were selected according to the findings of each recording. Reports including the tags have been collected and processed by the EEG report parser script written in PHP language. The resulting spreadsheet was analysed to calculate the prevalence and type of EEG features in a sample group of patients with toxic-metabolic encephalopathy.
Results: tag checking and extraction were very little time-consuming processes. Considering 5784 EEG recordings performed either in inpatients or outpatients over 2 years, toxic-metabolic aetiology was tagged in 218 (3.8 %). The most frequent background feature was severe slowing (5–6 Hz frequency), occurring in 79 (36.2 %). Epileptiform abnormalities were rare, reaching a maximum of 10 (4.6 %). Triphasic waves were tagged in 43 (19.7 %) recordings.
Conclusions: tagging and parsing processes are very fast and integrated into the daily routine. Sample analysis in patients with toxic-metabolic encephalopathies showed EEG slowing as the prevalent feature, while triphasic waves occurred in a minority of recordings. Existing software such as "SCORE" (Holberg EEG) requires the replacement of the currently used software for EEG reporting, minimizing additional costs and training. EEG Report Parser is free and open-source software, so it can be freely adopted, modified and redistributed, allowing further improvement and adaptability.

1. Introduction

EEG interpretation is a complex and time-consuming process that cannot be automatized. Reporting physicians write a textual description of EEG findings, but this information is unstructured and difficult to analyse and consequently retrieve. Indeed, functionality and flexibility in data retrieval depend on how they are structured and standardized. Usually, the data concerning EEG interpretations are stored in the non-structured and non-standardized free text within reports, which typically consist of MS Word documents. In the context of teaching hospitals, medical personnel is engaged either in clinical activity as well as research projects and clinical trials, therefore the possibility to store and consequently extract relevant data from many EEG recordings can provide data for research projects and facilitate patient selection for clinical trials. A major need is keeping to a minimum the extra time required to attain data organization during EEG interpretation. In the last 20 years, such need pushed the development of a solution to automatically structure and standardize the EEG interpretation and then

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store the categorized data in a computerized EEG database.

To our knowledge, the first attempt to develop software aiding EEG feature extraction involved a complex system which included the Nervus EEG editor communicating with a "Description Application" and linked to a Microsoft Access database storing the EEG waveforms/activity categories for consequent querying [1]. In the same year, a manuscript describing a system to collect and store EEG description data from multiple laboratories was published [2]. Developed also for teleconsultation purposes, the system was structured to store in a Microsoft Access database 3 sections consisting of an "Introduction" including patient information and montage, "Clinical information" consisting of the diagnosis, type of epilepsy, etc., and "EEG data", where interpretation of EEG background activity, pathological waveforms and seizure classification had to be compiled within a structured database mask and stored. To our knowledge, this software, originally developed in Microsoft Access 97 for Windows 95 within the European multi-centre project PRESTIGE, was no longer updated.

The most recent and currently available software for structured EEG reporting is "SCORE" [3,4]. This is commercially available as a full suite for EEG report generation, designed to replace the traditional free-text description of EEG findings and events. The software is designed to visually identify pathological waveforms on the recording and automatically transfer such information to the report while manually defining the spatial localization. Clinical events occurring during the recording can be also manually marked and inserted into the report. This software has been later called "Holberg EEG" and is being currently provided for both production and educational environments, obtaining international consensus [3–5].

The objective of this study is to assess the effectiveness of "EEG Report Parser", a script that automatically extracts information from EEG reports following pre-defined tags. The tagging process is easy and does not require the replacement of the existing reporting systems. Each EEG is characterized by one or more tags that the script extracts from the saved reports and copies into a database. Structured data can be consequently analysed for clinical and research purposes. This software has been released with a free and open-source software licence (GNU GPL 3) to allow customization, free implementation, improvement, and redistribution in EEG laboratories.

2. Materials and methods

2.1. EEG report parser script description

The EEG Report Parser software has been developed and tested at the Clinical Neurophysiology unit of the "IRCCS Ospedale Policlinico San Martino" teaching hospital in Genova, Italy. EEG acquisition, reviewing and report generation is managed by the Nicolet NicVue Patient Management Software (Natus Medical Incorporated). The report template is written in HTML language and during report generation, it is processed and edited by Microsoft Word, becoming an MHTML (MIME encapsulated aggregate HTML) document [6]. The inclusion of a list of tags (labels) describing EEG features allows a quick selection of those more appropriate tags during report editing. The generated MHTML files are consequently parsed by a custom script written in PHP language, able to extract the tags from each report and sort them in a table in comma-separated value (CSV) format, easily imported by spreadsheet, database and statistical software. The script called "EEG Report Parser" has been published as free and open-source software under a GNU-GPL licence on the version control repository "Gitlab" [7] where it may be freely downloaded. A copy of the commented script and tags to be added to the HTML template are also included as supplementary material to the present manuscript.

2.2. Tagging process

The standard EEG report generated by the NicVue software was modified and a list of tags has been appended to the generated Word document. The tags have been selected based on the standard international terminology [8–10] and divided into 5 groups, focusing on the neurophysiological and clinical findings more commonly observed during clinical practice in our hospital. The first group of tags concerns EEG background description and includes attenuation, suppression, 5–6 Hz or 7–8 Hz prevalent rhythm, absence of the physiological posterior-dominant gradient, right-left asymmetry (either in amplitude or frequency), continuity, reactivity to stimulations or complete absence of activity (brain death). The second group details the possible presence of epileptiform waveforms, differentiating among generalised, focal or multifocal distribution, ictal or interictal occurrence, presence of sharp-and-wave complexes and if the recording is compatible with status epilepticus, non-convulsive status epilepticus or epilepsia partialis continua. The third group encompasses periodic discharges: lateralised (LPD), bilateral independent (BIPD) or generalised (GPD), presence of stimulus-induced rhythmic, periodic, or ictal discharges (SIRPID), burst-suppression pattern or triphasic waves. The fourth group is needed to classify the aetiology when known or suggested on a clinical basis and includes anoxic, toxic-metabolic, lesional, traumatic, inflammatory (encephalitis), whether the patient was diagnosed with cognitive impairment or if a prion disease has been suspected. The fifth group includes tags that don't fit into previous groups but are useful for report classification: the presence of any normal variant of the background rhythm, focal slowing, rhythmic delta, extreme delta brush and if the patient is comatose (Table 1).

After completing the textual part of the report, the neurophysiologist checks all the tags that apply to the recording. The report is then stored on the EEG server for later offline data extraction (Fig. 1).

2.3. Offline data extraction and database generation

Saved reports are copied from the EEG server to a "report" folder on the computer where the script will run. For this study, we used a PC with an Intel Pentium G5600 @3.90 GHz CPU with a CPU benchmark value of 3696 [11] running Debian GNU/Linux operating system (Debian 12 "Bookworm" - AMD64) [12]. The EEG Report Parser script is written in PHP language [13] and was executed using the PHP command line interface (php-cli version 8.2). No additional dependencies or libraries are needed. Since the reports generated by NicVue are in MHTML format, which is not suited for data extraction, the script adopts a recursive text extraction where line breaks are removed, thus preventing the tags from getting split and incorrectly identified, using the *strpos ()* PHP function. Every time a checked tag is found, by matching the string with those present in a tag array defined at the beginning of the script, the value of the checked tag is set to "1" in a new array that, after analysing each report file, will generate a row in a CSV table. When all the report files in the report folder have been parsed, the script stops and the CSV table including all extracted tags is saved in a file that can be opened with any spreadsheet software such as Microsoft Excel or LibreOffice Calc and further analysed. Indeed, the first table column includes a univocal link to the report, so that all recordings can be re-assessed when needed. All study procedures were performed according to the Declaration of Helsinki. The study was approved by the local ethics committee.

3. Results

3.1. Tagging and data extraction

EEG tagging and extraction using the EEG Report Parser script has been used in our unit for more than 2 years of a daily routine without significant issues. After writing the EEG report, the neurophysiologists spent just a few seconds clicking on the appropriate tags at the bottom of the report page and the tagging process did not introduce significant delays in the process.

Table 1
Description of the tags divided by group.

	Tag description
Background	
attenuation	amplitude between 10 and 20 μV for most of the recording
suppression	amplitude below 10 μV for most of the recording
5–6 Hz	5–6 Hz prevalent frequency
7–8 Hz	7–8 Hz prevalent frequency
no gradient	absent fronto-occipital gradient
asymmetric	frequency or amplitude asymmetry
discontinuous	discontinuous pattern
unreactive	lack of reactivity
brain death	absent activity compatible with brain death
Epileptiform activity	
generalized	generalized epileptiform activity
focal	focal epileptiform activity
multifocal	multifocal epileptiform activity
ictal	ictal epileptiform activity
interictal	interictal epileptiform activity
S&W	occurrence of spike-and-wave activity
SE	Status Epilepticus
NCSE	Non-Convulsive Status Epilepticus
EPC	Epilepsia Partialis Continua
Periodic discharges	
LPD	Lateralized Periodic Discharges
BIPD	Bilateral Independent Periodic Discharges
GPD	Generalized Periodic Discharges
SIRPID	Stimulus-Induced Rhythmic, Periodic, or Ictal discharges
burst-suppression	burst-suppression pattern
TW	Presence of Triphasic Waves
Aetiology	
anoxic	brain anoxia
toxic-metabolic	toxic-metabolic encephalopathy
lesional	lesional aetiology (e.g. stroke, tumor…)
TBI	traumatic brain injury
encephalitis	inflammatory aetiology (e.g. immuno-mediated, infectious…)
dementia	neurodegerative dementias
prion disease	prion-induced encephalopaties
Other	
Normal variant	wicket spikes, 6 Hz spike and wave, 14–6 Hz positive bursts, SREDA, etc.
focal slowing	aspecific focal non-epileptiform and non-periodic slowing
rhythmic delta activity	rhythmic delta activity (usually bilateral)
EDB	Extreme Delta Brush
coma	patient is comatous

Data extraction is performed monthly and requires just a few minutes of work, with the script itself elapsing just 23.3 s to extract tags from the 5784 reports we are presenting, using quite old PC hardware (see Methods).

3.2. Sample data presentation

We present the results of an analysis focusing on the EEG findings in patients with toxic-metabolic encephalopathy obtained from a convenient sample of 5784 EEG recordings performed either in inpatients or outpatients between November 1st, 2020 and October 31st, 2022.

Toxic-metabolic aetiology was tagged in 218 recordings (3.8 %). The most frequent background abnormalities were moderate slowing (5–6 Hz frequency), occurring in 79 recordings (36.2 %), followed by mild slowing (7–8 Hz frequency) in 41 (18.8 %). Amplitude attenuation or suppression is very rare, accounting only for 12 (5.5 %) recordings (Fig. 2(A)). Epileptiform findings are also quite rare, reaching a maximum of 10 recordings (4.6 %) summing up focal, generalized and multifocal epileptiform waveforms (Fig. 2(B)). As expected, triphasic waves have been tagged in 43 (19.7 %) recordings and represent the most frequent pathologic waveform (Fig. 2(C)). The contemporary presence of both severe background slowing and triphasic waves occurred in 18 (8.3 %) of cases, therefore 61 (28.0 %) recordings showed severe slowing without triphasic waves and 25 (11.5 %) triphasic waves without severe slowing.

4. Discussion

Classification of EEG findings and related clinical information is very useful for research purposes but may be time-consuming and interfere with daily clinical routine. We present a customizable software called "EEG Report Parser" that fully integrates into pre-existing EEG reporting systems with negligible impact on the standard workflow. It allows tagging specific features related to each EEG recording and then quick extraction for offline analysis. The main advantage of EEG Report Parser is its ease of use: tag labelling is intuitive, almost no time is required by the neurophysiologist to learn how to use it and only a few seconds are added to the normal workflow to tag the EEG report. The script is currently designed for the Nicolet NicVue EEG suite, however, given its free and open-source software (FOSS) licence, it can be readapted for any EEG reporting software. Compared to the Holberg EEG [5], which can be considered the current state-of-the-art for EEG reporting, our script represents a completely different approach: instead of a full-featured suitable to classify all possible EEG features and generate the report, we suggest a minimalistic approach allowing to highlight only some EEG and clinical features for later retrieval. Holberg EEG is designed to completely replace the existing EEG reporting environment, therefore inevitably requires time to learn its usage and many fields need to be filled in to generate the report.

The interest in structured EEG report systems is growing, as demonstrated by the publication of many works using the SCORE system during the past two years [14–17]. Very recently, an evolution of the Holberg EEG SCORE software called "SCORE-AI" was developed to provide automatic EEG features detection through direct analysis of the EEG recording using artificial intelligence (AI) [18]. A similar AI-based approach could be used to automatically pre-tag features in EEG Report Parser during report generation.

A point of strength of EEG Report Parser is its efficiency and adaptability to the local healthcare context, typology of assisted patients and research interests. For example, when used in a paediatric hospital, tags to characterize the genetic profile and seizure types of young patients affected by many age-related electro-clinical syndromes may be added [19]. Large hubs with many intensive care unit patients could be interested in implementing specific tags related to the aetiology of consciousness impairment, respiratory failure, cardiovascular instability, biomarkers of neural injury, systemic inflammation and current anti-seizure therapy [20,21]. The script flexibility and customization stand out compared to the existing classification systems, which include pre-defined fields in a somewhat rigid framework.

Differently from all other solutions, EEG Report Parser is provided at no cost and can be freely downloaded from the Gitlab repository under a "GNU General Public License version 3.0" [7]. As for all FOSS, the cost may be applied for support, installation and customization, which is currently in charge of any potential users since this project has been started mainly for research purposes and the commercial support is lacking. Implementation for centres using NicVue EEG reporting software is quite simple since the main effort is represented by updating the EEG report template with the list of customizable tags. Offline tag exporting requires an initial setup of a PHP-CLI environment, which is also FOSS and available for GNU/Linux and MS Windows operating systems [13].

4.1. Sample data analysis

The reported analysis includes EEGs recorded in a large teaching hospital where inpatients come from any type of ordinary and intensive care wards and outpatients mostly come from the local epilepsy centre.

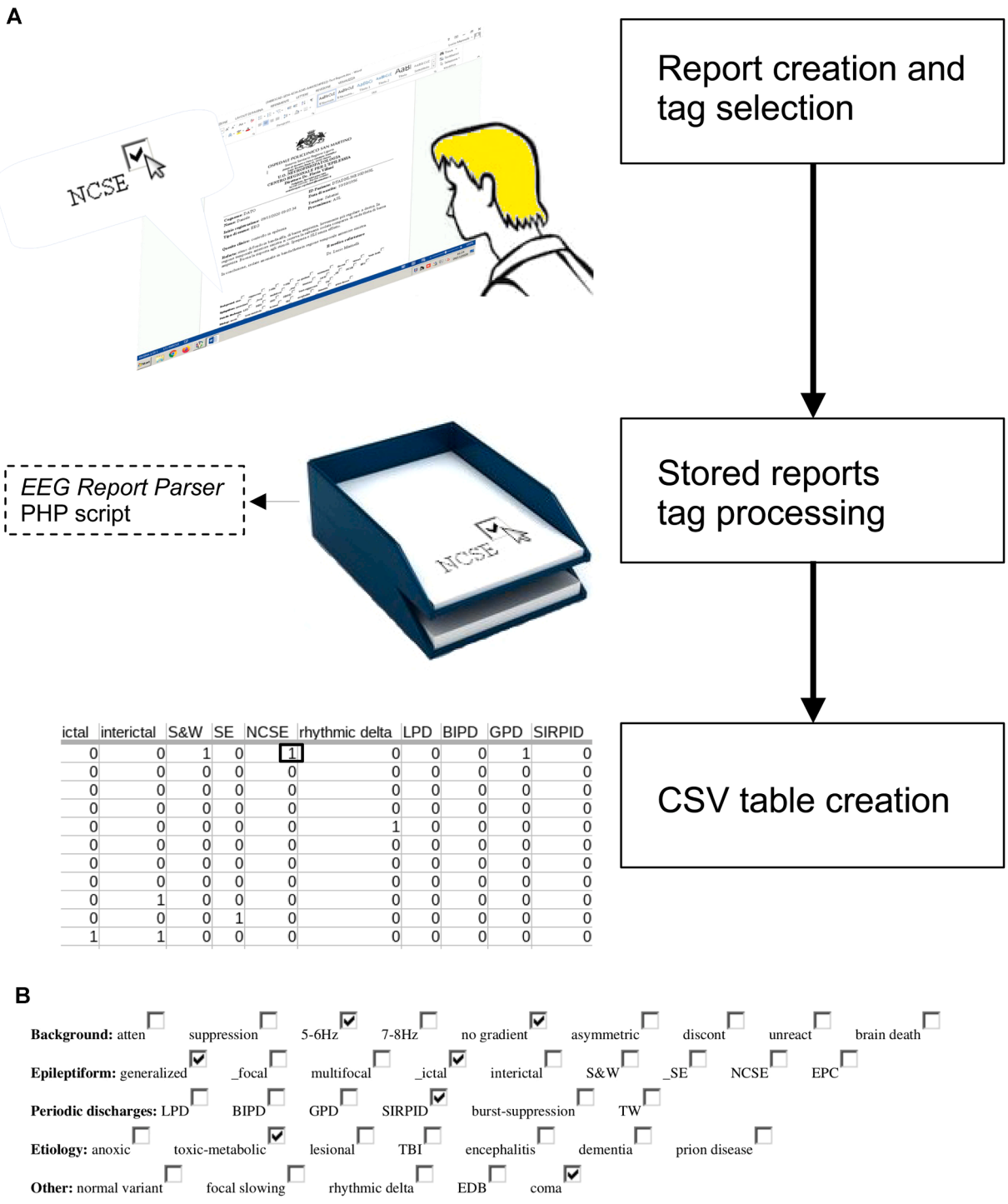

Fig. 1. Report tagging and data extraction.
(A) The upper picture graphically explains the whole procedure starting from 1) tag selection in the EEG reports, 2) tagged report are stored and then 3) undergo the parsing process by the EEG report parser PHP script, which 4) generates the spreadsheet where each line corresponds to a report and each column to a tag showing a "1'' if selected and "0'' if not selected.
(B) An excerpt of the EEG report in a patient with toxic-metabolic encephalopathy is showed.

The toxic-metabolic tag was checked when toxic-metabolic encephalopathy suspect was clearly stated in the diagnostic question field in the EEG request, or when it could be reasonably hypothesized based on the available medical information. Toxic-metabolic encephalopathy refers to a potentially reversible brain dysfunction with extracerebral cause, such as different metabolic disturbances including the effect of medications/drugs and their withdrawal [22].

The 3.8 % prevalence is likely underestimated, also considering that we did not differentiate between out- and inpatients. The high prevalence of triphasic waves was expected since this is a common finding in patients with toxic-metabolic encephalopathy [23]. However, it is interesting to observe that triphasic waves, although the most frequent finding, were present only in less than 20 % of the recordings. It can be therefore inferred that in the majority of cases, EEGs were performed in patients where encephalopathy was mild or reflected by other findings, such as background slowing, which indeed occurred in a large

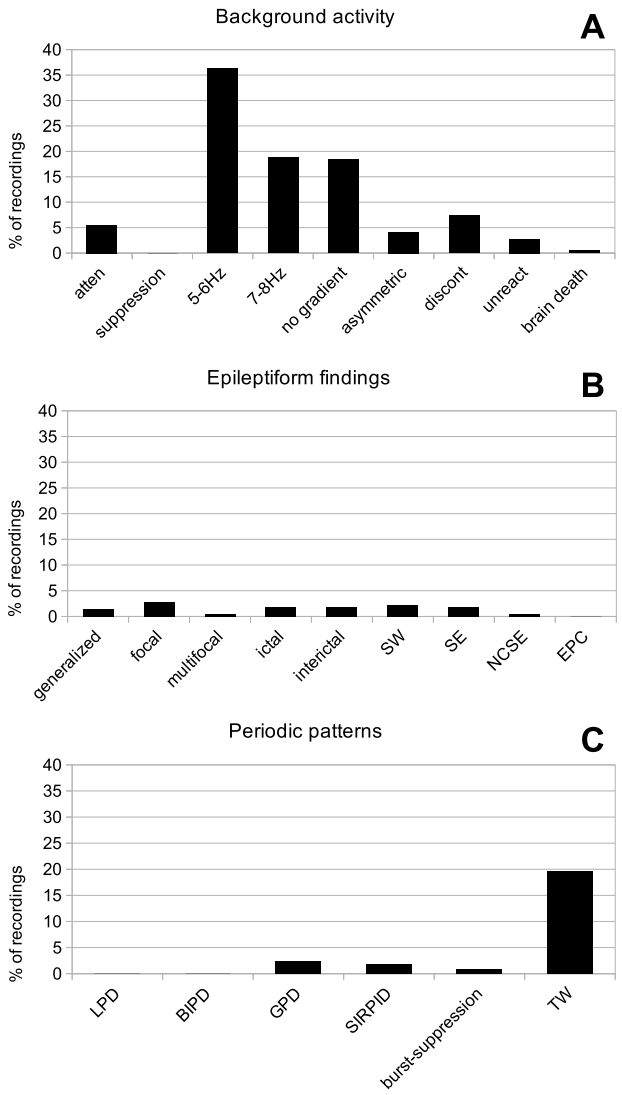

Fig. 2. Sample tag analysis in a group of patients with toxic-metabolic encephalopathy.
Three graphs show the prevalence of the EEG tags in a sample of EEG recordings tagged with a "toxic-metabolic" aetiology. Panel A includes tags related to background activity; "atten" = attenuation, "discont" = discontinuous, "unreact" = unreactive. Panel B includes tags related to epileptiform findings; "SW" = sharp-and-wave, "SE" = status epilepticus, "NCSE" = non-convulsive status epilepticus, "EPC" = epilepsia partialis continua. Panel C includes tags related to periodic patterns; "LPD" = lateralised periodic discharges, "BIPD" = bilateral independent periodic discharges, "GPD" = generalised periodic discharges, "SIRPID" = stimulus-induced rhythmic, periodic, or ictal discharges, "TW" = triphasic waves.

percentage (more than a third) of recordings, consisting with existing literature [24]. It must be noted that no information was collected on the clinical features of recorded patients, such as consciousness impairment apart from coma (stupor, delirium) and involuntary movements that may be present in patients with toxic-metabolic encephalopathy (myoclonus, asterixis) [22]. Specific tags reflecting these features could be added to investigate how EEG findings correlate with clinical findings.

4.2. Source code availability is important

The main objective of this publication is not the EEG Report Parser script itself, but rather presenting to the scientific community the idea of adding personalized tags to existing reporting solutions rather than using complex software alternatives. A few words must be spent to underline the importance of the EEG Report Parser being FOSS. The possibility to read the source code of the software is very important so that anyone can check whether the "open source" software actually does what the producer declares, without hidden functions or data leaks. The possibility to read the source code however is not enough, primarily within educational and research contexts. According to the Free Software Foundation [25], FOSS grants the user 4 important freedoms: run the program as you wish, for any purpose, study how the program works, and change it, so it does your computing as you wish (access to the source code is a precondition for this), to redistribute copies, so you can help others and distribute copies of your modified versions to others [26]. When it comes to research, being able to share scientific findings along with the methodology being used is of pivotal importance. In the case of software, the methodology is the source code, which allows researchers to understand how things work, reproduce the findings and also improve the processes and share these improvements with the scientific community. If the source code of the first two EEG reporting software we mentioned in the Introduction [1,2,27] had been released as FOSS, maybe those approaches could have been adopted more widely, improved, and kept up-to-date to run on modern computers, without the need to start the development of new software from the scratch. Since EEG recording suites are also continuously evolving, the possibility to change, adapt and redistribute existing software is of utmost importance and indeed EEG Report Parser can be adapted to other production environments.

4.3. Strengths of the study

The point of strength of EEG Report Parser and the results of the present study are:

- EEG features tagging fully integrates into the existing reporting workflow, it requires negligible learning effort from the reporting physicians and does not require significant additional time when preparing the EEG report
- Report processing is fully transparent and fast, not requiring closed-source and proprietary environment or file formats, as happens for the existing EEG reporting software such as SCORE
- The generated database is in a raw CSV format, which can be directly and readily analysed and processed by any spreadsheet or statistical software suite
- The analysis of toxic-metabolic encephalopathies prevalence with type and frequency of EEG abnormalities has been easily performed from a large sample of EEG recording

4.4. Limitations of the study

The main limitations of EEG Report Parser and the results of the present study are:

- Current EEG Report Parser works for the Nicolet NicVue EEG suite and code rewriting is required for use in other EEG reporting suites, which often store reports in other formats, such as MS Office Word docx
- Although EEG Report Parser is released as FOSS, implementation and customization costs are in charge of the users, although the GNU GPL licence warrants that customization and improvements can be given back to the developing community, avoiding the cost of replicating the same code changes in different laboratories
- The tagging system is not currently designed to process patient personal data and obtain a timeline of repeated EEG recording for each patient, suitable, for example, to monitor EEG feature changes over time and assess clinical outcomes or long-term follow-up. However, this feature can be added in future versions of the EEG Report Parser

- EEG features tagging depends on the subjective opinion of each reporting physician, there are no mandatory items or steps to follow during EEG features evaluation, so tagging accuracy might significantly differ depending on who is editing the report
- Currently, EEG Report Parser is not compatible with other EEG reporting systems. Indeed, as it is not intended for a systematic and comprehensive assessment of all EEG features, EEG Report Parser is designed to be customized based on the clinical needs of different hospitals and clinical neurophysiology diagnostic services
- The current analysis of toxic-metabolic encephalopathies does not involve assessment of medical records and no data have been collected about the actual aetiology and confounding conditions. Furthermore, there is likely a bias in the selection of the patients undergoing EEG recordings, since probably only those with the most severe clinical conditions and/or impaired consciousness were recorded. Our sample cannot be considered representative of a general population of patients with toxic-metabolic encephalopathy and EEG features should be probably referred to a subgroup of more severe cases
- Data about other clinical conditions such as patients with epilepsy or cognitive impairment have not been reported and specific limitations in other patient populations have not been discussed. Larger data samples involving multiple centres may be useful to improve and tune tag choice and EEG Report Parser accuracy

4.5. *Practical perspectives*

This work represents our first attempt to show the applicability in clinical practice of a software that allows to highlight aspects of the EEG based on the international classification with labels (tags) that can vary depending on the specific interests and the healthcare context. EEG is low-cost, easily repeatable and non-invasive, representing the easiest test to study brain function. Mostly in the emergency or clinical care setting, EEG reports include only a brief description of the main findings, lacking details that can be useful for later debriefing and for clinical research. In these cases, a quick feature selection during EEG reporting may help preserve important information for later use. In addition to the possibility of an inter-individual EEG analysis even in prolonged follow-up, the greatest usefulness of the software is to bring out EEG characteristics in certain subpopulations of patients, for example, patients exposed to therapies with new anti-seizure drugs which are not yet completely studied in their potential neurocognitive effects. For example, the analysis of EEG reports conducted with our system could, in large numbers, reveal more immediately any effects of drugs on the background rhythm or the presence and type of epileptiform waves. For this purpose, it could be useful to add a group of tags with the anti-seizure drugs taken by the patient, whose effect is of interest to investigate. In addition to being useful in prospective evaluations, the tag database can be useful for retrospective observational studies, for example, to retrieve all the patients who had an EEG showing non-convulsive status epilepticus, or all the patients with alterations EEG due to lesions such as brain tumours.

5. Conclusions

EEG Report Parser is an easy tool to quickly identify relevant features during EEG report editing and generate a large customizable dataset suitable for research purposes. To demonstrate how this software could be employed for clinical research, we performed a sample analysis with EEG recordings of patients with toxic-metabolic encephalopathies and found out that the most frequent finding was EEG slowing, while triphasic waves were tagged in a minority of cases.

If compared with previously validated software, EEG Report Parser does not require changes to the existing production environment. It is free to use and its licence allows customization, collaborative improvement and redistribution. Adaptability to different existing reporting systems could allow scalability, and the possibility to merge data from different laboratories to build larger datasets and facilitate multicentric research projects. Being released with a GNU GPL licence, EEG Report Parser can be adopted by a community-driven developing team, adapted to all centre's specific needs and further developed in a collaborative research environment.

CRediT authorship contribution statement

Lucio Marinelli: Conceptualization, Data curation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Corrado Cabona:** Data curation. **Irene Pappalardo:** Data curation. **Anna Bellini:** Data curation. **Alessandra Ferrari:** Data curation, Writing – review & editing. **Elisa Micalizzi:** Data curation, Writing – review & editing. **Daniela Audenino:** Data curation, Writing – review & editing. **Flavio Villani:** Supervision, Writing – review & editing.

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.

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Supplementary materials

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References

[1] H. Aurlien, I.O. Gjerde, N.E. Gilhus, O.G. Hovstad, B. Karlsen, H. Skeidsvoll, A new way of building a database of EEG findings, Clin. Neurophysiol. 110 (1999) 986–995, https://doi.org/10.1016/S1388-2457(99)00037-1.

[2] N.B. Finnerup, A. Fuglsang-Frederiksen, P. Røssel, P. Jennum, A computer-based information system for epilepsy and electroencephalography, Int. J. Med. Inform. 55 (1999) 127–134, https://doi.org/10.1016/S1386-5056(99)00002-7.

[3] S. Beniczky, H. Aurlien, J.C. Brøgger, L.J. Hirsch, D.L. Schomer, E. Trinka, R. M. Pressler, R. Wennberg, G.H. Visser, M. Eisermann, B. Diehl, R.P. Lesser, P. W. Kaplan, S. Nguyen The Tich, J.W. Lee, A. Martins-da-Silva, H. Stefan, M. Neufeld, G. Rubboli, M. Fabricius, E. Gardella, D. Terney, P. Meritam, T. Eichele, E. Asano, F. Cox, W. van Emde Boas, R. Mameniskiene, P. Marusic, J. Zárubová, F.C. Schmitt, I. Rosén, A. Fuglsang-Frederiksen, A. Ikeda, D. B. MacDonald, K. Terada, Y. Ugawa, D. Zhou, S.T. Herman, Standardized computer-based organized reporting of EEG: SCORE—second version, Clin. Neurophysiol. 128 (2017) 2334–2346, https://doi.org/10.1016/j.clinph.2017.07.418.

[4] S. Beniczky, H. Aurlien, J.C. Brøgger, A. Fuglsang-Frederiksen, A. Martins-da-Silva, E. Trinka, G. Visser, G. Rubboli, H. Hjalgrim, H. Stefan, I. Rosén, J. Zarubova, J. Dobesberger, J. Alving, K.V. Andersen, M. Fabricius, M.D. Atkins, M. Neufeld, P. Plouin, P. Marusic, R. Pressler, R. Mameniskiene, R. Hopfengärtner, W.E. Boas, P. Wolf, Standardized computer-based organized reporting of EEG: SCORE, Epilepsia 54 (2013) 1112–1124, https://doi.org/10.1111/epi.12135.

[5] Holberg EEG Report Software website, Holberg EEG. (2023). https://www.holbergeeg.com (accessed January 20, 2023).

[6] Wikipedia: MHTML, Wikipedia. (2023). https://en.wikipedia.org/w/index.php?title=MHTML (accessed January 20, 2023).

[7] Gitlab - EEG Report Parser website, GitLab. (2023). https://gitlab.com/luciomarinelli/eeg-report-parser (accessed January 20, 2023).

[8] L.J. Hirsch, M.W.K. Fong, M. Leitinger, S.M. LaRoche, S. Beniczky, N.S. Abend, J. W. Lee, C.J. Wusthoff, C.D. Hahn, M.B. Westover, E.E. Gerard, S.T. Herman, H. A. Haider, G. Osman, A. Rodriguez-Ruiz, C.B. Maciel, E.J. Gilmore, A. Fernandez, E.S. Rosenthal, J. Claassen, A.M. Husain, J.Y. Yoo, E.L. So, P.W. Kaplan, M. R. Nuwer, M. van Putten, R. Sutter, F.W. Drislane, E. Trinka, N. Gaspard, American clinical neurophysiology society's standardized critical care EEG terminology: 2021 version, J. Clin. Neurophysiol. 38 (2021) 1–29, https://doi.org/10.1097/WNP.0000000000000806.

[9] N. Kane, J. Acharya, S. Beniczky, L. Caboclo, S. Finnigan, P.W. Kaplan, H. Shibasaki, R. Pressler, M.J.A.M. van Putten, A revised glossary of terms most

commonly used by clinical electroencephalographers and updated proposal for the report format of the EEG findings. Revision 2017, Clin. Neurophysiol. Pract. 2 (2017) 170–185, https://doi.org/10.1016/j.cnp.2017.07.002.
[10] G. Strigaro, F. Bisulli, G. Assenza, O. Mecarelli, A. Grippo, S. Meletti, L. Alvisi, G. Cantalupo, R. Eleopra, A. Guerra, S. Lori, L. Marinelli, L. Tassi, P. Tinuper, F. Vigevano, Traduzione e adattamento alla lingua italiana del glossario dei termini più comunemente usati dagli elettroencefalografisti clinici e proposta per il formato del referto EEG (Revisione IFCN 2017), Clin. Neurophysiol. Pract. 7 (2022) 325–365, https://doi.org/10.1016/j.cnp.2022.09.006.
[11] PassMark Software - CPU Benchmarks website, (2023). https://www.cpubenchmark.net (accessed January 20, 2023).
[12] Debian OS website, (2023). https://www.debian.org/(accessed January 20, 2023).
[13] PHP: Hypertext Preprocessor, (2023). https://www.php.net/index.php (accessed January 20, 2023).
[14] E. Aanestad, N.E. Gilhus, H.K. Olberg, M.A. Kural, S. Beniczky, J. Brogger, Spike count and morphology in the classification of epileptiform discharges, Front. Neurol. 14 (2023), 1165592, https://doi.org/10.3389/fneur.2023.1165592.
[15] G. Japaridze, S. Kasradze, H. Aurlien, S. Beniczky, Implementing the SCORE system improves the quality of clinical EEG reading, Clin. Neurophysiol. Pract. 7 (2022) 260–263, https://doi.org/10.1016/j.cnp.2022.07.004.
[16] P. Meritam Larsen, S. Wüstenhagen, D. Terney, E. Gardella, H. Aurlien, S. Beniczky, Duration of epileptic seizure types: a data-driven approach, Epilepsia 64 (2023) 469–478, https://doi.org/10.1111/epi.17492.
[17] S. Wüstenhagen, D. Terney, E. Gardella, P. Meritam Larsen, C. Rømer, H. Aurlien, S. Beniczky, EEG normal variants: a prospective study using the SCORE system, Clin. Neurophysiol. Pract. 7 (2022) 183–200, https://doi.org/10.1016/j.cnp.2022.06.001.
[18] J. Tveit, H. Aurlien, S. Plis, V.D. Calhoun, W.O. Tatum, D.L. Schomer, V. Arntsen, F. Cox, F. Fahoum, W.B. Gallentine, E. Gardella, C.D. Hahn, A.M. Husain, S. Kessler, M.A. Kural, F.A. Nascimento, H. Tankisi, L.B. Ulvin, R. Wennberg, S. Beniczky, Automated interpretation of clinical electroencephalograms using artificial intelligence, JAMA Neurol. 80 (2023) 805, https://doi.org/10.1001/jamaneurol.2023.1645.
[19] A. McTague, K.B. Howell, J.H. Cross, M.A. Kurian, I.E. Scheffer, The genetic landscape of the epileptic encephalopathies of infancy and childhood, Lancet Neurol. 15 (2016) 304–316, https://doi.org/10.1016/S1474-4422(15)00250-1.
[20] S. Musick, A. Alberico, Neurologic assessment of the neurocritical care patient, Front. Neurol. 12 (2021), 588989, https://doi.org/10.3389/fneur.2021.588989.
[21] L. Marinelli, I. Pappalardo, C. Robba, L. Saitta, C. Cabona, D. Battaglini, M. Casaleggio, A. Bellini, A. Ferrari, I. Brunetti, F. Villani, The value of EEG attenuation in the prediction of outcome in COVID-19 patients, Neurol. Sci. 43 (2022) 6159–6166, https://doi.org/10.1007/s10072-022-06354-8.
[22] L. Le Guennec, C. Marois, S. Demeret, E.F.M. Wijdicks, N. Weiss, Toxic-metabolic encephalopathy in adults: critical discussion and pragmatical diagnostic approach, Rev. Neurol. 178 (2022) 93–104, https://doi.org/10.1016/j.neurol.2021.11.007.
[23] P.W. Kaplan, R. Sutter, Affair with triphasic waves—their striking presence, mysterious significance, and cryptic origins: what are they? J. Clin. Neurophysiol. 32 (2015) 401–405, https://doi.org/10.1097/WNP.0000000000000151.
[24] R. Sutter, P.W. Kaplan, M. Valença, G.M. De Marchis, EEG for diagnosis and prognosis of acute nonhypoxic encephalopathy: history and current evidence, J. Clin. Neurophysiol. 32 (2015) 456–464, https://doi.org/10.1097/WNP.0000000000000164.
[25] Free Software Foundation website, (2023). https://www.fsf.org/(accessed January 20, 2023).
[26] What is Free Software? - GNU Project - Free Software Foundation, (2023). https://www.gnu.org/philosophy/free-sw.html.en#four-freedoms (accessed January 20, 2023).
[27] H. Aurlien, I.O. Gjerde, G.E. Eide, J.C. Brøgger, N.E. Gilhus, Characteristics of generalised epileptiform activity, Clin. Neurophysiol. 120 (2009) 3–10, https://doi.org/10.1016/j.clinph.2008.10.149.