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Applications of machine learning for nursing monitoring of electroencephalography

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Abstract

The nursing monitoring of electroencephalography (EEG) during neurosurgery includes verifying the proper placement of electrodes on the patient's scalp and ensuring the accurate display of EEG readings on the monitoring apparatus. This study aims to examine the use of machine learning (ML) in EEG monitoring by analyzing the R programming language. The results will provide insights into surgical nursing care by evaluating EEG patterns. The preceding evidence was collected following the Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) guidelines in the present study. The logical analysis of the data was conducted using the R programming language. ML algorithms based on usage rate included logistic regression (LR), support vector machine (SVM), random forest (RF), artificial neural networks (ANN), and convolutional neural network (CNN). Also, the use of ML in nursing monitoring of EEG is categorized into three indications rehabilitation measurement (post-operation), delayed cerebral ischemia (DCI) detection (pre-operation), hypotension identification (intra-operation), surgical outcomes measurement(post-operation), and seizure prediction. In sum, the algorithm, including LR and SVM, have been frequently utilized in the realm of EEG evaluation, as indicated by the results obtained.

Keywords: Electroencephalography, Nurses, Nursing, Nursing Care, Machine Learning.

1 | Introduction

Intraoperative neurophysiological monitoring (IONM) is frequently utilized in neurosurgical interventions to evaluate the operational soundness of specific nervous system components [1]. In this regard, electrophysiological techniques such as motor-evoked potentials (MEPs), electroencephalography (EEG), and electromyography (EMG) are most frequently utilized during neurosurgical procedures [1]. The conventional definition of EEG is the electrical brain activity detected from the scalp of human beings [2]. During neurologic surgery, EEG oversees the brain's electrical activity and maintains it within safe parameters throughout the operation [3]. By placing electrodes on the scalp, surgeons can observe the EEG readings in real-time and adjust their approach accordingly to minimize the risk of complications [4]. This method is precious in surgeries that entail the excision of brain tumors or epileptogenic foci [5].

Within nurse care, machine learning (ML) (a subset of artificial intelligence (AI)) is being employed with greater frequency to identify and analyze a range of medical conditions, including diagnoses, complications, prognoses, and recurrence instances [6]. In contrast to conventional statistical models, ML can learn complex relationships among data actively, enabling it to overcome the limitations of nonlinearity and maintain stability even in datasets with many dimensions [7]. ML can offer a unique benefit in analyzing unstructured data, such as images and other types of information [8, 9]. Despite the outstanding performance of models on local datasets, numerous researchers have neglected to assess their ability to be reproduced in other clinical settings, which has restricted the expansion of this potent decision-support tool in clinical practice [10].

Additionally, the nursing monitoring of EEG during neurosurgery includes verifying the proper placement of electrodes on the patient's scalp and ensuring the accurate display of EEG readings on the monitoring apparatus [11]. Also, by tracking the patient's neurological signs, nursing care is essential in determining the strategy to find significant brain loci (epileptic focal points) and prevent damage to vital points [12]. In order to enhance the quality of nursing care during EEG monitoring, various methods have been developed to improve the adequacy of hemodialysis and prevent complications. Nevertheless, ML has emerged as a methodological approach to evaluate EEG patterns [13]. To the best of our knowledge, previous literature regarding ML-based prediction tasks in the context of EEG nursing monitoring has been inadequate in providing comprehensive descriptions. As a result, assessing both the benefits and drawbacks of the model construction process is essential to offer a summary of the ML applications for EEG monitoring. This study aims to examine the use of ML in EEG monitoring by analyzing the R programming language. The results will provide insights into surgical nursing care by evaluating EEG patterns.

2 │ Methods

2.1 │ Data collection

The study extracted relevant studies using the Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) guideline [14]. Between January and July 2023, an exhaustive exploration of Scopus, PubMed, and ISI databases was carried out using appropriate terms such as "EEG", "electroencephalography", "nursing", "monitoring", and "machine learning" to collect relevant information. Two researchers conducted separate searches autonomously utilizing Boolean operators "AND" and "OR" to connect keywords. All categories of EEG monitoring cases were encompassed. Furthermore, to prevent any loss of relevant information, the references of the acquired studies were examined, which led to the discovery of 42 related cases. In the final step, papers that lacked ML applications and cases published before 2015 were eliminated. Ultimately, five studies were selected for analysis.

2.2 │ R Programming language plot

Using the R programming language, a graphical representation was generated. R is a programming language specifically designed for statistical computing and graphics backed by the R Foundation for Statistical Computing and the R Core Team. The language was developed by statisticians Ross Ihaka and Robert Gentleman for data analysis and the creation of statistical software [15].

2.3 │ Sankey plot

A Sankey plot was utilized to depict ML's technical applications during EEG monitoring. In a Sankey plot, the indicator's width represents the quantity being visualized, and if an indicator is twice as broad, it signifies twice the amount being represented. Flow diagrams can demonstrate the flow of various elements such as energy, materials, water, or costs. To illustrate the directed flow, at least two nodes or processes must be depicted on the Sankey chart. As a result, the Sankey plot provides valuable insights into values, system structure, and distribution. Due to these advantages, Sankey plots are an excellent alternative to conventional flow charts and bar charts [16].

3 │ Results

3.1 │ ML algorithm

ML algorithms based on usage rate included logistic regression (LR), support vector machine (SVM), random forest (RF), artificial neural networks (ANN), and convolutional neural network (CNN) (Figure 1).

3.2 │ Application of ML in nursing EEG monitoring

In general, the use of ML in EEG nursing monitoring is categorized into three indications rehabilitation measurement (post-operation), delayed cerebral ischemia (DCI) detection (pre-operation), hypotension identification (intra-operation), surgical outcomes measurement (post-operation), seizure prediction (post-operation) [17-21] (Figure 1).

4 │ Discussion

The proliferation of ML has been facilitated by advancements in AI and computer technology, and in some studies, ML has been utilized as a diagnostic tool. Despite the broad range of nursing topics to which ML has been applied, there has been a relative dearth of research in this area. By examining five papers and utilizing the "R" programming language, we determined the most commonly utilized ML algorithm for nursing monitoring of EEG. This will enable us to develop robust predictive targets for future research endeavors.

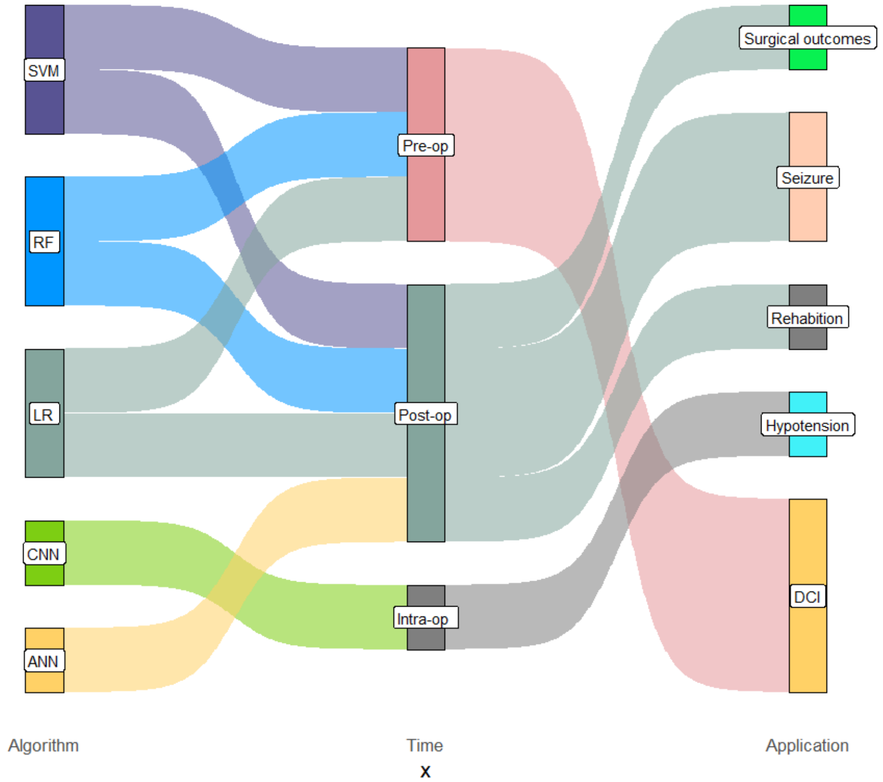

Figure 1. The Sanky plot of extracted data, the first column indicates the type of ML algorithm, the second column shows the operation time and the third column reveals the predicting criteria; note the thickness of the connection lines between the columns. (**LR:** Logistic Regression; **SVM:** Support Vector Machine; **RF:** Random Forest; **ANN:** Artificial Neural Networks; **CNN:** Convolutional Neural Network; **DCI:** Delayed Cerebral Ischemia; **Post-op:** Post-operation; **Intra-op:** Intra-operation; **Pre-op:** Pre-operation).

In the current investigation, the LR, RF, and SVM were recognized as the most commonly used ML algorithms for the nursing monitoring of EEG during neurosurgeries. The LR model computes the logistic output based on the input features, and it is frequently employed for analyzing binary and ordinal data in medical research [22, 23]. Moreover, LR has demonstrated its usefulness in estimating and assessing the relative risks of infrequent occurrences in both cross-sectional and longitudinal studies [24]. Guerrero et al. demonstrated that the LR algorithm could be applied for the evaluation of EEG; however, compared to the ANN algorithm, this algorithm has a lower accuracy than ANN [25]. Based on obtained data, the LR algorithm was predominantly employed for the pre-operative and post-operative analysis of EEG during neurosurgery. However, the results indicated that the ANN algorithm can also examine EEG patterns. Rajaguru et al. also revealed that the LR accuracy for seizure prediction through EEG was over 90% [26]. Furthermore, Rincón et al. recommended the LR algorithm for an exact evaluation of EEG to predict seizures [27]. While our results indicated significant utilization of LR, further research is required to evaluate the mentioned algorithm.

Furthermore, SVMs have diverse applications in classifying linear and non-linear systems. The dimensionality of the input space indirectly affects the quality and complexity of SVM solutions. SVMs possess several salient features, including the capability to function in high-dimensional spaces, economical memory consumption, and efficiency even when the number of samples is lesser than the dimensional spaces. Additionally, SVMs offer a variety of kernels for decision-making, among which a customized kernel can be an intricate option. Using SVM for data analysis can overcome the limitations inherent in the human ability to identify latent patterns in data [28]. Bin Altaf et al. applied the SVM algorithm to detect seizures in EEG patterns [29] and revealed the acceptable accuracy of the algorithm for EEG evaluation. Consistent with our results, Perera et al. demonstrated that this algorithm can analyze EEG data satisfactorily through rehabilitation [30].

In the current study, seizure diagnosis was the most frequent field identified by ML. The significance of this detection lies in the fact that the accurate and prompt diagnosis of seizures can pose a challenge, especially when patients experience infrequent or atypical seizure episodes [31]. ML algorithms can scrutinize vast amounts of data and recognize patterns that may elude human clinicians, thus resulting in more precise and timely diagnoses [32]. On the contrary, the accurate diagnosis of seizures based on EEG has always been challenging due to disturbances in electric currents. In this regard, recent studies have demonstrated that ML can improve the quality of EEG recordings by performing precise filtering, thereby enhancing the accuracy of seizure diagnosis. Additionally, using ML algorithms in EEG analysis can improve nursing care by providing more detailed and accurate seizure information for clinicians to base their treatment decisions on [33].

Also, the neurosurgical outcome was another field evaluated by ML through EEG. In this regard, Senders et al. showed that ML can generally be beneficial in evaluating neurosurgical outcomes [34]. Nonetheless, the assessment of outcomes based on EEG is a relatively novel concept that can encompass various aspects, such as the examination of seizure occurrence following surgery or rehabilitation [17, 19, 20]. In summary, the mentioned scenario presents a novel avenue for conducting research at the intersection of AI and medicine.

4.1 │ Limitations

The current study represents the first technical investigation into the utilization of ML for nursing monitoring of EEG during neurosurgery. It is important to note that the study is not exempt from limitations. Firstly, the review only included English-language publications since 2015, which could potentially introduce a bias in the findings. Furthermore, the overall low quality of the reviewed studies may have influenced the review results in some way. Lastly, while the study concentrates on the technical application of ML in EEG analysis, there may be valuable information in other domains, such as clinical research, that was not explored in this study.

4.2 │ Implications for nursing clinical practice

EEG is a valuable diagnostic tool for monitoring brain activity during neurosurgical procedures. However, interpreting EEG assessments can be difficult for healthcare providers. ML shows promise in improving the accuracy and efficiency of EEG monitoring by automatically identifying patterns and abnormalities in brain activity. ML can facilitate the early detection of changes or irregularities in brain activity, enabling healthcare providers to make timely and well-informed decisions regarding patient care and treatment during neurosurgery. Also, Integrating ML into EEG monitoring can alleviate the workload of healthcare personnel, such as nurses, freeing up their time to attend to other critical tasks. By continuously monitoring EEG data, ML algorithms can automatically alert healthcare professionals to any significant changes or abnormalities in brain activity, minimizing the need for manual monitoring and enabling providers to concentrate on other aspects of patient care. This can enhance the overall efficiency of healthcare delivery and potentially improve patient outcomes.

4.3 │ Recommendations for future research

Based on the data that has been amassed, it seems that ML has the potential to be utilized for nursing monitoring of EEG during neurosurgery with encouraging outcomes. Nevertheless, additional technological advancements are required for ML to be considered a practical assistant for assessment. Furthermore, the following research objectives may be regarded as potential areas for exploration in future studies: 1) Detecting the most appropriate complementary algorithms to develop the ML-Based concept for EEG monitoring; and 2) Development of a bioelectrical-based AI instrument for EEG monitoring.

5 │ Conclusions

The application of ML for nursing monitoring is regarded as a promising research field in nursing care. Overall, the data gathered suggests that ML has been employed in several key areas, including rehabilitation management, seizure prediction, DCI, hypotension detection, and prediction of surgical outcomes. Additionally, it may be worthwhile to explore the practicality of developing an AI instrument for EEG monitoring using algorithms such as SVMs and LR. These algorithms have demonstrated potential in the context of EEG monitoring and may be suitable for further development of an AI-assisted monitoring tool. However, there is still a need for improvement in data management, preprocessing, and model validation to create practical models that can be effectively applied in clinical contexts. Ongoing research and development in these areas are essential to enhance the efficiency and effectiveness of ML-supported EEG monitoring in clinical practice.

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Authors' contributions

Substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work: MRZ, KR, SR, TA, MA; Drafting the work or revising it critically for important intellectual content: MRZ, KR, SR, TA, MA; Final approval of the version to be published: MRZ, KR, SR, TA, MA; Agreement to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved: MRZ, KR, SR, TA, MA.

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Availability of data and materials
The datasets used during the current study are available from the corresponding author on request.

Using artificial intelligent chatbots
None.

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