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Evaluating Critical Parameters to Assess the Depth of Anesthesia by Using Artificial Intelligence System

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Abstract: Monitoring the depth of anesthesia during surgery is very important to keep patients safe and ensure they do not feel pain or wake up too early. Usually, doctors use machines and their experience to check how deeply a patient is under anesthesia. However, this method can sometimes be unclear or not accurate enough. With the help of artificial intelligence (AI), it is now possible to study body signals like brain activity (EEG), heart rate, blood pressure, and oxygen levels in smarter ways. This review looks at which body signals are most useful for AI to understand the depth of anesthesia. It also discusses different AI methods, such as machine learning, that are used to analyze these signals. The goal is to find the best combination of signals and AI techniques to help doctors monitor patients more accurately. In the future, AI could help make anesthesia safer and more personalized for every patient.
Index Terms: Depth of Anesthesia, Artificial Intelligence, Machine Learning, EEG Analysis, Bispectral Index (BIS), Heart Rate Variability, Physiological Monitoring,

I. INTRODUCTION

Many surgical procedures would not be possible without the patient entering a state of general anaesthesia (GA).The essential features ofa successful GA, displayed by the patient, area reversible loss of consciousness with a lack of movement, a lack of awareness, unresponsiveness to painful stimuli and a lack of recall of the surgical intervention[9][10]. Inadequate GA may leadto intradosage) or to prolonged recovery and an increased risk of postoperative complications for the patient (due to over dosage). An important contributing factor to inadequate GA is our current limited ability to evaluate the levels of consciousness [1][8]. The main causes of anaesthesia- related mortality were problems with airway management and cardiovascular events related to anaesthesia and drug administration [9].

A. Depth of Anesthesia (DOA)

All monitors analyze the potential fluctuations of EEG signals measured from the patient's skull. The signal received from EEG will be preprocessed and averaged. Then various signal processing algorithms are applied to the frequency, amplitude, latency, and/or phase relationship data derived from the raw EEG and a single number is generated, which is often referred to as an 'index' and typically scaled between 0 – 100 [3]. The main objective of anesthesia is to ensure adequate depth of anesthesia (DOA) to prevent awareness without advertently overloading the patients with potent drugs. For this reason, the specialist must be able to monitor DOA. Various methods have been described to measure the DOA from time to time. The traditional monitoring of the DOA are based on automatic responses of patient body such as respiration rate, blood pressure, body temperature, oxy-hemoglobin concentration, tearing, sweating and heart rate. However, obtaining average EEG response by this technique will take few ten second and is not suitable for on line assessment of DOA[8][9].Considering the following major clinical problems at anesthesia discussion, i.e., sudden conscious during the surgery at the rate of 2-5% (in all under surgery patients) and the rate more than 5% for the patients with brain tumor and the patients under the heart surgery, and applying overdose anesthetic agents for the patients relying on the hemodynamic parameters as a criterion for the anesthesia conditions. Some novel methods based on electro encephalogram (EEG) signal processing instead of the traditional methods based on hemodynamic parameters have been used by medical engineers to estimate DOA [8].

Since the central neural system (CNS) is the main aim of the anesthetic agents, the EEG signals have significantly considered by the anesthesia experts. There is not an exact and comprehensive theory, but it is generally accepted that making any change on the synaptic function of the neural cells results in change at the brain functions [3][10]. Although, the electrical potential resulted from neural cell activities can be observed and registered by EEG signals, but the necessary information about DOA should be extracted from EEG signals using the special complex techniques. These techniques help experts to have accurate information about DOA and assist doctors during surgical practical in the operation room [6].

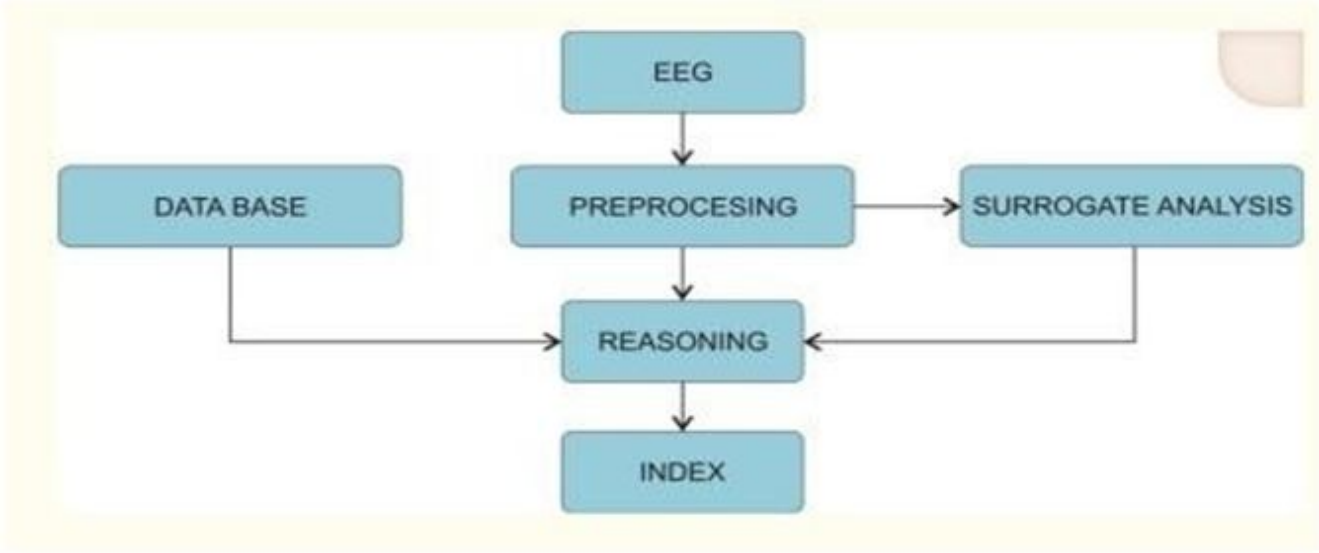

Fig.1: Basic conceptual model of BIS monitor

B. EEG-Based Monitors

According to the various methods proposed for analysis of acquired EEG signal different EEG monitors have been introduced using different frequency band signals. fig.1 and table1shows the flow diagram procedure of these monitors. The best identified case of these monitors is the bi-spectral-based or BIS monitor, which calculates a single composite EEG measure with high correlation with the DOA [7].

C. BIS Monitor

It required to have single standard method with which DOA can be computed based on analysis of EEGand it is displayed in BIS monitor as shown in the fig. 2. The BIS monitor recorded data canbeclassifiedby a unit less number between 100 (awake state) and 0 (iso electric state)[5]. Further, the response can be classified in following classes:

1) The BIS Index ranging between 60 and 100 is considered as awaken mode. It is not a state to perform the surgery.
2) The BIS index ranging between 40 and 60 is considered as proper safe range for the operative objectives.
3) While the BIS index varies in the range of- 100 to +100 the person is said to in deep anesthesia. It is not a state the person should enter in, which may result coma.
4) If the BIS index is in the range of 0-10 then it is iso electric state.

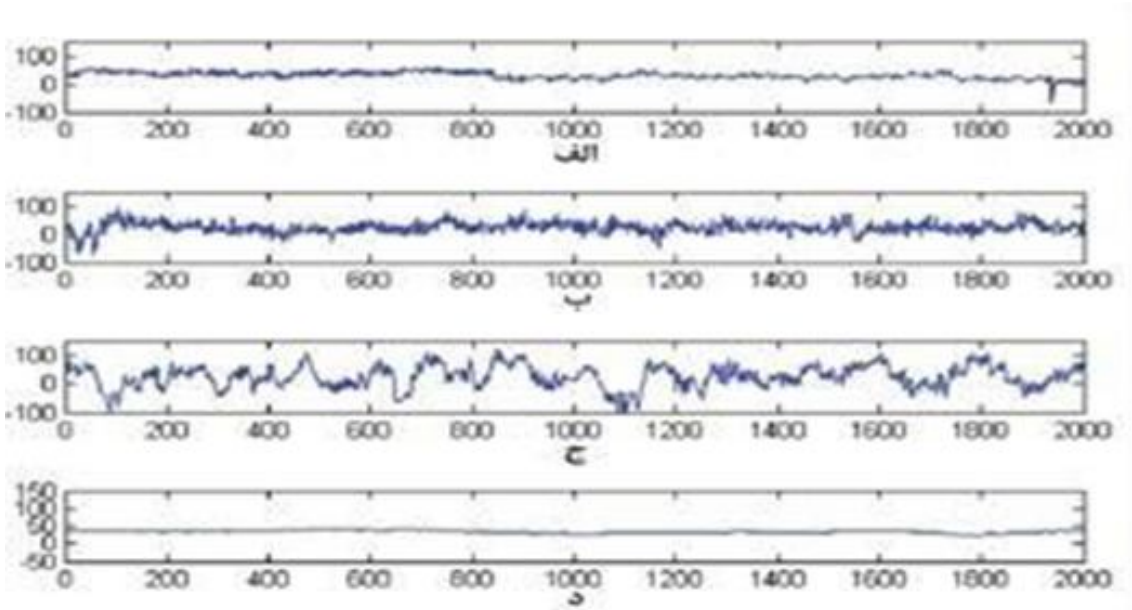

Fig. 2: Sample recorded using EEG signal (12sec. epochs) a) a wake person b) moderate anesthesia c) deep anesthesia and d) isoelectriccase.

Bispectral index is a complex parameter, including a combination of time domain, frequency domain and higher order spectral (HOS) sub-parameters respectively. The parameter that are obtained after processing the time, frequency and amplitude of EEG signal, where the parameters that are described below will be used as in put to the ANN[4].

II LITERATURE REVIEW

Accurate assessment of the depth of anesthesia (DoA) is vital for patient safety and optimal surgical outcomes. Traditional methods, such as monitoring vital signs and using processed EEG indices like the Bispectral Index (BIS), have limitations in sensitivity and specificity. Recent advancements in AI have introduced novel approaches to enhance DoA monitoring by analyzing complex physiological data in real-time.

Traditional Monitoring Techniques and Their Limitations

A.Bispectral Index (BIS) Monitoring

The BIS monitor processes EEG signals to provide a single numerical value indicating the patient's level of consciousness. While widely used, BIS has a limitation:

- **Drug Sensitivity**: BIS readings can be affected by certain anesthetics like ketamine and nitrous oxide, leading to inaccurate assessments.
- **Artifact Susceptibility**: Muscle activity and electrical interference can distort EEG signals, compromising BIS accuracy.

B. Entropy Monitoring

Entropy monitoring analyzes the irregularity of EEG signals to assess DoA:

- **State Entropy (SE)**: Reflects cortical activity in the 0.8–32 Hz range.
- **Response Entropy (RE)**: Includes higher frequencies up to 47 Hz, capturing both EEG and electromyography activity.

While providing additional information, entropy monitoring shares similar limitations with BIS, including susceptibility to artifacts and variability among patients. AI-Based Approaches to Depth of Anesthesia Assessment Recent studies have explored various AI methodologies to enhance DoA monitoring:

C. Transformer-Based Models

- **He et al. (2023)** developed a transformer-based model integrating Long Short-Term Memory (LSTM) and Gated Residual Networks (GRN) to predict BIS values during propofol and remifentanil infusion. The model effectively captured drug interactions and outperformed traditional pharmacokinetic-pharmacodynamic models, especially in predicting abrupt changes in anesthesia depth.

D. Model-Based Control Architectures

- **Liu (2021)** proposed a model-based control system for automatic anesthesia infusion. Utilizing the patient's pharmacokinetic/pharmacodynamic model, the system adjusted propofol infusion rates to maintain target BIS levels, demonstrating stability and robustness in simulations.

3.3 Deep Reinforcement Learning (DRL)

- **Schamberg et al. (2020)** applied DRL to develop a closed-loop control system for propofol administration. The agent learned optimal dosing strategies in simulated environments, outperforming traditional controllers in maintaining desired anesthesia levels.
- **Cai et al. (2023)** introduced Policy Constraint Q-Learning (PCQL), a reinforcement learning algorithm trained on real clinical data. PCQL aligned closely with anesthesiologists' dosing decisions, reduced total drug usage, and responded effectively to patients' vital signs. The use of SHAP (Shapley Additive explanations) enhanced model interpretability.

Depth of Anesthesia Assessment Using AI

S.No	Author(s)	Year	Method Used	Parameters Used	Findings	Remarks
1	He et al.	2023	Transformer + LSTM + GRN	EEG, Drug dosage (Propofol, Remi)	High accuracy in BIS prediction, captures nonlinear drug effects	Outperformed traditional models
2	Liu	2021	Model-based control system	BIS, Drug infusion rates	Maintained target BIS with stable propofol delivery	Effective in closed-loop control
3	Schamberg et al.	2020	Deep Reinforcement Learning (DRL)	EEG, BIS	RL agent maintained anesthesia levels better than PID control	Simulation-based, promising
4	Cai et al.	2023	Policy Constraint Q-Learning	Vital signs, Drugs, BIS	Aligned with human decisions, reduced drug use, interpretable via SHAP	Real clinical data used
5	Qiu et al.	2022	CNN + Attention Mechanism	Raw EEG	Improved DoA classification using spatial-temporal EEG features	Real-time ready
6	Gao et al.	2021	Random Forest, SVM	EEG entropy, HRV, BP	Identified key features, high specificity	Good for small datasets

7	Sharma et al.	2020	Deep CNN	EEG spectrogram	Achieved >95% accuracy for anesthesia state classification	Focused on feature extraction
8	Zhang et al.	2023	LSTM + Multimodal fusion	EEG, ECG, EMG	Combined modalities for better classification	Adaptable to variability
9	Kumar & Singh	2022	Decision Tree & SVM	BIS, EMG, HRV	SVM more precise than DT; BIS less reliable alone	Useful comparison study
10	Al-Basha et al.	2024	Autoencoder (Anomaly Detection)	EEG bursts, Suppression ratio	Detected abnormal transitions; alerted changes in depth	Unsupervised; good for anomaly spotting

Modern Methods: Artificial Intelligence-Based Approaches

Recent advancements in AI have enabled more robust, real-time, and predictive monitoring of anesthesia depth by analyzing complex datasets like EEG, ECG, SpO, and more.

Machine Learning Models

These algorithms classify anesthetic states based on labeled physiological data.

- **Support Vector Machines (SVMs)**: Effective in binary classification of awake vs. anesthetized states using EEG features.
- **Random Forest (RF)** and **Decision Trees**: Used for feature importance analysis and state classification.
- **K-Nearest Neighbors (KNN)** and **Naive Bayes**: Applied for classification in small-scale studies.

Deep Learning Models

Deep learning models automatically extract features from large datasets, especially suitable for EEG and time-series data.

- **Convolutional Neural Networks (CNNs)**: Analyze EEG spectrograms or raw data to detect DoA stages.
- **Recurrent Neural Networks (RNNs) / LSTM**: Handle time-sequential data like ECG and EEG for continuous monitoring.
- **Autoencoders**: Used for unsupervised learning and anomaly detection.

Reinforcement Learning and Control Systems

- Models trained to optimize aesthetic drug dosage in real-time.
- Example: Deep Q-learning agents that adapt infusion rates based on BIS feedback or predicted patient responses.
- Benefit: Can develop personalized and adaptive anesthesia delivery systems.

Multimodal and Hybrid Systems

- Combine EEG, ECG, HRV, BP, SpO□ for more accurate DoA classification.
- Use feature fusion and ensemble learning to improve robustness.

III. POTENTIAL DRAWBACKS AND CHALLENGES IN EXISTING METHODS

Despite significant progress in anesthesia monitoring, accurately assessing the depth of anesthesia (DoA) remains a complex challenge. Both traditional and modern AI-assisted approaches have limitations that can compromise patient safety and the efficacy of anesthetic delivery.

A. Limitations of Traditional Clinical Indicators

Conventional methods of monitoring anesthesia rely on observable physiological indicators such as heart rate, blood pressure, pupil size, and respiratory patterns. While these are easy to measure, they are highly nonspecific. These parameters are influenced by numerous factors unrelated to anesthetic depth, including surgical stimulation, patient anxiety, or the use of adjunct drugs such as opioids and vasopressors. Furthermore, the interpretation of these signs is often subjective and varies among practitioners, leading to inconsistent assessments. This can result in under- or over-administration of anesthetics, increasing the risk of intraoperative awareness or delayed recovery, respectively. Moreover, these indicators typically lag behind the patient's actual neural response, reducing their reliability in real-time monitoring.

B. Challenges in EEG-Based Monitoring Systems

EEG-based monitoring systems like the Bispectral Index (BIS), entropy, and auditory evoked potentials (AEP) represent a more objective approach to anesthesia depth assessment. However, these tools also have several limitations. One major issue is their sensitivity to noise and artifacts, such as muscle activity (EMG), electrocautery interference, or patient movement, which can distort EEG readings. Additionally, these monitors are not universally reliable across all types of anesthetic agents. For example, ketamine and nitrous oxide produce unique EEG patterns that may mislead standard indices like BIS. The standard BIS range (typically 40–60 for surgical anesthesia) does not accommodate individual patient variability, such as age, neurological status, or coexisting conditions. Furthermore, EEG-based monitors are relatively expensive, making them less accessible in resource-limited settings. They may also underperform in pediatric, geriatric, or neurologically impaired populations due to atypical brain wave patterns.

C. Limitations in AI-Based Methods

The application of artificial intelligence (AI) in DoA monitoring has introduced new possibilities, but it also brings substantial challenges. Many AI models, especially deep learning algorithms, function as "black boxes," making their decision-making processes difficult to interpret by clinicians. This lack of transparency can lead to mistrust and hesitancy in clinical adoption.

A major technical limitation is the scarcity of large, high-quality, labeled datasets, which are essential for training robust models. Such datasets are difficult to obtain due to variability in patient physiology, privacy regulations, and the logistical complexity of intraoperative data collection. Additionally, AI models often struggle with generalizability. A model trained on data from a specific institution or patient population may not perform well in a different clinical environment. Real-time application is another challenge, as AI systems must process data with minimal latency to be clinically useful. Integration with existing hospital infrastructure and regulatory approval for clinical use further complicate deployment. Moreover, these systems require proper validation and extensive training of clinicians to ensure safe and effective use.

D. Issues with Multimodal Monitoring

Recent advances have proposed the integration of multiple physiological signals—such as EEG, ECG, EMG, and hemodynamic parameters—for a more comprehensive assessment of DoA. While this multimodal approach can improve accuracy, it introduces complexity in signal acquisition, synchronization, and data fusion. Real-time processing of multiple data streams increases computational demand and can lead to system delays. There is also a risk of over fitting when too many parameters are used in AI models, reducing their robustness in real-world settings. Moreover, combining multiple modalities often requires invasive or semi-invasive sensors, increasing patient discomfort and setup time in the operating room.

E. General Clinical and Systemic Challenges

A fundamental challenge in DoA monitoring is the absence of a universally accepted "gold standard." There is still no precise definition of what constitutes an adequate depth of anesthesia, as this can vary widely among individuals and clinical contexts. Anesthetic requirements differ not only due to patient characteristics but also based on surgical type, comorbidities, and drug interactions. Another concern is "alert fatigue"—the desensitization of clinicians due to frequent alarms or notifications generated by automated systems. This can lead to critical alerts being ignored or missed. Lastly, ethical and legal concerns surrounding AI in healthcare, such as data privacy, accountability in adverse outcomes, and regulatory compliance, remain unresolved and pose additional barriers to implementation.

IV. DATASET DETAILS AND PERFORMANCE MEASUREMENT PARAMETERS

A.Dataset Details

The development and evaluation of artificial intelligence (AI) systems for assessing the depth of anesthesia (DoA) heavily depend on the availability and quality of datasets. These datasets typically contain multi-modal physiological recordings, such as electroencephalogram (EEG), heart rate (HR), blood pressure (BP), oxygen saturation (SpO□), drug infusion rates, and in some cases, audio or video of patient responses. EEG remains the most commonly used signal in DoA-related studies due to its strong correlation with the central nervous system's activity and consciousness level. Publicly available datasets in this field are limited. Among the few open-access databases, the MIMIC-III and MIMIC-IV (Medical Information Mart for Intensive Care) datasets provide vital signs and clinical data but are not specifically curated for intraoperative anesthesia monitoring. The CHB-MIT Scalp EEG Database and TUH EEG Corpus are popular for EEG analysis but do not contain labeled anesthesia depth information. Some recent research has been conducted using institutional datasets obtained during surgeries from operating room monitors and anesthesia machines. These proprietary datasets are often enriched with synchronized EEG recordings and BIS (Bispectral Index) values, drug dosages (e.g., propofol and remifentanil infusion rates), and vital signs. However, due to privacy, legal, and ethical restrictions, most of these remain unpublished or available only on request. An important challenge is the heterogeneity of data sources**,** patient populations, and equipment configurations, which affects the generalizability of AI models. Moreover, data pre-processing**,** including artifact removal (e.g., muscle noise, electrode drift), signal normalization, and feature extraction, plays a crucial role in determining the quality of the input to AI algorithms. Techniques such as band-pass filtering, Fast Fourier Transform (FFT), wavelet transforms, and principal component analysis (PCA) are commonly used in EEG data preparation.

Performance Measurement Parameters

The performance of AI models designed to assess the depth of anesthesia is evaluated using both classification and regression metrics**,** depending on whether the system predicts discrete states (e.g., awake, light anesthesia, deep anesthesia) or continuous indices (e.g., predicted BIS value).

For Classification Models:

- **Accuracy**: The percentage of correct predictions among all predictions made.
- **Precision**: The proportion of true positives among all predicted positives, reflecting reliability.
- **Recall (Sensitivity)**: The ability to correctly identify positive cases (e.g., correctly detecting deep anesthesia).
- **Specificity**: The ability to correctly identify negative cases (e.g., not falsely detecting wakefulness).
- **F1 Score**: Harmonic mean of precision and recall, balancing both metrics.
- **Confusion Matrix**: A detailed breakdown of true vs. predicted classes, useful for understanding misclassifications.
- **ROC Curve and AUC (Area under Curve)**: Visual and numerical evaluation of classification performance across thresholds.

For Regression Models (e.g., BIS prediction):

- **Mean Absolute Error (MAE)**: Average absolute difference between predicted and actual BIS values.
- **Mean Squared Error (MSE)** and **Root Mean Squared Error (RMSE)**: Provide an indication of the variance of prediction errors.
- **R^2 Score (Coefficient of Determination)**: Indicates the proportion of variance in the BIS explained by the model.
- **Pearson Correlation Coefficient**: Measures the linear correlation between predicted and actual BIS values.

Real-Time Evaluation Metrics:

- **Latency**: The time delay between receiving input signals and providing predictions, critical in clinical settings.
- **Robustness**: The model's ability to handle noisy data and missing signals without significant performance degradation.
- **Interpretability**: While not a statistical metric, the ease with which clinicians can understand and trust model outputs is increasingly considered vital.

V. CONCLUSION AND FUTURE WORK

This review highlights the ongoing advancements in using artificial intelligence (AI) to assess the depth of anesthesia (DoA) by analyzing critical physiological and neurological parameters, particularly EEG. While AI-based systems have shown promising accuracy and automation in DoA monitoring, existing methods still face challenges related to data quality, model generalizability, real-time application, and clinical interpretability. Current approaches, though innovative, are limited by the lack of standardized datasets, noise interference, and variability in patient responses. Future research should focus on building large, diverse, and publicly accessible datasets tailored for anesthesia monitoring. There is also a need for interpretable AI models that integrate multimodal signals (e.g., EEG, ECG, hemodynamic data) and provide real-time, clinically actionable insights. Improving robustness to noise, enhancing model adaptability across different patient demographics, and integrating AI systems into existing clinical workflows will be crucial for widespread adoption. Collaborative efforts between clinicians, data scientists, and engineers are essential to develop reliable and ethical AI-driven anesthesia monitoring tools.

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