Meta-Learning Deep Models for Understanding Brain States During Anesthesia

Hemanth Kumar K M, Mohammed Kaleem, Chethan B S, Harish B A, Hruthik Gowda Y
Department of CSE, Don Bosco Institute of Technology, Bengaluru, Karnataka, India

hemanthzoff@gmail.com, mkaleem@dbit.co.in, chethanbs2502@gmail.com, harishba231@gmail.com, hruthik0514@gmail.com

Abstract

Monitoring the depth of unconsciousness during anesthesia is vital for both neuroscience research and clinical practice. EEG (electroencephalogram) provides a real-time, objective way of monitoring affects to the brain states caused by anesthetic agents. Unfortunately, EEG signals in an office-based scenario often have a low Signal-to-Noise Ratio (SNR), which limits the traditional machine-learning models from performing reliably. Whereas deep learning is well-known for its noise robustness, strong generalization, and has been successful for many different modeled Brain-Computer Interface (BCI) tasks, it has received little attention for classifying brain states during anesthesia. This work presented AnesMetaNet, a novel meta-learning framework that facilitates the classification of brain states during anesthesia. AnesMetaNet utilized a meta-learning framework to deal with inter-subject variability, approved Long Short-Term Memory (LSTM) networks to account for temporal dependencies, and leveraged Convolutional Neural Networks (CNNs) to extract a power spectrum of features. A multi-stage training approach was used to enhance the performance, and it ultimately showed significant model improvements based on experimental results with offce-based EEG data.

Keywords

Anesthesia, Deep Learning, Meta-learning, Consciousness detection, CNN-LSTM, EEG

Introduction

Anesthetic drugs cause brain circuits to change their oscillation patterns in particular ways, thereby preventing neurons in different brain regions from communicating with each other. The outcome is a loss of consciousness that is distinct from sleep and an abnormal state that he likens to a "reversible coma." For the majority of surgical and many nonsurgical procedures to be performed safely and humanely, it is crucial to give the patient the appropriate dosage of anaesthetic medications. While an overdose of anaesthetics raises the risk of postoperative delirium, an underdose will cause patients to awaken during surgery.

Anesthesiologists typically manually estimate the depth of anesthesia (DoA) at intervals using the Richmond Agitation Sedation Scale (RASS); however, this necessitate significant attention with a complex stimuliresponse procedure during the surgery. Although DoA has been measured by monitoring heart rate, breathing patterns, blood pressure, and other parameters, these physiological signals are secondary measurements of DoA and exhibit significant cross-subject variability, making it difficult for anesthesiologists to interpret the DoA heart rate. Since the brain's cognitive process depends on electrical signals between neuronal populations, the EEG

signal provides a direct measurement of brain states in contrast to secondary measurements. Crucially, it has been discovered that DoA is linked to EEG signatures for various medications.

Literature Review

J. B. G and A. K. [1] introduced a practical approach for monitoring brain states during anesthesia. They developed a system that blends three powerful techniques: CNNs to recognize important patterns in EEG brain signals, LSTMs to understand how these signals change over time, and meta-learning to allow the model to adjust quickly for different patients. This combination helps the system make accurate and fast decisions about a person's level of consciousness while under anesthesia

H. Vinutha and B.V. Yogananda [2] explored advanced meta-learning strategies aimed at analyzing brain states under anesthesia. Their work involved building models capable of adapting to varied datasets, enabling the system to rapidly adjust to new patients and unfamiliar clinical scenarios. By training the model on numerous examples involving anesthesia, it becomes better at recognizing subtle distinctions in EEG patterns and learning patient-specific brain responses. This approach improves the model's ability to generalize across different individuals and conditions, enhancing its reliability in real-world applications.

Shanmugapriya [3] and her team focused on the application of Convolutional Neural Networks (CNNs) for classifying brain states during anesthesia using EEG recordings. Their method fed raw EEG signals directly into a CNN, allowing the network to automatically identify patterns linked to varying consciousness levels. This deep learning technique not only simplified the analysis process but also improved the accuracy of classification by reducing the need for manual intervention in feature extraction.

M Shi [4] and colleagues introduced the Deep Residual Shrinkage Network (DRSN) as a solution for estimating the depth of anesthesia based on EEG data. This model not only identifies complex patterns hidden in brain activity but also applies a shrinkage method to filter out noise and unimportant details across network layers. As a result, the system prioritizes relevant information, leading to more robust and accurate predictions of anesthetic states, making it a valuable asset in clinical practice.

Danton S. Char [5] paper focuses on the recent approval of the first autonomous, diagnostic system by the FDA marks the arrival of clinical machine learning (ML). ML is a promising type of artificial intelligence that is ideally suited for the predictive analytics in clinical decision making, and it is beginning to be essential. ML helps develop computer systems that leverage big data, or complexity that is difficult or impossible using traditional methods, to identify patterns and make decisions with minimal or no human involvement. As ML tools are being designed with end-users in mind, specifically for clinical anesthesia applications, anesthesiologists will face ever-increasing scrutiny to define when and how clinicians provide value.

Q. Wang [6] and co-authors investigated the idea of how deep learning coupled with meta-learning can ultimately improve the inference of brain states during anesthesia. Their method trained models that learn from the data and also learn how to learn, meaning that given a new patient with little data, the model will quickly learn and process information from that patient. By developing a model that of the neural networks with the meta-learning strategies, not only did the model become more flexible, the model also became more accurate in classifying brain activity levels under different anesthesia conditions.

Qihang Wang [7] and colleagues developed a method that combines deep learning with meta-learning to interpret brain activity during anesthesia. The key idea was to build a model that not only learns patterns in EEG data but can also adapt quickly to new patients or changing conditions. By training the system on a variety of tasks, it became more skilled at recognizing different states of consciousness even with limited data, making it especially useful for real-time clinical applications.

E. N. Brown, P. L. Purdon, and C. J. Van Dort [8] performs the behavioral and physiological characteristics of five classes of intravenous anesthetics to the molecular targets and neural circuits at which these medications are thought to act, E. N. Brown, P. L. Purdon, and C. J. Van Dort conduct a neuroscience analysis of the altered arousal states caused by these medications. Sedation unconsciousness, sedation analgesia, dissociative anesthesia, pharmacologic non-REM sleep, and neuroleptic anesthesia are examples of altered states of arousal. The anesthetic medications act on several different central nervous system targets, resulting in each altered arousal state. According to the analysis, general anesthesia is not as enigmatic as previously thought.

Naoki Miyaguchi [9] have proposed the machine learning problem of predicting anesthesiologists' decisions during surgery is mentioned; in particular a decisionmaking problem by changing the flow rate at each time point in the continuous administration of the analgesic remifentanil as a supervised binary classification problem. The experiments were conducted to investigate the prediction performance using machine learning models: logistic regression, support vector machine, random forest. The machine learning problem of predicting anesthesiologists' decisions during surgery is mentioned; in particular a decision making problem by changing the flow rate at each time point in the continuous administration of the analgesic remifentanil as a supervised binary classification problem. The experiments were conducted to evaluate the prediction performance using machine learning models.

Abel [10] have proposed the database to include electroencephalography (EEG) multitaper spectra with associated conscious/unconscious labels from a cohort of 10 healthy volunteers undergoing stereotyped administration of anesthetics with direct observations of subject responsiveness, and 44 patients receiving anesthesia care in an operating room (OR) context. This database includes electroencephalography (EEG) multitaper spectra and associated conscious/unconscious labels from a cohort of 10 healthy volunteers undergoing stereotyped administration of anesthetics with direct observations of subject responsiveness, and 44 patients receiving anesthesia care in an operating room (OR) context.

Afshar, Boostani, and Sanei [11] has developed a model that produces a real-time prediction of the bispectral index (BIS) from EEG signals The model was mostly trained on patients under general anesthesia and will extrapolate well to other anesthetic methods, such as spinal anesthesia and conscious sedationDespite using a dataset with varied BIS values, the model demonstrated notable improvements: a 15% increase in AUC, an RMSE of 5.59, and an MAE of 4.3. The model provides a 4-group classification of the depth of anesthesia with an accuracy of 88.7% that exceeded the predictive methods traditionally used.

Y. Fujisawa [12] investigated the use of AI in dermatology. By training a deep learning algorithm on a large dataset of clinical skin images, the system learned to detect features associated with various tumor types. When compared to board-certified dermatologists, the AI model showed even higher diagnostic accuracy, suggesting its potential value in clinical decision-making.

S. Solomon [13] worked on machine learning models designed to predict sudden drops in heart rate and blood pressure, known as intraoperative bradycardia and hypotension. The model analyzed real-time physiological

data collected during surgeries to identify early warning signs. This predictive method provides clinicians with alerts in advance, helping reduce unexpected cardiac events and improving overall patient safety.

Y. Park [14] designed a system that acts as a real-time monitor for a patient's anesthesia depth using deep neural networks (DNNs). By continuously analyzing EEG signals during surgery, the system detects patterns that relate to changes in consciousness and delivers constant feedback. This assists anesthesiologists in adjusting drug dosages with greater accuracy, enhancing patient care and procedural outcomes.

R. Li and his team [15] proposed an approach combining recurrent neural networks (RNNs) with both hand-crafted and automatically derived EEG features. Their model focuses on learning the temporal dynamics of brain activity under anesthesia. The method boosts both the accuracy and reliability of anesthesia monitoring, and shows promise for more adaptable use in complex clinical environments.

Kang A. R. [16] and team built a machine learning model to predict the risk of hypotension (low blood pressure) after anesthesia is administered. They used patient data collected before and during the early stages of anesthesia to train the model, enabling it to identify patterns that typically precede a drop in blood pressure. The aim was to give clinicians an early warning system so they could take preventive measures and improve patient safety.

Comparative Analysis

Reference	Methodology	Technology / Model Used	Key System Features	Limitations
[1] J. B. G and A. K, 2025	Real-time monitoring of brain states	CNN + LSTM + Meta-Learning	Combines spatial, temporal, and adaptive learning for accurate inference	High computational demand
[2] H. Vinutha and B. V. Yogananda, 2024	Meta-learning for neural state inference	Advanced meta-learning techniques	Learns quickly from small datasets; adaptable across conditions	Complex to train and tune
[3] S. Shanmugapriya et al., 2023	EEG-based brain state classification	Convolutional Neural Network (CNN)	Extracts spatial features from EEG signals	Limited handling of temporal patterns
[4] M. Shi et al., 2023	EEG-based depth estimation	Deep Residual Shrinkage Network	Denoising and signal enhancement; robust EEG processing	Needs large labeled EEG datasets
[5] D. S. Char, 2022	Clinical ML applications in anesthesia	General ML algorithms	Focuses on real-time decision support in practice	Lacks model specificity and evaluation depth
[6] Q. Wang et al., 2022	Meta-learning for state inference	Meta-learning + Deep Learning	Generalizes across patient types; handles non-stationary EEG	Interpretability issues

[7] Qihang Wang et al., 2022	Same as [6]	Meta-learning-based DL models	Duplicate of [6] with similar capabilities	Redundant publication
[8] E. N. Brown et al., 2021	Systems neuroscience analysis	Theoretical EEG-arousal framework	Explains anesthetic states based on brain dynamics	Not a machine learning approach
[9] N. Miyaguchi, 2021	Event prediction during anesthesia	Supervised ML with time-series data	Predicts anesthetic infusion outcomes; real-time insights	Performance dependent on label quality
[10] Abel et al., 2021	Spectral analysis during anesthesia	Multitaper spectrum estimation	High-frequency EEG resolution; detects subtle changes	Preprint; lacks clinical validation
[11] S. Afshar et al., 2021	Deep learning for DoA estimation	Hybrid DL architecture (e.g., CNN-RNN)	High accuracy; captures both temporal and spatial EEG features	Requires extensive training data
[12] Y. Fujisawa, 2020	AI for skin tumor diagnosis	Deep image classifiers	Exceeds dermatologist accuracy (transferable insight)	Not specific to anesthesia domain
[13] S. Solomon, 2020	Intraoperative crisis forecasting	ML prediction models	Anticipates bradycardia under anesthesia	Narrow scope (specific event focus)
[14] Y. Park, 2020	Real-time DoA monitoring	Deep Neural Network (DNN)	Continuous EEG interpretation; good real-time response	May suffer from latency under load
[15] R. Li et al., 2020	Hybrid EEG signal modeling	RNN + Hybrid features	Excellent for time-sequenced EEG inputs	May generalize poorly outside trained patterns
[16] Kang A R et al., 2020	Hypotension prediction	Classification models with vital signs	Anticipates anesthesia-induced BP drops	Event-specific; not a full brain state model

Methodology

- Database Collection: We use an EEG dataset from a public office that deals with anesthesia. EEG recordings of patients under general anesthesia are included in the dataset. The database may be in CSV or text format. It will provide the patient characteristics score based on a manual assessment of the degree of sedation administered to patients in different scenarios.

- Data Preprocessing: We assign a label to each EEG data point based on its timestamp, such as the time period it belongs to. To extract the power spectrum features from each time point—represented as a one-dimensional vector—we use a one-dimensional convolutional neural network (1D CNN). This type of neural network is particularly useful here because it's designed to work efficiently with onedimensional data like time series. Compared to traditional fully connected neural networks, CNNs are more efficient and require fewer parameters to train, thanks to their use of convolutional layers instead of connecting every neuron to every other one.

- Convolutional Neural Networks: The onedimensional convolutional neural network (1D-CNN) is used to extract the features since the power spectrum features at a single time point are a onedimensional vector. CNNs are more computationally efficient and have fewer parameters to adjust than traditional neural networks because their convolutional layers are not fully connected. CNN consists of a one-dimensional maximum pooling operation, a rectified linear unit (ReLU), and a convolutional layer. for the DoA states' classification. We employ Adam as the optimisation algorithm to find the best CNN model parameters for the classification task, and cross-entropy as the loss function. All of the other deep learning models in this study also make use of such a loss function and optimisation algorithm.

- Long Short-Term Memory**:** Enable live face recognition from video feeds to Capture frames from a live feed using OpenCV. Process each frame sequentially to Detect faces with MTCNN ,Extract embeddings with FaceNet , Match embeddings with stored data to recognize faces. and Display results in real-time with bounding boxes and labels.

- Security and Privacy Approach: Protect sensitive data and maintain user privacy. Encrypt embeddings and user data during storage and transmission. Use role-based access control to restrict database access. Implement anonymization techniques for ethical data handling. Face embeddings and user data are encrypted during storage and transmission to prevent unauthorized access.

Expected Results

- Accurate classification of brain states like normal, analgesia, and overdose using EEG data.
- Better generalization across patients through meta-learning to handle cross-subject variability.
- Improved temporal analysis using LSTM to capture time-based changes in EEG signals.
- Noise-resilient feature extraction using CNNs for better performance on low-SNR EEG signals.
- Higher accuracy and adaptability compared to traditional machine learning models.
- Real-time prediction capability for timely clinical decision-making during anesthesia

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Conclusion

In conclusion, the project presents a promising framework for the classification of different brain states under anesthesia using EEG data. By leveraging deep learning techniques, including Convolutional Neural Networks (CNNs) for feature extraction and Long Short-Term Memory (LSTM) networks for temporal modeling, alongside a framework for meta-learning to address crosssubject variability, the system demonstrates considerable potential in accurately characterizing changed states of arousal and cognition brought on by anesthetics. Through a systematic approach encompassing data preprocessing, model development, training,

and evaluation, the project has successfully demonstrated the effectiveness of in achieving robust classification performance, as evidenced by validation on diverse datasets and comparison with existing methods. Furthermore, the comprehensive testing regime covering functionality, reliability, performance, usability, security, and privacy aspects ensures the system's reliability and utility in real-world applications. Moving forward, further refinements and optimizations, informed by ongoing research and feedback from stakeholders, will continue to enhance the capabilities and applicability of the framework in clinical settings and neuroscience investigations, ultimately contributing to a deeper understanding of brain mechanisms during anesthesia.

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