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Article Title: Brain State Inference While under Anesthesia using CNN-Based Deep Learning Models

Brain State Inference While under Anesthesia using CNN-Based Deep Learning Models

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ABSTRACT

Anaesthesia is a critical procedure for surgeons because it allows them to operate on unconscious and pain-free patients. This paper proposes using CNN-based deep learning models to infer brain state while under anesthesia. Both neuroscience research and clinical situations can help determine how deeply unconscious a patient is during anesthesia. The electroencephalogram (EEG) is a real-time, objective method for detecting anesthetic-induced changes in brain states of arousal and/or cognition. To pre-process the signal, the adaptive median filter is used. The median filter is a signal-filtering method used to remove noise from signals. The feature extraction process is carried out using wavelet decomposition, which allows for perfect signal reconstruction. To classify anesthetized brain states, this paper employs a CNN-based technique.

Keywords: Richmond Agitation-Sedation Scale (RASS), Convolutional Neural Networks (CNN), Depth of Anesthesia (DoA), Electroencephalography (EEG).

1 Introduction

In the operating room, anaesthesia is a critical process that allows physicians to operate on patients while they are unconscious and pain-free. Early depth of anaesthesia (DOA) monitoring techniques lacks precise quantitative signs and the capacity to prevent outside influence. Instead, they rely mostly on the patient's physiological response, which is refereed by skilled anaesthesiologists [1]. The majority of the time, anaesthesiologists evaluate the depth of anaesthesia manually at intervals based on the Richmond Agitation-Sedation Scale (RASS) nevertheless, this would take significant attention with a complex stimuli-response procedure during the surgery [2]. Because incorrect depth of anaesthesia (DoA) might result in unwanted intraoperative consciousness or excessive hemodynamic instability, as well as postoperative mortality and morbidity, it is obvious that aesthetic drugs should be appropriately titrated during general anaesthesia. A precise DoA monitoring system was required not only for a safer procedure, but also for patients to recover faster postoperatively [3]. In recent years, anaesthesiologists have become increasingly interested in EEG as a powerful tool for measuring brain activity. In comparison to secondary measurements, EEG signal is a direct assessment for brain states since the brain cognitive process relies on electrical signal communications between neuronal populations. Importantly, DoA has been linked to EEG

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patterns associated with several medications [4]. In adding to the above standard machine learning models, recently, many researchers employed deep learning as classification models for monitoring the DoA [5]. Brain activity can be recorded using an electroencephalogram (EEG). It is possible to monitor the electrical signals produced by the brain by attaching tiny sensors to the scalp during this painless examination. Conductors are useful to the subject's scalp to best the electrical impulses that the brain naturally produces, a process known as an electroencephalogram. Neuronal dendritic extracellular synaptic transmembrane currents are responsible for the measured electrical potentials [6]. Anaesthesia is a medical or veterinary-induced state of regulated, transient loss of feeling or awareness. It may include some or all of the following: analgesia (pain reduction or prevention), paralysis (muscle relaxation), amnesia (loss of recollection), and unconsciousness [7]. An individual who is under the influence of anaesthetic medications is said to be anesthetized. Anaesthesia allows for the painless execution of procedures that would otherwise cause severe or intolerable pain in a non-anesthetized person, or would be technically impossible [8]. When preparing for a medical or veterinary exam when preparing for a medical or veterinary procedure, the clinician selects one or more drugs to achieve the types and degree of anaesthesia characteristics appropriate for the procedure and the patient. During a procedure, the clinician selects one or more drugs to achieve the types and degrees of anaesthesia appropriate for the procedure and the patient [9]. In many computer vision and natural language processing tasks, deep learning has demonstrated superior performance compared to classical machine learning models, among other applications [10]. To identify brain states while under anaesthesia, a Convolutional neural networks (CNN)-based model is used to evaluate accuracy using the feature extraction method of Wavelet decomposition, and noise is reduced using an adaptive median filter.
The list below demonstrates how the paper is organised: Section I gives a description of the introduction. The recent works are described in Section II. The proposed model and description are explained in Part III. The results are presented in Section IV. In Section V, the conclusion is presented.

2 Recent Works

Dheeraj Rathee *et al* [2018][11] have proposed Brain connectivity measurements, as previously described, can offer vital details regarding ongoing brain functions. In this study, we propose to investigate the binary categorization of partial Granger causality analysis-induced sedation states with propofol. This lends credence to the conclusion that can be identified by means of an AUC by analyzing signal segments. These findings highlight the discriminant power of scalp level connectivity actions for online brain monitoring. Key challenge for applying these findings in clinical settings is effectively distinguishing Propofol-induced sedation states from their effect on awareness.

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Kimia Kashkooli *et al* [2019][12] have introduced the use of automated brain-state prediction arrangements to maintain anaesthetic states is expected to reduce medicine overdosage and associated side effects. On drug class groupings, commercially available brain-state monitoring schemes achieve unwell. It creates a nearest neighbours' model to see if it is possible to improve automated brain-state prediction of drug-class groupings. Using drug-specific models, it improved performance in predicting anaesthesia-induced brain states. When compared to a one-model-fits-all-drugs approach, EEG-based automated brain-state prediction systems based on drug-specific models perform better. Improved brain-state monitoring systems are expected to promote widespread use and patient monitoring guidelines.

Gunasekaran Manogaran *et al* [2018] [13] proposed a several clinical studies have used artificial intelligence applications in magnetic resonance imaging. Because the extracted brain images must be optimized using a segmentation algorithm that is highly resistant to noise and cluster size sensitivity issues and automatically detects the region of interest (ROI), the analysis of brain tumours without human intervention is regarded as an important area of research. An improved machine-learning approach using the orthogonal gamma distribution technique is utilized to examine the under and over segments of brain tumor locations in order to identify anomalies in ROI. By matching edge coordinates and sensitivity further data imbalances in the aberrant region are sampled, and the machine learning technique is used to estimate the selectivity parameters.

Yijie Zhou *et al* [2020][14] have employed scythe volume conduction effect, conventional non-invasives electroencephalogram (EEG) has poor spatial resolution. To address this limitation, High sequential and spatial resolution mapping of brain electrical activity is proposed using AE-based acoustoelectric brain imaging. Moreover, the deciphered AE signal for each PRF has the same frequency and phase as the current source. Lastly, the coding mechanism is validated in an in vivo rat experiment using different PRFs. These theory and research results confirm that has a coding effect on current source at and demonstrate the feasibility of restoring current foundation from the coded signal, both of which are required for ABI to be used in clinical settings. Both the AE signal wrapper and the interpreted signal contain substantial information.

Oleksii Avilov *et al* [2021][15] have provided EEGNet architectures were investigated in order to improve MI detection. They were tested against cutting-edge classifiers in deep learning architectures and Brain-Computer Interfaces. This research aims to improve the detection of intraoperative awareness during general anesthesia. The planned method helps to advance the development of Brain computer Interface systems based on MI detection in EEG. Education systems can outperform in detecting, owing to the fact that they only use filtered data and not well known extracted features. It also confirms that adding median nerve stimulation (MNS) makes this detection easier. MNS with a greater quantity of anodes achieves greater exactness.

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3 Proposed Work Explanation

For aesthetic brain state inference, the proposed system employs CNN-based deep learning models. The signal acquisition process is enabled by the input signal. a adaptive median filter is used to pre-process the given signal. An adaptive median filter reduces noise in a signal by performing spatial processing. Following pre-processing, this dataset is sent to the feature extraction block. For wavelet decomposition, a feature extraction block is used. Wavelet decomposition is used to extract information from a wide range of data types. For machine learning data classification, the selected characteristics are fed into the convolutional neural network classifier. CNN's classification method is used to advance accuracy. Finally, the output result specified was obtained.

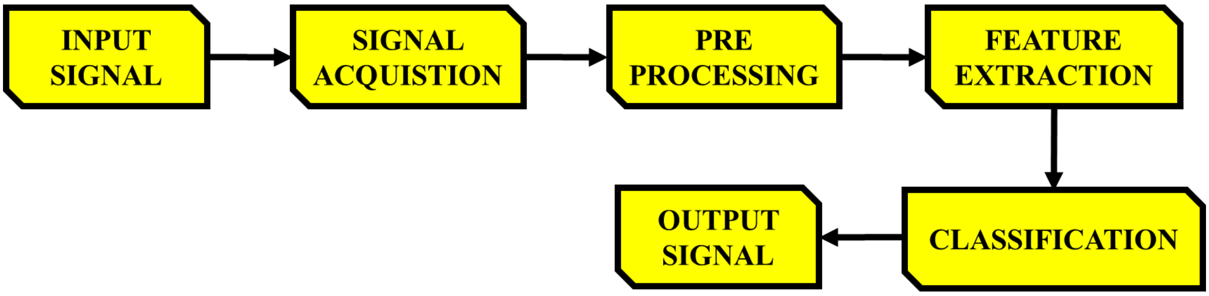

Figure 1: *Proposed system Block diagram*

3.1 Input signal

The dataset contains recordings made of patients when they were sedated. A low-dose protocol ramp is used to induce and sustain sedation, and then boluses of protocol, ketamine, and lidocaine are given. The data for a considerable proportion of patients contains noise because to high motion artifacts during recordings.

3.2 Signal Acquisition

It is the procedure of taking samples of signals that quantify physical properties in the real world and transforming them into digital numeric values that can be worked with by computers. Data collection (sampling/holding, quantization, coding), signal conditioning, signal pickup, computer storage, and display processing are all part of the EMG signal acquisition and transmission process. Signal acquisition is a difficult task. Photographic images contain noise in the light intensity signal (photon noise, for example), and additional noise can occur during processing after the fact or within the sensor.

3.3 Preprocessing

By reducing undesirable distortions or enhancing particular image components that are crucial for further processing, pre-processing pursues to improve image data, even though geometric

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changes to pictures are possible. A behind error normalized adaptive filter is used in ECG signal preprocessing to achieve high rapidity and low potential enterprise with fewer computational elements. Because the signal processing technique was created for remote healthcare systems, white noise removal is the primary focus.

3.4 Adaptive Median filter

This processes an image spatially to lower noise. Every pixel in the image is compared to its surrounding pixels by the filter. If one of the pixel values is significantly from the majority of the surrounding pixels, the pixel is considered noise. Calculates the median value in the pixel's close neighbourhood for each in the image. To reduce signal noise spatial processing employs an adaptive median filter. If one of the pixel values is meaningfully different from the majority of the neighbouring pixels, the pixel is considered noise.

3.5 Future extraction

Feature extraction begins with a baseline set of measured data and produces derived values that are intended to be non-redundant and informative in machine learning, pattern recognition, and image processing. By extracting features from input data, feature extraction improves the accuracy of learned models. This stage of the general framework reduces data dimensionality by removing redundant information. Of course, it speeds up training and inference.

3.6 Classification

The process of categorizing and labelling groups of pixels or vectors within an image based on specific rules is known as image classification. One or more spectral or textural characteristics can be used to develop the categorization law. 'Supervised' and 'unsupervised' are two general classification methods.

3.7 Convolutional neural network

The convolutional neural network is a architecture for deep learning algorithms that is specifically used for signal recognition and pixel data dispensation. A CNN based algorithm is primarily used in signal and speech recognition applications. They can also be useful for categorizing audio, time series, and signal data. Convolutional neural networks (CNNs) have made significant advances in radar imaging and semantic segmentation in recent years. Instead of manually analysing MRI images, a CNN based algorithm will assist medical professionals in their treatment role by accelerating the recovery process. Applications include face recognition, image categorization, and other computer vision applications.

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3.8 Classification of CNN

A feature extraction procedure divorces and identifies distinct characteristics of an image for study using a convolution tool. The fully connected layer that employs previously extracted features to identify the image's class using the convolutional process' output.

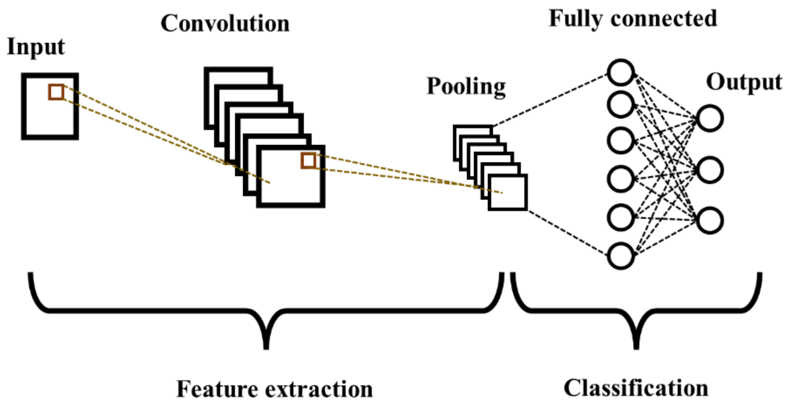

Figure 2: *Classification of CNN diagram*

3.9 Convolution layer

The first layer used to extract various features from the effort pictures. Complication is a accurate process that occurs among the input image and a filter of a detailed size, at this layer. The dot product between the filter and the input image's constituent parts in respect to the filter's size is computed by swiping the filter over the input image.

3.10 Pooling layer

After a convolutional layer, a pooling layer is commonly employed. The primary goal of this layer is to reduce the convolved feature map's size in order to minimize computing costs. This is achieved by cutting the linkages between layers and doing this independently on each feature map. Pooling procedures differ based on the employed method. It is essentially a summary of the features produced by a convolution layer.

3.11 Fully connected layer

The masses and partialities, as well as the nerve cell, comprise the Fully Connected layer, which connects the neurons between two layers it is common practice to arrange the last few layers of a CNN architecture prior to the output layer. In this FC layer receives the flattened input image from the layers below. The standard operations on mathematical functions are then performed on the flattened vector after it has been passed through a few more FC layers.

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3.12 Algorithm Used

CNN classification

Convolution kernel startup.

Convolution layer output evaluation.

$$C_{out} = f\left(\sum_{j=0}^{J-1}\sum_{i=0}^{I-1} y_{m+i,n+j} w_{ij} + b\right) \tag{1}$$

Where,

y - Filtered input of M*N matrix;

w - Convolution kernel of J*I matrix;

b - Bias=1; f- activation function (ReLu).

$$f(y) = max(0, y) \tag{2}$$

It ranges from 0 to infinity.

Pooling layer

Compute dimensions of c_{out} using pooling layer. For this method max pooling layer is taken. It takes the largest element from the rectified feature map.

$$p = \frac{n_h - f + 1}{s} * \frac{n_w - f + 1}{s * n_c} \tag{3}$$

Where,

n_h - Height of feature map,

n_w - Width of feature map,

n_c - Number of channels in the feature map,

f - Size of filter

s - Stride length

Fully connected layer

Dropout layer reduce over-fitting on neural networks

n- Output of neuron, if chosen no. is less than n then output will be dropped.

Determine output of fully connected (dense) layer.

$$F_j^l = f\left(\sum_{i=1}^{n} p_i^{l-1} w_{ij}^l + b^l\right) \tag{4}$$

Where,

l - Current layer

w_{ij} - Connection weights

4 Result

The spectrum of a signal shows the relative strengths of the various frequency components that make up the signal. The data used to calculate the power spectrum must reflect sufficient signal excitation. One of the standard methods for EEG quantification is spectral analysis.

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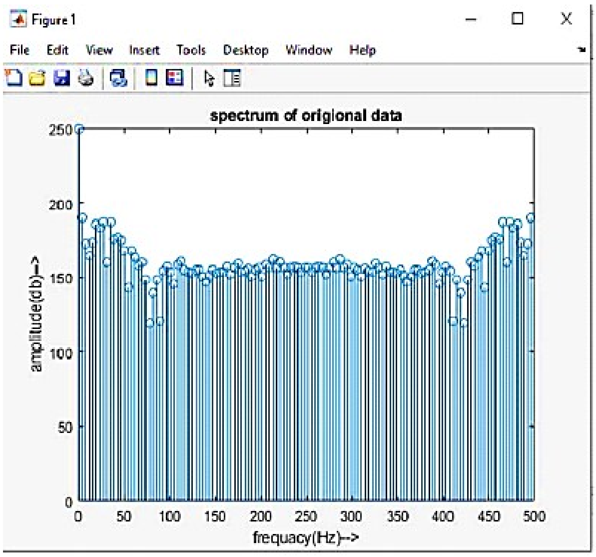

Figure 3: *Spectrum of Original Data*

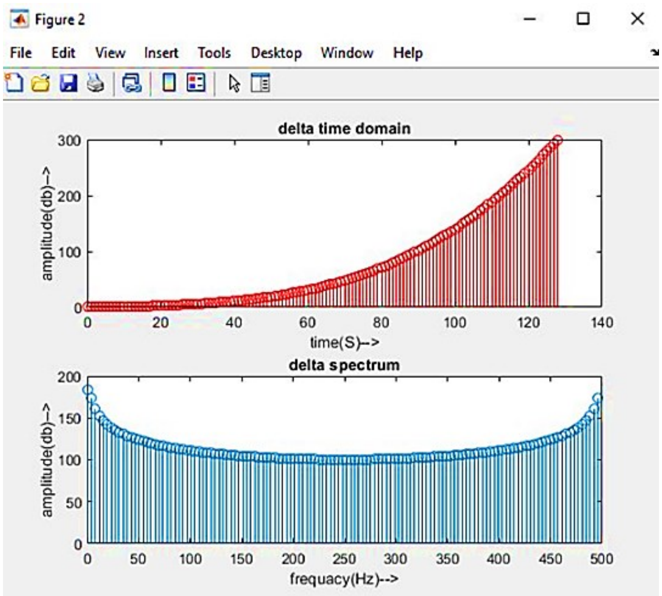

Figure 4: *Delta Time Domain & Spectrum*

Figure 4 depicts the Delta Time Domain and Spectrum images. Following preprocessing, the EEG data was separated into two frequency bands known as the Important and Beta occurrence bands. A spectrum analyser takes an analogy input signal in the time domain and converts it to the regularity field using the Fast Fourier Transform (FFT). Delta waves are the slowest brain waves ever recorded in humans.

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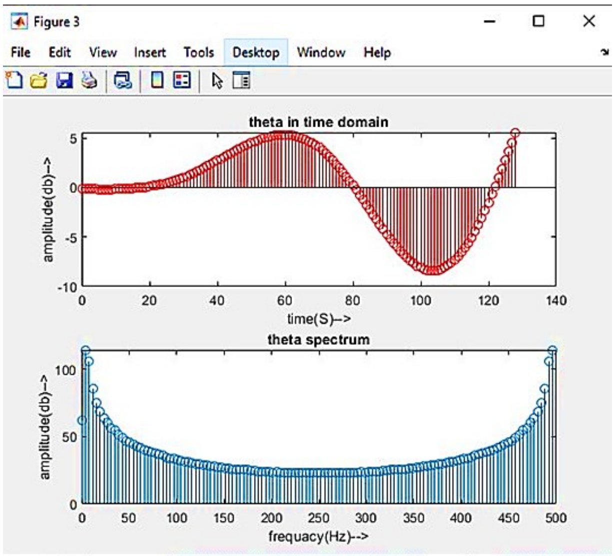

Figure 5: *Theta in Time Domain & Spectrum*

The images for the Theta Time Domain and Spectrum are shown in Figure 5. Theta brainwave states are associated with the sensation of being asleep or dreaming. This is due to the fact that when we are in theta brainwave state, our conscious awareness begins to fade and we become more relaxed. The theta rhythm, which is produced by the waves, is a brain oscillation that supports a variety of animal behaviours and aspects of cognition, such as learning, memory, and spatial navigation.

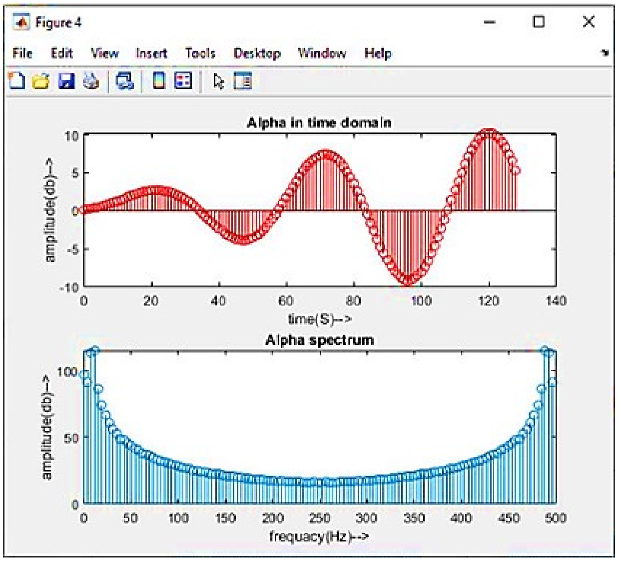

Figure 6: *Alpha in Time Domain & Spectrum*

Figure 6 depicts the images for the Alpha Time Domain and Spectrum. Alpha waves enhance creativity, calmness, and your capacity to take in new information. Meditation and mindfulness

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practice are two of the most obvious ways to extend your ability to stay in an alpha state, but there are others.

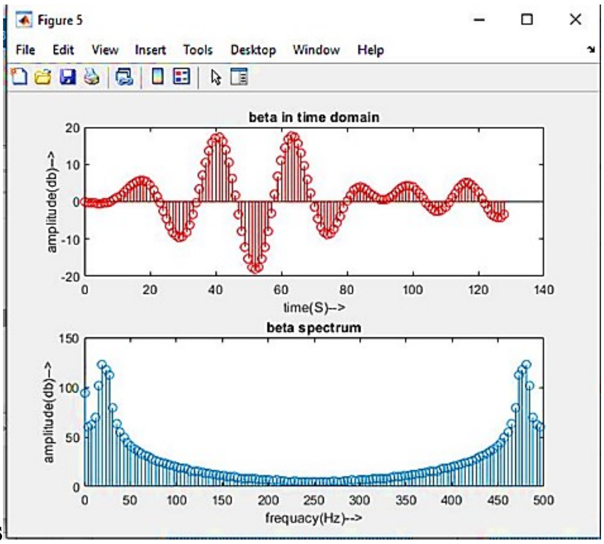

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Figure 7: *Beta in Time Domain & Spectrum*

The images for the Beta Time Domain and Spectrum are shown in Figure 7. Beta is a higher frequency brainwave that aids in maintaining focus. Problem solving and analytical thinking. Increasing energy and action. Beta waves are associated with mental activity and alertness. This is the brain wave you have when you are wide awake and working on a problem or other mentally challenging task. Beta waves can aid in memory and cognitive performance.

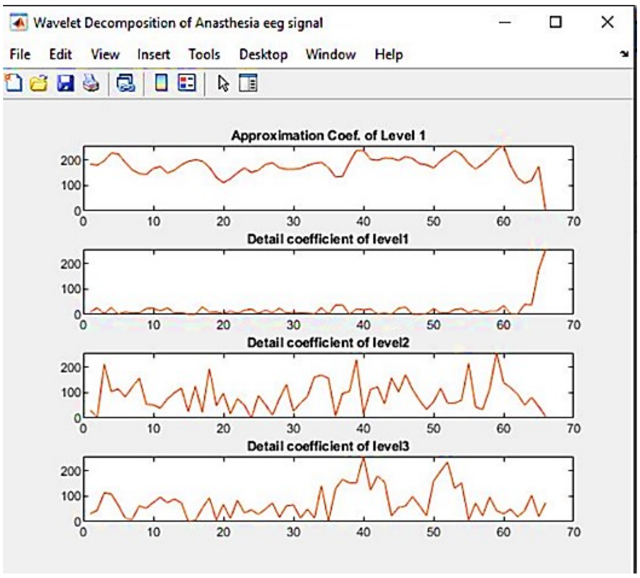

Figure 8: *Wavelet Decomposition of Anesthesia EEG Signal*

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Figure 8 shows images of wavelet decomposition of anesthesia EEG signals. The wavelet Decomposition is the most widely used and positive technique for nonstationary signal denoising, such as electrocardiogram (ECG) and electroencephalogram (EEG). The best arrangement of WT's control parameters, which are typically established experimentally, determines the systems

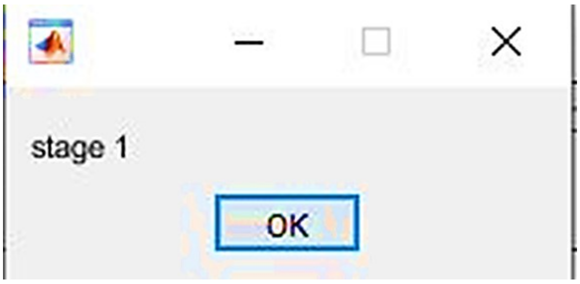

Figure 9: *Stages of Anesthesia*

Figure 9 depicts the Anesthesia Stages. The proposed method provides a clear classification of anesthesia stages. This technique is effective at detecting edges in anesthesia areas as well as classification, which is extremely beneficial for the radiologist's quick treatment.

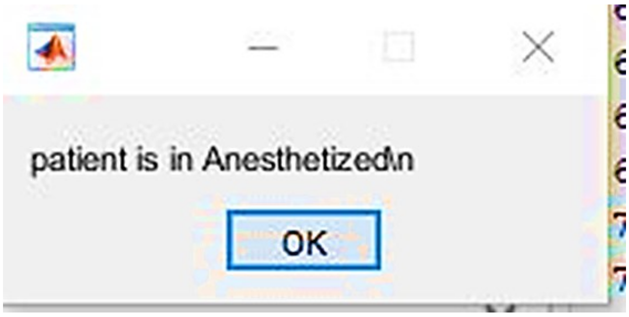

Figure 10: *Predicted Output*

The anesthesia output images are shown in Figure 10. The proposed method provides precise predictions and identification of anesthesia stages.

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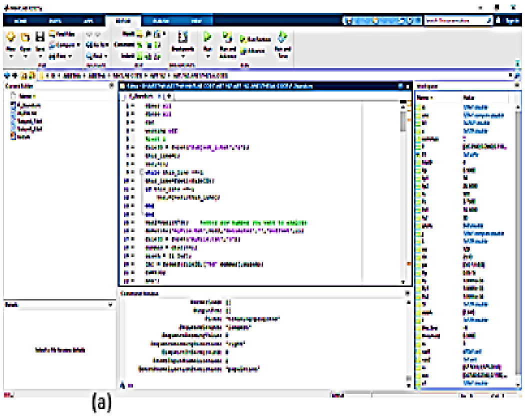
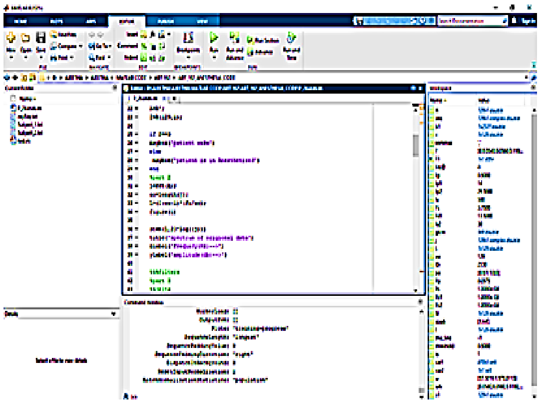
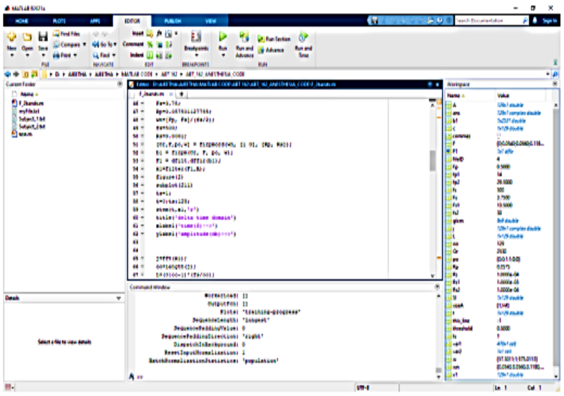
4.1 Appendix A. Screenshot

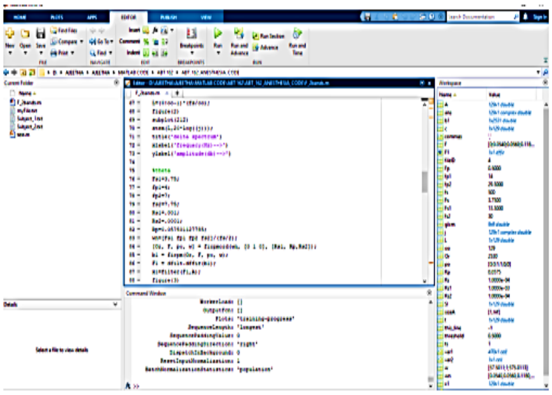


(a)



(b)





(d)

(c)

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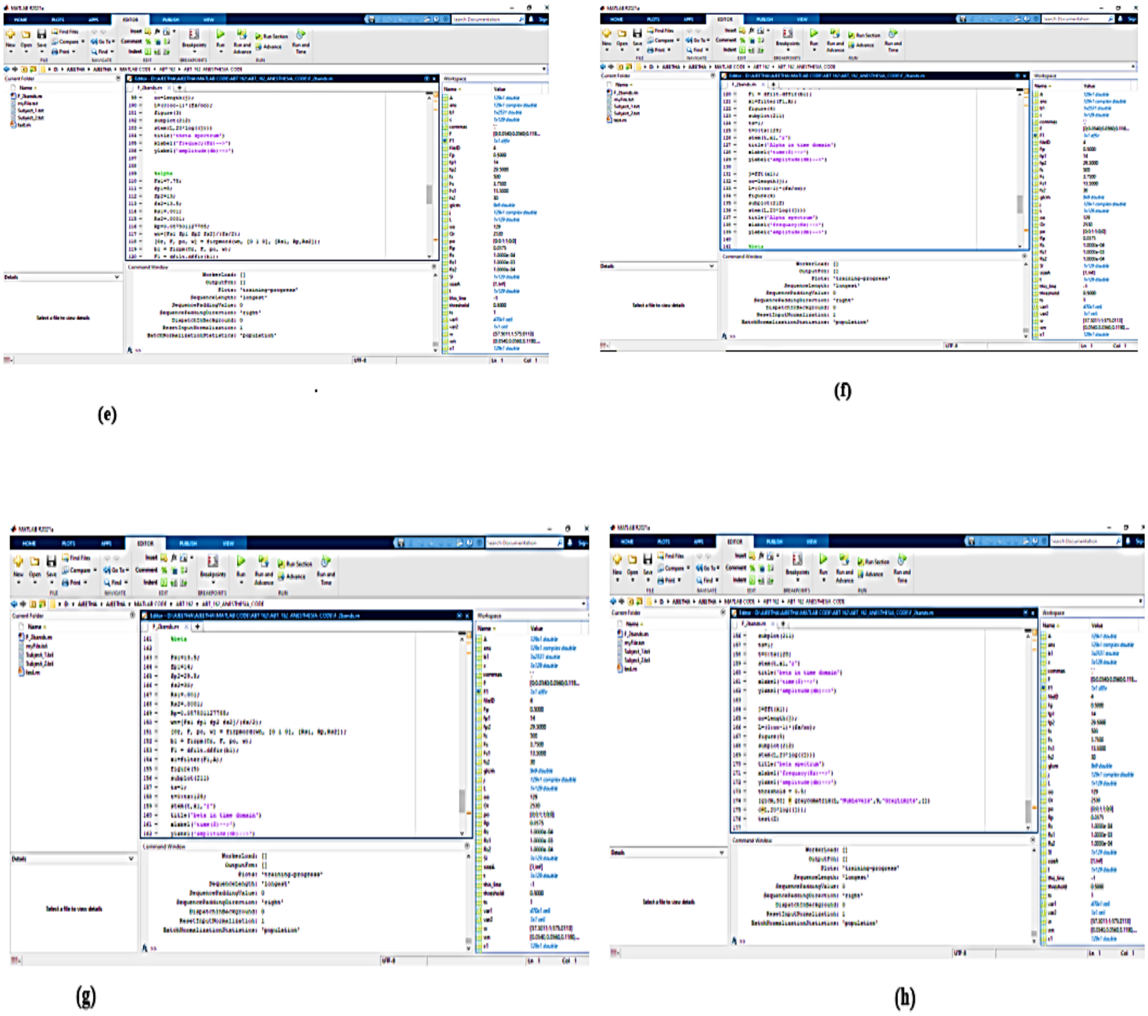

Figure 11: *Screenshot of this work's implementation*

The screenshot of this work's implementation is shown in Figure 11(a, b, c, d, e, f, g, h).

5 Conclusion

Anesthesia is a medical procedure used to keep patients pain-free during operations like dental work, surgery, diagnostic testing, and the removal of tissue samples. It enables people to have procedures that allow them to live healthier and longer lives. This paper uses CNN-based deep learning models to infer brain state while under anesthesia. Using a CNN-based model, our paper identifies brain states while under anesthesia. In addition, four different types of brain wave frequencies are studied separately in the time and spectrum domains. It successfully evaluates accuracy by utilizing the feature extraction method of Wavelet decomposition. Finally, the proposed method provides precise predictions and identification of anesthesia

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stages. These findings are used as the key to clinically explaining and identifying loss of consciousness.

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