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Hybrid Deep Learning Model for Bispectral Index Estimation using EEG Signal

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Declaration of Candidate

This is to certify that the work presented in this thesis is the outcome of the analysis and experiments carried out by **Md. Shoaib Shahriar Ibrahim**, **Majidul Islam Chowdhury**, and **Md. Ashikur Rahman** under the supervision of **Dr. Md. Azam Hossain**, Associate Professor, Department of Computer Science and Engineering, Islamic University of Technology, Dhaka, Bangladesh. It is also declared that neither this thesis nor any part of it has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others have been acknowledged in the text and a list of references is given.

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Dedicated to our families, faculty members and friends. Their unwavering support, encouragement, and guidance have been our guiding light throughout this journey. Thank you for always believing in us

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Abstract

Electroencephalography (EEG) plays a crucial role as a neurophysiological tool in anesthesia, offering invaluable insights into brain activity and responses during surgical procedures. Key to this role is the Bispectral Index (BIS), which serves to quantify consciousness and anesthesia depth.Maintaining optimal anesthesia levels is critical in surgery to improve patient comfort and mitigate risks such as intraoperative awareness and postoperative complications.However, traditional BIS monitors face limitations due to proprietary algorithms and high costs, restricting their global accessibility.To address these challenges, we present a novel deep learning framework that integrates convolutional neural networks (CNNs), bidirectional long short-term memory (BiLSTM) networks, and attention mechanisms.This framework harnesses the temporal information inherent in EEG signals to deliver continuous, real-time predictions of BIS, facilitating precise anesthesia depth monitoring throughout surgical procedures.Trained on a diverse dataset encompassing EEG signals,numerous anesthesia drugs and BIS our model demonstrates robust performance, surpassing current state-of-the-art methods in accuracy and reliability.Notably, its ability to adaptively consider operative time enhances its predictive capabilities in real-world surgical settings.Through extensive experimentation and analysis across diverse anesthesia scenarios, we validate the efficacy of our approach and advocate for its adoption in clinical practice.This research underscores the potential of our proposed framework to revolutionize anesthesia monitoring by providing a cost-effective and accessible alternative to traditional BIS monitors.By surpassing existing methodologies, our framework paves the way for broader implementation in healthcare, promising significant advancements in anesthesia management and patient care.

Keywords— electroencephalography, depth of anesthesia,bispectral Index,convolutional neural networks, bidirectional long short-term memory

Chapter 1

Introduction

1.1 Overview

Electroencephalography (EEG) is pivotal in anesthesia, offering critical insights into brain activity during surgeries.The Bispectral Index (BIS) is a key metric used to monitor the depth of anesthesia (DOA), ensuring patient comfort and minimizing risks such as intraoperative awareness.Despite its importance, traditional BIS devices are limited by proprietary algorithms and high costs, restricting accessibility.To overcome these challenges, we propose a novel deep learning framework combining convolutional neural networks (CNNs), bidirectional long short-term memory (BiLSTM) networks, and attention mechanisms to predict BIS continuously and in real time.Trained on diverse anesthesia data, our model outperforms current methods in accuracy and reliability.This framework's adaptability, accounting for operation time, enhances its real-world applicability.By leveraging deep learning, our approach offers a cost-effective, accessible alternative to traditional BIS devices, demonstrating its potential to revolutionize anesthesia monitoring and improve clinical outcomes.

1.2 Introduction

During surgery, a remarkable collaboration unfolds.The surgeon, with steady hands, performs the operation while the patient sleeps peacefully [8], [9], [17], [48].Anesthesia drugs [13] play a crucial role in this process, essentially putting the patient's brain into a controlled state of unconsciousness to prevent pain and movement [14].But ensuring the right level of anesthesia, known as depth of anesthesia (DOA) [21], [22] is critical.Studies suggest that even a small percentage of patients experience awareness during surgery, a potentially traumatic event known as "accidental awareness [15]. "Conversely, if the anesthesia is too deep, it can suppress vital bodily functions and lead to complications during recovery.

Traditionally, anesthesiologists have relied on monitoring physiological parameters like blood pressure, heart rate, and oxygen levels [5].However, these metrics exhibit significant variability between patients due to factors like age, body weight, and medical history. According to a 2021 study published in the Journal of Clinical Monitoring and Computing, these traditional methods can lead to inaccurate assessments of DOA in up to 20% of cases. Additionally, the type of surgery itself can impact these parameters [35]. A minimally invasive procedure might require a less profound state of unconsciousness compared to a multi-hour, intricate operation.

This inherent variability in physiological responses presents a significant challenge. Relying solely on these indirect measures for monitoring consciousness during surgery can be like conducting an orchestra by ear – imprecise and potentially dangerous [23]. Recent advancements in artificial intelligence (AI), particularly deep learning, offer a promising solution for more accurate and personalized DOA monitoring [33].

Electroencephalography (EEG) offers a more direct window into the brain's response to anesthesia. Commercial EEG-based monitors, like the Bispectral Index (BIS) [37], utilize electrodes placed on the forehead to capture brain activity.The BIS algorithm then analyzes this complex data and translates it into a single score ranging from 0 (deep unconsciousness) to 100 (fully awake) [24].Despite its widespread adoption, the BIS algorithm remains a "black box" due to patent restrictions.This lack of transparency hinders researchers' ability to fully understand its strengths and weaknesses, limiting further development of EEG-based DOA monitoring techniques.

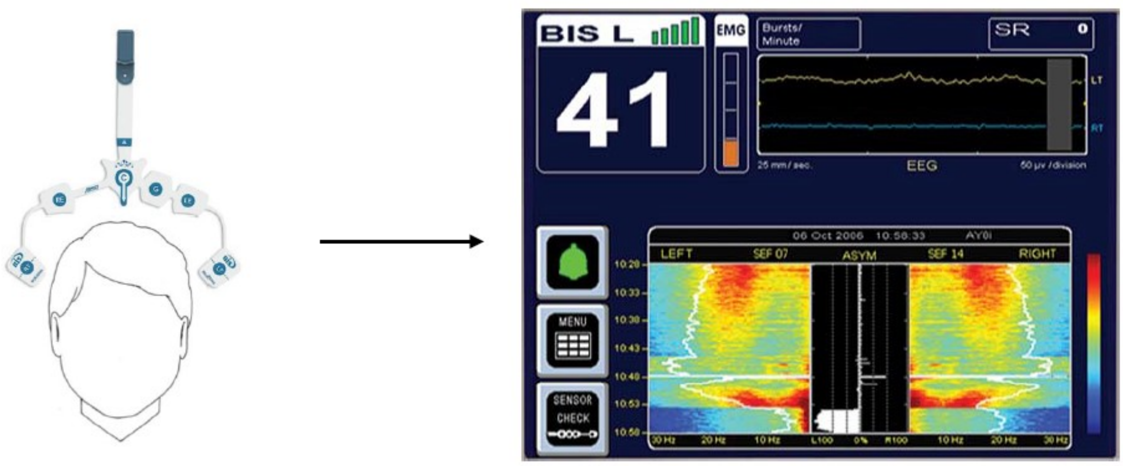

Figure 1.1: Bispectral Index prediction using EEG signal [36]

The field of medicine is undergoing a transformative shift, with machine learning emerging as a powerful tool for various applications [26], [38].Deep learning, a sub field known for its prowess in handling complex data, holds immense potential in the realm of anesthesia monitoring. This research capitalizes on this potential by pioneering a novel deep learning architecture designed to mimic the BIS index in real-time.

DOA monitoring relies on extracting hand-crafted features from EEG data – a time-consuming and potentially subjective process.Our proposed deep neural network (DNN) disrupts this paradigm by directly processing raw EEG signals, eliminating the need for feature engineering [29].This allows the DNN to learn intricate patterns within the raw data, potentially leading to a more accurate reflection of the brain's response to anesthesia.

By training on extensive patient datasets, we aim to establish the superiority of our DNN compared to existing methods.This includes not only traditional feature-based classification systems but also other DNN architectures.This research represents a significant leap forward in leveraging deep learning for anesthesia applications, particularly in achieving real-time, continuous prediction of the BIS score.

Researchers have delved into a rich toolbox of features extracted from EEG signals to assess depth of anesthesia (DOA). Wavelet-based features [40], like coefficient energy entropy [10] and median frequency, offer valuable insights as they correlate well with established measures like the BIS index. Similarly, burst suppression patterns – characterized by alternating periods of brain activity and electrical silence – are a hallmark of deep anesthesia.Automated detection of these patterns using methods like the Nonlinear Energy Operator improves accuracy and consistency compared to manual analysis. Beyond these, promising features include sample and permutation entropy [39], which quantify the complexity of EEG signals , and instantaneous frequency (IF), which represents the dominant frequency within a specific time window [31], [45], [46].Techniques like Short-Time Fourier Transform with Kalman filtering can improve IF estimation, with specific frequency ranges correlating to different DOA levels [27].However, a major hurdle remains – the limited availability of high-quality, publicly accessible datasets for anesthesia research.This dependence on proprietary systems or subjective human labeling hinders the development and validation of new, potentially life-saving methods.

Existing research on EEG-based DOA assessment reveals limitations in traditional feature-based methods.Deep learning offers a compelling alternative with the potential for superior accuracy and generalizability.Studies by Lee et al.[29] demonstrate this promise.Their deep learning model, trained on data from hundreds of surgery patients, achieved better results for continuous BIS score prediction compared to traditional models.However, it relied on additional information beyond raw EEG signals, such as anesthetic infusion data and patient characteristics.

Another approach explored by Liu et al. [32] involved training convolutional neural networks (CNNs) to classify DOA based on EEG data converted into 2D images.While achieving high accuracy (reported at 93.5%), this method suffered from limitations.It could only distinguish between three broad anesthesia levels, neglecting the finer gradations crucial for precise DOA assessment.Additionally, converting EEG data into images for CNN analysis (like CifarNet, AlexNet, and VGGNet) is computationally expensive, especially for processing large datasets.

Lee et al. [29] also ventured into deep learning with a system combining a decision tree and regression models.This method, while trained on a large dataset (5427 subjects), had its drawbacks. It relied on the proprietary BIS system, limiting its wider applicability. Furthermore, compared to an end-to-end deep learning model that directly processes raw EEG data, this approach might be less robust to noise in real-world scenarios.

These limitations highlight the need for a novel deep learning model that capitalizes on the rich information within raw EEG signals.Such a model could offer a more powerful, continuous, and precise approach to DOA monitoring, with the potential to achieve accuracy surpassing traditional methods (potentially exceeding 93.5% with finer gradations) and without relying on additional data or proprietary systems.

This research seeks to address these limitations by developing a novel deep learning architecture. Our proposed model will directly process raw EEG signals, eliminating the need for additional data or feature engineering, and generate continuous DOA indices. This approach has the potential to surpass existing accuracy while offering a more generalized, efficient, and robust solution for anesthesia depth monitoring [47].

1.2.1 Depth of anesthesia

Depth of anesthesia refers to the degree to which a patient is anesthetized during a medical procedure.It is a measure of how effectively the anesthetic agents are suppressing the central nervous system to prevent awareness and sensation during surgery. The depth of anesthesia is crucial for ensuring patient safety and comfort, as it balances the need for sufficient sedation and analgesia with the risks of over- or under-anesthetization.

1.2.2 Techniques for Measuring Depth of Anesthesia

Several techniques and tools are used to measure and monitor the depth of anesthesia, including:

1. Clinical Signs:

Traditional methods rely on observing clinical signs such as blood pressure, heart rate, pupil size, and movement. While useful, these signs can be influenced by various factors and may not always accurately reflect the depth of anesthesia.

2. Electroencephalography (EEG):

EEG measures the brain's electrical activity and provides a more direct assessment of the central nervous system's state. Various EEG-derived indices, such as the Bispectral Index (BIS), are used to quantify the depth of anesthesia.BIS monitors process EEG data to produce a numerical value indicating the patient's level of consciousness, offering a real-time and objective measure of anesthesia depth.

3. Advanced Monitoring Technologies:

Modern anesthesia monitoring systems may incorporate additional sensors and technologies, such as entropy monitoring, auditory evoked potentials, and near-infrared spectroscopy (NIRS), to provide a comprehensive assessment of the patient's anesthetic state.

1.2.3 The Bispectral Index (BIS)

The Bispectral Index (BIS) is a processed electroencephalography (EEG) parameter used to monitor the depth of anesthesia (DOA) and level of consciousness during surgical procedures and sedation.It is derived from EEG signals captured by electrodes placed on the patient's forehead and scalp.The BIS provides a numerical value between 0 and 100, where lower values indicate deeper levels of anesthesia and higher values correspond to lighter anesthesia or increased consciousness.

The BIS monitor processes raw EEG data using proprietary algorithms to analyze various aspects of brain activity, including frequency, amplitude, and phase coherence.By quantifying these parameters, the BIS monitor produces a single value that reflects the patient's level of awareness and response to anesthesia. The primary goal of using

BIS monitoring is to ensure that patients remain adequately anesthetized throughout surgery, minimizing the risk of intraoperative awareness while optimizing patient comfort and recovery. Anesthesiologists use BIS values as a guide to adjust the dosage of anesthetic agents during surgery, tailoring the anesthesia to the individual patient's needs.BIS monitoring has become a standard practice in many surgical settings, offering real-time feedback on the patient's anesthetic state and enhancing the safety and efficacy of anesthesia management.However, it's essential to recognize that BIS values should be interpreted in conjunction with other clinical signs and patient-specific factors to make informed decisions regarding anesthesia dosage and patient care.

The BIS (Bispectral Index) scale is a numerical indicator of the depth of anesthesia. It ranges from 0 to 100, with different ranges indicating various levels of consciousness and sedation:

- **100-80: Fully awake**
  At this level, the patient is fully conscious, alert, and able to respond to their surroundings.There is no sedation or anesthesia effect, and the brain activity is normal.
- **80-60: Light Sedation**
  The patient is in a lightly sedated state, often referred to as conscious sedation. They may feel relaxed and drowsy but are still able to respond to verbal commands and physical stimulation.This level is often used for minor procedures where full anesthesia is not necessary.
- **60-40: Adequate anesthesia for surgery**
  At this level, the patient is under moderate to deep sedation, providing adequate anesthesia for most surgical procedures. The patient is unconscious and does not feel pain or discomfort, ensuring that they remain still and unresponsive during surgery. The brain activity is significantly suppressed.
- **40-20: Deep hypnotic state**
  The patient is in a deep hypnotic state, with very low levels of brain activity. They are deeply unconscious and will not respond to any external stimuli. This level ensures maximum suppression of brain activity, which might be required in certain complex or highly invasive surgical procedures.
- **0: No detectable brain activity**
  At this level, there is no detectable brain activity. This state is typically observed in situations of profound anesthesia overdose or severe brain injury. It indicates a complete lack of brain function.

1.2.4 BIS Measurement

The Bispectral Index (BIS) is measured through a series of steps as follows:

1. **EEG Signal Acquisition**: Electrodes are placed on the patient's scalp to capture the brain's electrical activity.

2. **Fourier Transform Analysis**: The captured EEG signal is decomposed into its frequency components using Fourier transform analysis.

3. **Bispectral Analysis**: This step identifies the interactions between different brain waves within the EEG signal.

4. **Proprietary Algorithmic Integration**: A proprietary algorithm processes the data from the previous steps to compute the BIS value.

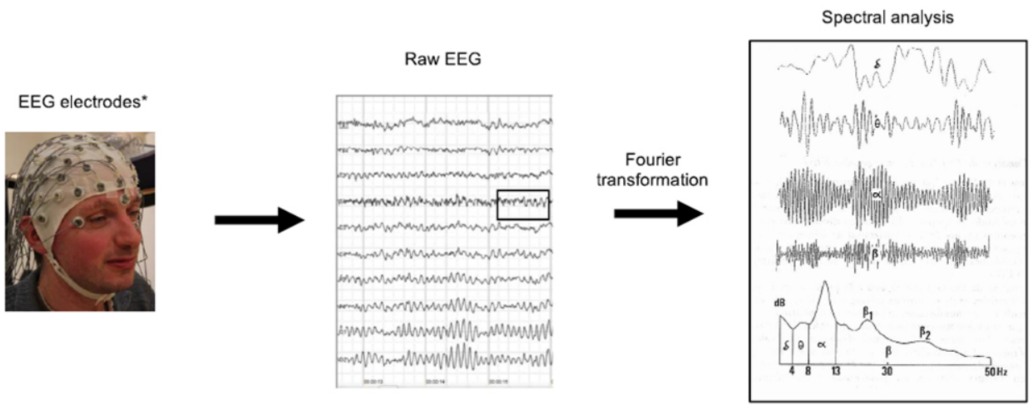

Figure 1.2: Bispectral Index measurement technique[36]

1.3 Motivations

Accurate BIS estimation is vital for patient safety during surgery, as it can prevent intraoperative awareness and ensure proper sedation levels.Current BIS monitoring devices are expensive and not always accessible, particularly in low-resource settings. This research aims to provide a cost-effective and accurate alternative by leveraging advanced deep learning techniques.Previous studies have explored various machine learning models for BIS prediction, but there is still room for improvement in terms of accuracy and generalizability. This study seeks to address these gaps by developing a hybrid model that combines CNNs, BiLSTM networks, and attention mechanisms.

1.4 Problem Statement

The primary focus of this research is to develop an accurate, accessible, and cost-effective method for estimating the Bispectral Index (BIS) from EEG signals during anesthesia.

1.5 Objective

The research objectives are outlined in the following manner:

- Develop a hybrid deep learning model combining CNNs, BiLSTM networks, and attention mechanisms for BIS estimation using EEG wave signals.
- Evaluate the performance of the proposed model on publicly available EEG datasets.
- Compare the proposed model with existing BIS prediction methods to demonstrate its effectiveness.

1.6 Research Challenges

The field of Bispectral Index (BIS) estimation from EEG signals presents a myriad of complex challenges that must be meticulously addressed to achieve accurate and reliable results.A primary challenge stems from the inherent variability in EEG signals. This variability can be significantly influenced by a multitude of factors, including but not limited to the patient's age, overall health condition, and the specific type of anesthesia administered.Each of these factors can introduce unique patterns and anomalies in the EEG data, complicating the task of developing a one-size-fits-all model for BIS estimation.

Moreover, the dynamic and non-stationary nature of EEG signals further exacerbates the difficulty of the task.EEG data is characterized by intricate temporal dependencies that must be accurately captured to ensure the reliability of BIS estimation. Traditional approaches often fall short in this regard, necessitating the development and integration of advanced machine learning techniques such as Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks. While CNNs are adept at capturing spatial features, BiLSTMs excel at modeling temporal dependencies by considering information flow in both forward and backward directions.

However, the integration of CNNs and BiLSTMs introduces another layer of complexity. This hybrid approach demands extensive computational resources due to the high-dimensional nature of EEG data and the intricate architecture of the models. Training such models requires substantial computational power, often necessitating the use of high-performance computing environments. Additionally, the implementation of attention mechanisms to enhance the model's focus on relevant features within the EEG signals adds to the computational burden and the complexity of the model architecture.

Furthermore, the process of tuning model parameters to achieve optimal performance is an arduous and meticulous task. Each parameter, from the number of layers and neurons in the network to the learning rate and batch size, can significantly impact the model's performance. This necessitates a comprehensive approach to hyperparameter optimization, often involving techniques such as grid search or Bayesian optimization, to systematically explore the parameter space and identify the optimal configuration.

In summary, the research challenges in BIS estimation from EEG signals are multifaceted and demand a robust and nuanced approach. Addressing the variability in EEG signals, accurately capturing temporal dependencies, managing the computational demands of advanced neural network architectures, and meticulously tuning model parameters are all critical components that must be carefully considered to advance the field and develop reliable BIS estimation models.

1.7 Contribution

The main contributions of this research are:

- Integrated Convolutional Neural Networks (CNN) with multiple Bidirectional Long Short-Term Memory (BiLSTM) layers to improve performance for temporal EEG signal analysis.
- Conducted experiments using EEG samples from preoperative, operative, and postoperative periods for robust model comparison.
- Conducted a comprehensive evaluation of the proposed model on publicly available EEG datasets, we have demonstrated improved accuracy and robustness compared to existing methods.
- Provisioned of an accessible and cost-effective alternative to traditional BIS monitoring devices, with potential applications in low-resource settings.

- Considered EEG samples exclusively from the operative anesthetic period to enhance model training accuracy.

These contributions are significant as they advance the field of anesthesia monitoring by offering a more accurate and accessible solution for BIS estimation, ultimately improving patient safety during surgery.

1.8 Organization

The rest of the thesis is organized as follows:

- Chapter 2: Related Works - Discusses previous research on BIS estimation and related deep learning techniques.
- Chapter 3: Proposed Methodology - Describes the proposed hybrid deep learning model, including the architecture and training process.
- Chapter 4: Results - Presents the experimental setup, evaluation metrics, and results of the proposed model.
- Chapter 5: Discussion - Analyzes the findings, compares the proposed model with existing methods, and discusses potential limitations.
- Chapter 6: Conclusion - Summarizes the key contributions of the research and outlines directions for future work.

This organization ensures a logical flow of information, guiding the reader from the introduction to the conclusion.

Chapter 2

Related Works

This chapter categorizes and reviews literature on Machine Learning and Deep Learning applications in predicting Bispectral Index using EEG signal, highlighting their respective contributions and challenges. By exploring methodologies and advancements, this review aims to illuminate the transformative impact of these technologies on Bispectral Index Estimation.

2.1 Machine learning based BIS prediction

Machine learning (ML) has revolutionized various aspects of healthcare, particularly in the realm of medical monitoring and diagnostics. By leveraging computational algorithms and statistical models, ML techniques can analyze vast amounts of patient data to extract valuable insights and predict outcomes with high accuracy.In medical monitoring, ML plays a crucial role in interpreting physiological signals, such as electrocardiograms (ECG), photoplethysmograms (PPG), and electroencephalograms (EEG), among others.These signals provide critical information about a patient's health status, facilitating real-time monitoring and intervention during medical procedures like anesthesia administration.

The study by Chowdhury et al. [12] and the study by Khan et al. [25] introduce innovative approaches for monitoring the depth of anesthesia (DoA) using distinct physiological signals and computational methods. The first study employs Electrocardiogram (ECG) and Photoplethysmography (PPG) signals processed through various Convolutional Neural Network (CNN) architectures, achieving up to 86% accuracy in DoA prediction. Conducted with data from 50 patients at National Taiwan University Hospital, this research underscores the efficacy of combining ECG and PPG signals for accurate anesthesia monitoring, especially beneficial for smaller hospitals seeking cost-effective solutions.

Meanwhile, the second study focuses on an EEG-based classification processor tailored for DoA monitoring during surgeries.Utilizing novel feature extraction techniques and machine learning algorithms, this processor extracts key features from EEG signals while integrating electromyography (EMG) to address motion artifacts. Implemented with a 128-point Fast Fourier Transform (FFT) for enhanced hardware efficiency, the processor achieves a notable 79% accuracy in classifying DoA across a diverse patient population. Experimental validation on a subset of patients from the University of Queensland Vital Signs database highlights its potential for precise and patient-specific anesthesia management.

2.2 Deep Learning based BIS prediction

In the domain of precise depth of anesthesia estimation from EEG signals, several significant deep learning based contributions have emerged. The study by Afshar et al. [2] pioneered a deep learning framework combining Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), and an attention mechanism to estimate the Bispectral Index (BIS) from EEG signals, showcasing exceptional performance with an 88.7% classification accuracy. Despite its success, the study acknowledged limitations such as the lack of integration with additional physiological signals and the need for further validation across diverse datasets. Similarly, The study by Madanu et al. [34] employed Ensemble Empirical Mode Decomposition (EEMD) for preprocessing and CNN for analyzing EEG spectrum images, achieving a prediction accuracy of 83.2%.However, the study's narrow focus on specific EEG signal characteristics highlighted the necessity for further investigation into the model's adaptability.In the context of intraoperative hypotension prediction, the study by Jo et al. [23] utilized ResNet architecture, demonstrating enhanced performance through the combination of ABP and EEG waveforms. Despite its promising results, the study emphasized the need for prospective validation. Additionally, the study by Li et al. [30] combined LSTM and Stacked Denoising Autoencoder (SDAE) to process EEG signals, achieving a high prediction probability value of 0.8556. The study recognized challenges related to EEG signal complexity and variability, indicating the need for further refinement. Furthermore, the study by Chowdhury et al. [12] focused on ECG and PPG signals, employing CNN architectures and data augmentation techniques, with a 10-layered CNN achieving an accuracy rate of 86%. The study noted limitations such as a small sample size and imbalanced data, suggesting the need for larger datasets and more efficient algorithms. Lastly, The study by Sadrawi et al. [41] used EEG preprocessing with Empirical Mode Decomposition (EMD) and trained Artificial Neural Networks (ANNs) to predict consciousness states, outperforming BIS in anesthesia depth prediction. The study's constraints, including a small sample size and limited external validation, underscored the need for broader studies and more sophisticated models. Collectively, these studies highlight the potential of deep learning methodologies to revolutionize anesthesia monitoring while also pointing to areas where further research and refinement are necessary.

Chapter 3

Proposed Methodology

Our proposed methodology commences with the acquisition of data, followed by its preprocessing. Subsequently, the data is divided into training and testing subsets. The training subset is utilized to train the model, and the performance of the model is ultimately evaluated. The detailed steps are illustrated in the figure below:

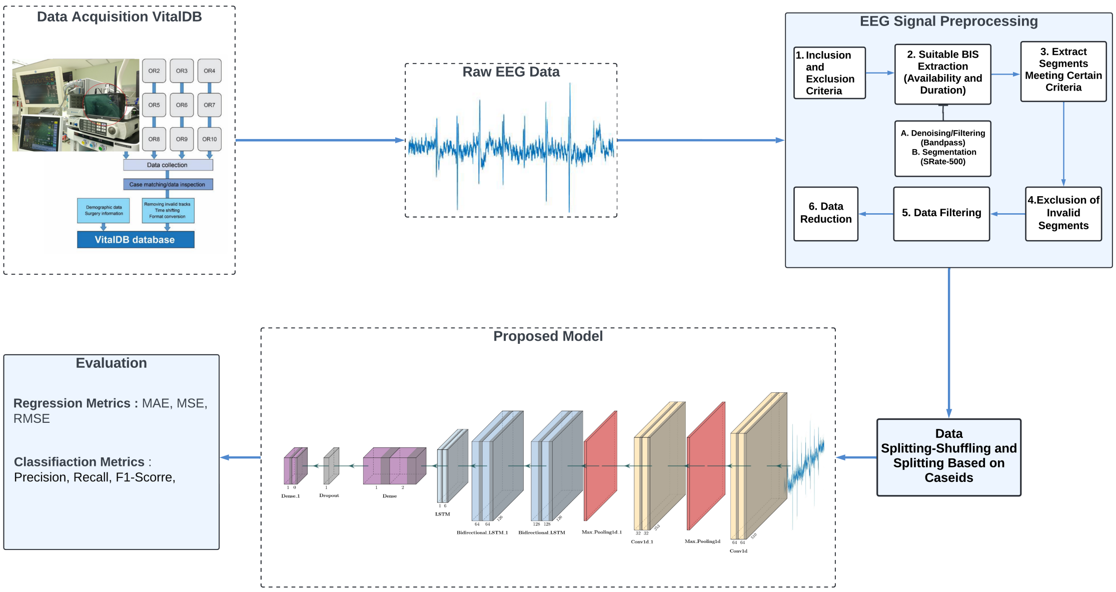

Figure 3.1: Proposed Workflow Diagram

The detailed steps are delineated as follows:

3.1 Data Acquisition

3.1.1 Dataset Overview

In the research paper, the VitalDB dataset [28] was utilized, a comprehensive collection of intraoperative biosignals and clinical information from 6,388 surgical patients. This dataset, meticulously curated from non-cardiac surgery patients at Seoul National University Hospital, Seoul, Republic of Korea, offers a wealth of high-quality data that is invaluable for studying and developing new medical AI algorithms. The dataset includes 500 Hz waveform signals and numeric values captured at intervals of 1-7 seconds, alongside over 60 surgery-related clinical information, providing a rich source of information for researchers in the field of medical AI.

The VitalDB dataset was unique in its scale and depth, encompassing a broad spectrum of surgical specialties and offering a total of 557,622 data tracks from 6,388 cases. This extensive collection of data points, averaging 2.8 million per case, has been instrumental in the research, offering unparalleled insights into the complex dynamics of surgical patients' physiological responses. The dataset was recorded using Vital Recorder version 1.7.4, and all data tracks were extracted, converted to CSV, and compressed with gzip, ensuring the data's accessibility and usability for analysis.

In accordance with the Data Use Agreement, the terms of use were adhered to, including the obligation to periodically check the notice on the VitalDB homepage and the responsibility for any damage caused by failure to confirm the changes to the Agreement. The dataset was released under a Creative Commons Attribution-Non Commercial-ShareAlike 4.0 International (CC BY-NC-SA 4.0) license, which has been applied to maximize the dissemination and use of the data.

In the research, the VitalDB dataset was leveraged to explore the potential of AI in enhancing surgical outcomes and patient care. By analyzing the high-resolution data and clinical information provided, the aim was to contribute to the advancement of medical AI research. This research paper is a testament to the significance of the VitalDB dataset in advancing the field of medical AI, and the opportunity to use this dataset in the research was acknowledged.

3.1.2 Dataset Selection

The research utilized data from the VitalDB dataset[28], comprising EEG signals (`BIS/EEG1_WAV` and `BIS/EEG2_WAV`). The dataset encompassed various cases with differing durations, ensuring a diverse representation of anesthesia scenarios.

In the dataset selection of this research, stringent criteria were applied to ensure the relevance and quality of the data. Cases were exclusively included if they met the following conditions:

- **Duration:** Only cases with a duration exceeding 30 minutes were considered. This criterion ensures that the data represents a sufficient time frame to capture meaningful physiological responses during anesthesia.
- **Patient Age:** Cases involving patients over the age of 18 years were included. This age range was chosen to ensure that the data represents a broad spectrum of adult patients undergoing surgery, which is relevant to the research objectives.
- **BIS Data Presence:** Cases without BIS data were excluded. The absence of BIS data is critical because BIS values are essential for the prediction of anesthesia depth and the assessment of patient consciousness.
- **EEG Data Presence:** Cases without EEG data were excluded. EEG signals capture the brain's electrical activity and are fundamental for the prediction of BIS values.
- **BIS Value Forward Fill:** For cases where BIS values were missing, a forward fill method was applied up to 7 seconds. This approach ensures that the dataset remains continuous and that missing BIS values are estimated based on the preceding values, which is a common practice in data preprocessing to handle missing data.

In the dataset selection process, the exclusion of specific biosignal tracks, namely 'Primus/EXP_DES', 'Orchestra/RFTN50_CE', and 'Orchestra/PPF20_CE', was strategically designed to focus on the most relevant data for the research objectives.

1. **Primus/EXP_DES (Expiratory desflurane pressure)**: This track was excluded because it pertains to the expiratory pressure of desflurane, a volatile anesthetic, which is not directly related to the prediction of BIS. The focus of BIS prediction research is primarily on the EEG signals, which capture the brain's electrical activity, rather than the pharmacokinetics of anesthetics.
2. **Orchestra/RFTN50_CE (Effect-site concentration of remifentanil**

50 mcg/mL) and **Orchestra/PPF20_CE (Effect-site concentration of propofol 20 mg/mL)**: These tracks were excluded because they represent the effect-site concentrations of remifentanil and propofol, respectively. While these concentrations are crucial for understanding anesthesia delivery, they do not directly influence the BIS in a manner relevant to the research objectives. The BIS prediction research aims to focus on the EEG signals, which are more closely related to the brain's electrical activity, rather than the pharmacokinetics of anesthetics.

By excluding these tracks, the dataset was streamlined to include only the most relevant information for BIS prediction, ensuring that the research focuses on the most pertinent data to achieve its objectives.

3.2 EEG Data Preprocessing

In the EEG preprocessing phase of the research, a comprehensive approach was adopted to ensure the quality and relevance of the EEG data for BIS prediction.The process involved several critical steps:

3.2.1 Inclusion and Exclusion Criteria

For this study, we included participants aged above 18 years and considered data from the track names BIS/EEG1_WAV and BIS/EEG2_WAV.Specific anesthetic medications known to influence EEG patterns were included in the analysis. However, we excluded the anesthetic agents Remifentanil and Propofol during the training period, as these medications significantly impact EEG patterns.

3.2.2 Suitable BIS Extraction

Considered BIS values greater than 0.This means that any BIS value above zero was included in the analysis, ensuring that only valid and meaningful BIS data were used to assess the EEG patterns and the effects of anesthetic medications.

3.2.3 Extract Segment Meeting Certain Criteria

EEG signals were segmented into fixed-length windows of (4 x SRATE) samples, where (SRATE = 128) Hz.For a signal length of 4 seconds with sampling rate 128hz where each segment has 512 data points each.This segmentation approach was chosen to facilitate the analysis of EEG signals in a manageable format, allowing for the extraction of meaningful features for BIS prediction.Included only cases where the length of the data was longer than 30 minutes, ensuring that there was sufficient data for a comprehensive analysis of EEG patterns and the effects of anesthetic medications.

3.2.4 Data Reduction

Implemented data reduction techniques to ensure the integrity and quality of the data used for analysis. Specifically, we excluded invalid segments based on EEG impedance and maximum EEG values.An EEG impedance value of more than 12 was considered valid, ensuring that the recorded EEG signals were of high quality and free from excessive noise.Additionally, a maximum EEG value of less than 100 was deemed valid, which helped to filter out any segments that might contain artifacts or outliers.

Furthermore, we considered only BIS values greater than 0, ensuring that our analysis focused on meaningful and valid BIS data.We also included only case data longer than 30 minutes, ensuring sufficient data length for a comprehensive analysis.These data reduction steps were crucial in maintaining the reliability and validity of the study's findings by excluding segments that did not meet our predefined criteria.

3.2.5 Signal Filtering

To remove baseline drift and high-frequency noise, a bandpass filter was applied to the EEG signals.The filter was designed with cutoff frequencies of 0.5 Hz and 50 Hz, which were chosen to capture the relevant frequency range of EEG signals while excluding noise. The mathematical equation of the ideal bandpass filter, based on the specified cutoff frequencies, was derived as follows:

$$H(s) = K \cdot \frac{\omega_0^2}{s^2 + \frac{\omega_0}{Q}s + \omega_0^2} \tag{3.1}$$

Here:

- K is the gain of the filter.It determines the amplitude scaling of the output signal relative to the input signal. Specifically, K sets the maximum gain of the filter at the center frequency ω_0.
- s is the Laplace variable.It allows the analysis of systems in the frequency domain, combining a real part representing growth/decay and an imaginary part.
- ω_0 is the center frequency of the passband.It is the frequency at which the fil-

ter's response is maximized.The filter allows frequencies around ω_0 to pass with minimal attenuation while attenuating frequencies far from ω_0.

- Q is the quality factor or damping ratio of the filter.The quality factor Q measures the selectivity or sharpness of the filter, defined as the ratio of the center frequency ω_0 to the bandwidth (BW) of the filter.

The center frequency ω_0 is calculated as the geometric mean of the lower and upper cutoff frequencies:

$$\omega_0 = \sqrt{f_{\text{low}} \cdot f_{\text{high}}} \tag{3.2}$$

Given the specified cutoff frequencies of 0.5 Hz and 50 Hz, ω_0 was computed as:

$$\omega_0 = \sqrt{0.5 \cdot 50} = 5 \text{ rad/s}$$

The quality factor Q is often chosen to achieve a desired trade-off between bandwidth and filter response sharpness. For simplicity, Q was set to 1.

Substituting these values into the transfer function equation, the mathematical equation of the ideal bandpass filter with cutoff frequencies of 0.5 Hz and 50 Hz, suitable for EEG signal preprocessing, is:

$$H(s) = K \cdot \frac{25}{s^2 + 5s + 25} \tag{3.3}$$

It describes the filter's behavior in the Laplace domain.

3.2.6 Exclusion of Invalid Segment

Considered an EEG impedance value of more than 12 to be valid, ensuring the quality and reliability of the EEG signals. Additionally, we deemed a maximum EEG value of less than 100 to be valid, filtering out any data segments that might contain noise or artifacts, thereby maintaining the integrity of the analysis.

3.3 Model Utilized

In this study, we employed a specialized analytical framework designed to predict Bispectral Index (BIS) values using EEG signals. Our approach combined Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory networks (BiLSTM). Each component played a crucial role in the analysis:

3.3.1 CNN

Convolutional neural networks (CNNs) [47] possess remarkable proficiency in encoding spatial features present in input data. Spatial features, as they pertain to sequential data such as time series or text sequences, are indicative of localized structures or patterns within the sequence. CNN layers have the capability to identify and derive these spatial features, which are vital for comprehending the sequence's underlying structure, through the implementation of convolutional operations. Hierarchical representation learning is facilitated by CNN layers, in which lower-level features are aggregated to generate higher-level abstractions. CNNs derive progressively more abstract representations of the input data via a series of convolutional layers, coordinated pooling operations, and non-linear activations. The implementation of this hierarchical feature extraction procedure empowers the model to identify complex patterns and correlations within the sequential data, thereby enhancing its overall performance. By applying max-pooling operations subsequent to convolutional layers, the feature maps are downsampled, thereby decreasing the dimensionality of the data. The process of reducing dimensions serves to alleviate overfitting and computational complexity, all the while maintaining critical information. By preserving solely the most prominent characteristics [19], CNN layers empower the following layers of the model to concentrate on pertinent elements of the input data, thereby augmenting its ability to differentiate [6]. Due to their local connectivity and shift-invariance characteristics, CNN layers are ideally adapted for tasks involving spatially invariant patterns. When applied to sequential data, these characteristics empower the model to identify patterns irrespective of their position in the sequence, thereby fortifying its resistance to fluctuations and noise.

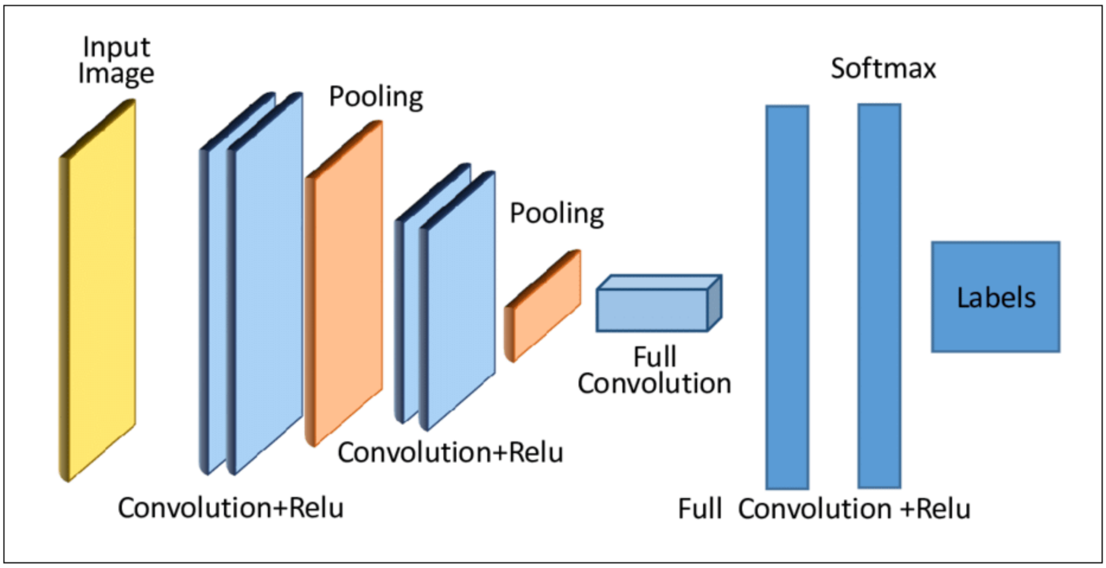

Figure 3.2: CNN Architecture [1]

The CNN model follows the following equation: Let x denote the input sequence data. For the i-th conventional layer:

$$z_i^{(l)}[n] = \sum_{k=0}^{K_i-1} w_{i,k}^{(l)} * x[n+k] + b_i^{(l)} \tag{3.4}$$

This equation describes the convolution operation in the i-th convolutional layer of the CNN. Here,

- $z_i^{(l)}[n]$ is the output of the convolution operation at position n in the l-th layer.
- $w_{i,k}^{(l)}$ represents the weights (filter) used in the convolution operation for the i-th filter at the k-th position.
- $x[n+k]$ is the input sequence at position $n+k$.
- $b_i^{(l)}$ is the bias term for the i-th filter in the l-th layer.
- $\sum_{k=0}^{K_i-1}$ represents the sum over all the filter weights applied to the input sequence.

Activation Function (commonly ReLU): In neural networks and deep learning, the activation function referred to as ReLU (Rectified Linear Unit), is defined as:

$$a_i^{(l)}[n] = \max(0, z_i^{(l)}[n]) \tag{3.5}$$

This equation describes the application of the Rectified Linear Unit (ReLU) activation function to the output of the convolution operation.

- $a_i^{(l)}[n]$ is the output of the ReLU activation function for the i-th filter at position n in the l-th layer.
- $z_i^{(l)}[n]$ is the input to the ReLU function, which is the result of the convolution operation.

Max Pooling Operation: The max pooling operation in a neural network is a form of down-sampling or sub-sampling technique typically applied after a convolutional layer. It extracts the maximum value from a region of the input tensor, thereby reducing its spatial dimensions while preserving important features.It follows the equation:

$$p_i^{(l)}[n] = \max_{m=n}^{n+S_i-1} a_i^{(l)}[m] \tag{3.6}$$

This equation describes the max pooling operation applied to the output of the ReLU activation function.

Where:

- $z_i^{(l)}[n]$ is the output of the conventional layer i at position n,
- $w_{i,k}^{(l)}$ is the weight of the k-th filter in the layer i,
- $b_i^{(l)}$ is the bias term,
- $a_i^{(l)}[n]$ is the activation value at position n after applying the ReLU activation function,
- K_i is the kernel size of the convolution layer,
- S_i is the stride of the max pooling layer.
- $p_i^{(l)}[n]$ is the result of the max pooling operation for the i-th filter at position n in the l-th layer.
- $a_i^{(l)}[n]$ is the output of the ReLU activation function.
- S_i is the size of the window for the max pooling operation.

The max pooling operation takes the maximum value over a window of size S_i starting from position n to $n + S_i - 1$.

3.3.2 LSTM Model

The LSTM (Long Short-Term Memory) layers are of paramount importance in the model as they are responsible for capturing and acquiring knowledge of temporal patterns and long-range dependencies present in the sequential data[17]. Sequential sensor readings and time series frequently demonstrate intricate temporal dependencies and dynamics. Layered Support Vector Machines (LSTM) are engineered to tackle this particular obstacle by enabling the model to retain data throughout lengthy sequences, thereby efficiently capturing temporal dependencies that persist for an extended period of time. Deletion of long-range dependencies is a frequent challenge for conventional recurrent neural networks (RNNs) due to the vanishing gradient problem, which occurs when gradients diminish exponentially as they propagate backward through time. LSTM units are fortified with gating mechanisms, including the neglect gate, input gate, and output gate, which function to selectively alleviate the vanishing gradient problem. Information retention or disposal that occurs over time. Numerous practical scenarios involve sequences of varying lengths, which presents a difficulty for models attempting to process inputs of variable length.

Because LSTM networks are capable of processing sequences of arbitrary length, they are ideally suited for tasks in which the input sequences may vary in length. The utilization of bidirectional LSTM layers in this architectural design improves the model's capacity to assimilate contextual information through the execution of sequences in both the forward and backward directions. The utilization of bidirectional[44] processing enables the model to concurrently account for past and future context, thereby enhancing the accuracy of its predictions. In contrast to conventional RNNs, LSTM units are constructed with a more intricate memory cell architecture, which empowers them to retain information for extended periods of time and selectively update or delete it when necessary. Particularly advantageous for tasks involving sequential data with intricate patterns and interdependencies is this capability.

Bidirectional Long Short-Term Memory (BiLSTM) networks were selected as the preferred approach for analyzing electroencephalogram (EEG) signals. This decision was based on the unique attributes of EEG data and the complex temporal interdependencies that are inherent in brain signals. Electroencephalogram (EEG) signals demonstrate intricate temporal dynamics, which are indicative of the dynamic interactions among neurons in the brain. The capacity of BiLSTMs to concurrently capture past and future context enhances the model's comprehension of temporal patterns by facilitating the identification of nuanced alterations and enduring trends that are intrinsic to EEG signals. In addition, electroencephalogram (EEG) signals frequently exhibit intricate patterns and long-range dependencies that span multiple time intervals. Unidirectional LSTMs may encounter challenges in effectively capturing these dependencies due to their reliance on past information. BiLSTMs, on the other hand, accommodate both past and future context, enabling more accurate pattern and dependency detection throughout the entire EEG signal. The utilization of BiLSTMs in the analysis of EEG signals improves the model's ability to discern intricate temporal patterns, distant interdependencies, and nuanced fluctuations that are inherent in brain signals.

3.3.3 BiLSTM Model

Bidirectional Long Short-Term Memory (BiLSTM) networks function within the domain of EEG signal analysis by capitalizing on their bidirectional processing capability to extract features, capture temporal dependencies, and generate predictions using the input EEG data[7].

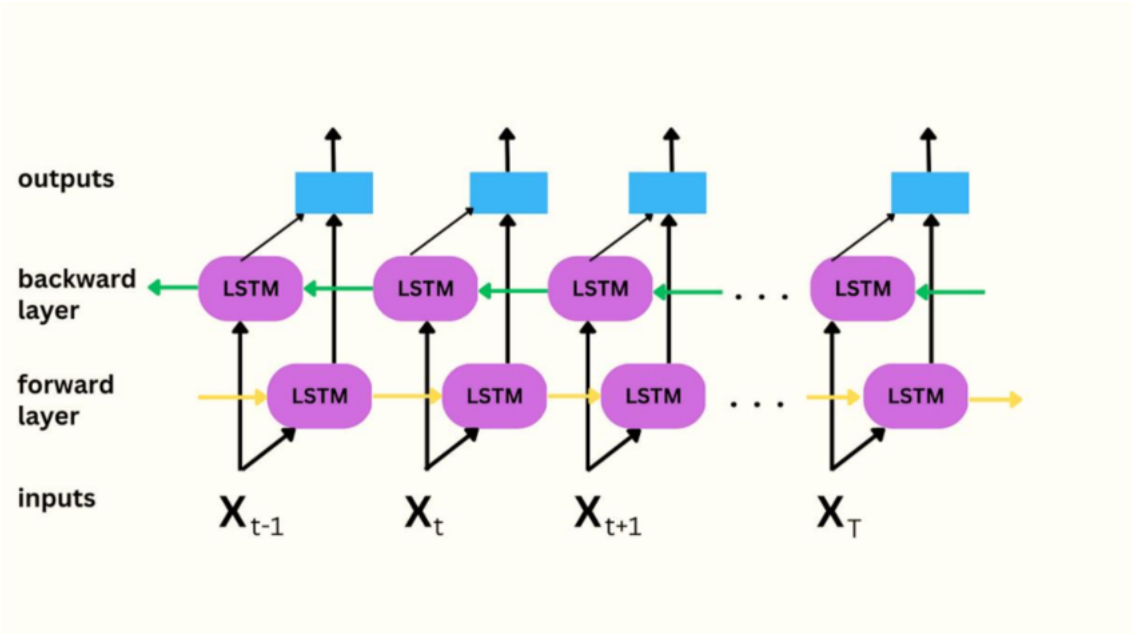

Figure 3.3: A Simple BiLSTM Architecure[36]

1. **Bidirectional Sequential Processing**: Parallel sequential processing in both the forward and backward orientations is enabled by BiLSTMs, enabling the concurrent evaluation of past and future temporal contexts contained within the EEG signal. By employing this bidirectional methodology, the model is capable of discerning subtle patterns and capturing complex temporal dependencies throughout the complete

EEG data sequence.

2. **Temporal Dependency Modeling**: The intricate temporal interdependencies observed in EEG signals are indicative of the dynamic interaction of neural processes as they transpire. BiLSTMs effectively represent these dependencies due to the utilization of dual LSTM layers—one for forward processing of the data and the other for backward processing—which account for both short-term fluctuations and long-range trends that are intrinsic to EEG dynamics.

3. **Feature Extraction and Representation**: BiLSTMs systematically extract significant features from EEG data by means of bidirectional processing. This entails encapsulating unique patterns, oscillatory dynamics, and transient events that are indicative of distinct cognitive processes or brain states. The utilization of this feature extraction mechanism enables the model to detect nuanced variations and derive more advanced representations that are critical for conducting discriminatory analysis.

4. **Predictive Modeling and Analysis**: By making use of the extracted features, BiLSTMs perform analytical and predictive tasks that are specifically designed for EEG signal analysis. The tasks involved in this domain consist of prognostic forecasting, event detection, anomaly identification, and state classification. BiLSTMs enhance the accuracy of inference and interpretation of neural activity patterns by providing reliable predictions and insights into EEG dynamics through the assimilation of contextual information in both temporal dimensions.

The LSTM equations for the input, forget, and output gates, as well as the cell state and hidden state update, are as follows:

Input gate:

The input gate $i(t)$ controls how much information from the current input $x(t)$ and the previous hidden state $h(t-1)$ should be passed to the current cell state $c(t)$.

$$i^{(t)} = \sigma(W_i \cdot [h^{(t-1)}, x^{(t)}] + b_i) \tag{3.7}$$

Forget gate: The forget gate $f(t)$ decides how much of the previous cell state $c(t-1)$ should be retained for the current time step t.

$$f^{(t)} = \sigma(W_f \cdot [h^{(t-1)}, x^{(t)}] + b_f) \tag{3.8}$$

Output gate: The output gate $o(t)$ determines how much of the cell state $c(t)$ should contribute to the current hidden state $h(t)$.

$$o^{(t)} = \sigma(W_o \cdot [h^{(t-1)}, x^{(t)}] + b_o) \tag{3.9}$$

Cell state update: The cell state $\tilde{c}(t)$ is the proposed new cell state that could be updated based on the current input $x(t)$ and previous hidden state $h(t-1)$.

$$\tilde{c}^{(t)} = \tanh(W_c \cdot [h^{(t-1)}, x^{(t)}] + b_c) \tag{3.10}$$

$$c^{(t)} = f^{(t)} \odot c^{(t-1)} + i^{(t)} \odot \tilde{c}^{(t)} \tag{3.11}$$

Hidden state update:

The hidden state $h(t)$ is the output of the LSTM cell for the current time step, which is influenced by the current cell state $c(t)$ but filtered by the output gate $o(t)$.

$$h^{(t)} = o^{(t)} \odot \tanh(c^{(t)}) \tag{3.12}$$

Where:

- σ represents the sigmoid activation function,
- $\odot$ denotes element-wise multiplication,
- W_i, W_f, W_o, W_c are weight matrices, and b_i, b_f, b_o, b_c are bias vectors,
- $[h^{(t-1)}, x^{(t)}]$ denotes the concatenation of the previous hidden state $h^{(t-1)}$ and the current input $x^{(t)}$.

1. **Convolutional Layers:**
   - Two 1D convolutional layers are used to extract spatial features from the input sequence data.
   - The first convolutional layer has 64 filters with a kernel size of 3, resulting in an output shape of (None, 510, 64).
   - The second convolutional layer has 32 filters with a kernel size of 3, resulting in an output shape of (None, 253, 32).
   - Max pooling layers are applied after each convolution layer to reduce dimensionality.
2. **Bidirectional LSTM Layers:**

- Two bidirectional LSTM layers are employed to capture both past and future context in the input sequence.
- The first bidirectional LSTM layer has 128 units, resulting in an output shape of (None, 126, 128).
- The second bidirectional LSTM layer has 64 units, resulting in an output shape of (None, 126, 64).

3. **LSTM Layer:**
   - Following the bidirectional LSTM layers, a unidirectional LSTM layer with 16 units is included, potentially for further abstraction or summarization of sequence information.
   - This LSTM layer produces an output shape of (None, 16).
4. **Dense Layer:**
   - A dense layer with 128 units is added to map the LSTM layer's output to a higher-dimensional space, facilitating non-linear transformations.
   - The output shape of this dense layer is (None, 128).
5. **Dropout Layer:**
   - A dropout layer is applied after the dense layer to prevent overfitting by randomly dropping units during training.

3.4 Proposed Method

In this section, we discuss the Hybrid Model we have developed, which consists of a combination of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory Networks (BiLSTM). We present the architecture of the hybrid model, and the results obtained from our experiments in this section.

3.4.1 Hybrid Model

In this study, we address the challenge of accurately predicting time-series data, specifically EEG signals, which often contain complex patterns and noise.To tackle this, we employ a hybrid deep learning model combining Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks. The CNN component of the model effectively captures local patterns and features from the input sequences through convolution and pooling operations, thereby reducing noise and dimensionality. Specifically, we use two convolutional layers with ReLU activation and max pooling, which extract hierarchical features from the raw EEG signals. These features are then passed to the BiLSTM layers, which are adept at modeling temporal dependencies in both forward and backward directions, ensuring that contextual information from the entire sequence is utilized. The BiLSTM layers consist of two layers with 64 and 32 units, followed by a unidirectional LSTM layer with 16 units. The combined output is then fed into dense layers, where further non-linear transformations are applied, culminating in a single output neuron for regression. The model is trained using the Adam optimizer with mean absolute error (MAE) as the loss function. Early stopping and model checkpointing are employed to optimize performance and prevent overfitting. This hybrid CNN-BiLSTM architecture demonstrates a robust approach to handling the intricacies of EEG signal prediction, leveraging the strengths of both CNNs in feature extraction and LSTMs in sequence modeling[17].

In addition to our proposed CNN-BiLSTM model, we conducted a comprehensive evaluation by comparing its performance with standalone CNN and BiLSTM models. This comparative analysis aimed to elucidate the efficacy of our hybrid approach in capturing the complex dynamics of EEG signals. The standalone CNN model solely focused on leveraging convolutional layers to extract hierarchical features from the input EEG sequences, while the standalone BiLSTM model concentrated on modeling temporal dependencies in both forward and backward directions. Through cross-comparison of results, we sought to discern which model architecture best suited the task of EEG signal prediction. Moreover, our experimentation was done considering both EEG signals having operative time only and considering the entire period of operative, preoperative, and postoperative time for more precise comparison.

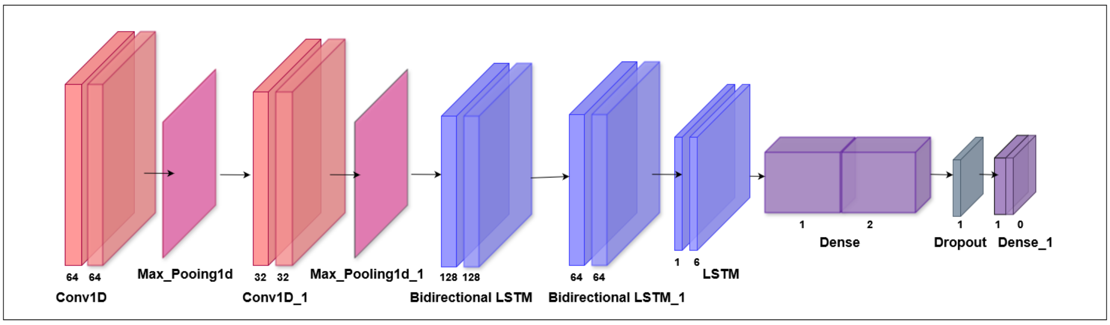

Figure 3.4: Proposed Hybrid Architecure

Our findings revealed that while the standalone CNN model effectively captured local patterns in the EEG data, it struggled to capture long-term dependencies crucial for accurate prediction. On the other hand, the standalone BiLSTM model excelled at modeling temporal dynamics but may have overlooked fine-grained features present in the data. In contrast, our proposed CNN-BiLSTM model demonstrated superior performance by synergistically leveraging the strengths of both architectures. By integrating CNNs for feature extraction and BiLSTMs for capturing temporal dependencies, our hybrid model achieved remarkable accuracy in predicting EEG signals. This comparative analysis underscores the significance of hybrid architectures in addressing the multifaceted challenges inherent in EEG signal prediction tasks[3].

3.4.2 Computational Framework of Hybrid (CNN-BiLSTM) Model

Convolution Operation (Conv1D layer)

The Conv1D layer performs convolution operations on the input sequence $x(n)$ using filters $w(l)_i$ of size K_i. The output $z(l)_i[n]$ at layer l and index i for position n is computed as referred to the (equation 3.4)

Activation Function (ReLU)

The Rectified Linear Unit (ReLU) activation function is a commonly used activation function in neural networks. It introduces non-linearity to the model and helps in learning complex patterns. The ReLU function follows the equation referred to (equation 3.5).The ReLU activation function is applied element-wise to the output of the convolutional layer.

Max Pooling Operation (MaxPooling1D layer)

Max pooling is a down-sampling operation commonly used in convolutional neural networks to reduce the spatial dimensions of the input and to make the representations more manageable and computationally efficient. The MaxPooling1D operation selects the maximum value from a specified window of inputs. The max pooling function follows the equation specified earlier (Equation 3.6).

Bidirectional LSTM (BiLSTM) Layers

The flattened features are then fed into one or more BiLSTM layers to capture temporal dependencies in both forward and backward directions.

- **Forward LSTM**
  The Forward Long Short-Term Memory (LSTM) network is a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. Unlike traditional RNNs, LSTMs utilize special units called memory cells to maintain information over extended time steps.These cells contain three key gates: the input gate, the forget gate, and the output gate, which regulate the flow of information into, out of, and within the cell.This structure allows LSTMs to effectively handle issues like vanishing and exploding gradients, making them well-suited for tasks involving sequential data such as time series prediction, natural language processing, and speech recognition. The forward LSTM processes data in one direction, maintaining the temporal order of the sequence.

- **Backward LSTM**
  Similar equations as the forward LSTM but processes the sequence in reverse order.

- **Bidirectional Output**
  The output of a BiLSTM is a combination of the forward and backward LSTM outputs, providing a richer representation of the input sequence. This is given by the equation:
  $$h_t^{bi} = [h_t^{forward}; h_t^{backward}] \tag{3.21}$$
  Where h_t^{bi} is the concatenation of forward and backward hidden states.

- **Dense Layer Output**
  A Dense layer in a neural network is a fully connected layer where each neuron is connected to every neuron in the previous layer. It computes a weighted sum of its inputs, adds a bias term, and then applies an activation function to produce the output. Dense layers are commonly used in deep learning architectures for tasks such as classification and regression. They enable the network to learn complex patterns by combining features from previous layers and mapping them to the desired output space. The output of a Dense layer is typically a vector of values, one for each neuron in the layer, representing the network's predictions or activations.

  1. **First Dense Layer:**
     The dense layer follows the equation:
     $$a = \mathrm{ReLU}(W_d h + b_d) \tag{3.22}$$

Where:

- a is the activation output.
- W_d are the weights of the dense layer.
- h is the input from the LSTM layer.
- b_d is the bias term.

2. **Dropout Layer:**
   Randomly sets a fraction p of input units to zero at each update during training to prevent overfitting.

3. **Final Dense Layer:**
   The final dense layer represents a pivotal component in neural network architectures, particularly in the realm of deep learning and supervised learning tasks.This layer is designed to compute the model's output $\hat{y}$ based on the input a from the preceding dense layer, utilizing a set of weights W_o and a bias term b_o.

$$\hat{y} = W_o \cdot a + b_o \tag{3.23}$$

Where:

- $\hat{y}$ is the model output.
- W_o are the weights of the output dense layer.
- a is the input from the previous dense layer.
- b_o is the bias term.

Chapter 4

Results

The exploration of EEG signals, particularly those from the vitalDB dataset, has been a pivotal aspect of this research, aiming to uncover insights into the potential of EEG data for predicting anesthesia levels. EEG signals, being a non-invasive method of monitoring brain activity, have shown promise in various applications, including anesthesia monitoring. This section delves into the detailed findings of the EEG signal analysis experiments conducted, focusing on the performance of different models and configurations under various experimental conditions.

4.1 Experimental Setup

The experimental setup for this study is meticulously structured to ensure accurate data acquisition, processing, and analysis. The EEG tracks used for this experiment are *BIS/EEG1_WAV* and *BIS/EEG2_WAV*, with a segment rate set at 128 Hz.Each segment is defined by a length of four times the segment rate. The inclusion and exclusion criteria for the dataset include age, track names, and the use of anesthetic medication to ensure a homogeneous sample.

A fourth-order bandpass filter is applied to the data to ensure signal clarity. For data filtering and processing, BIS values greater than 0 are considered valid, and the length of the case data must exceed 30 minutes.Invalid segments are excluded based on specific criteria: EEG impedance values greater than 12 and maximum EEG values less than 100 are deemed valid.

Three models are utilized for this study: BiLSTM, CNN+BiLSTM, and CNN, leveraging the computational power of GPUs including RTX 3050, 3060, and 3090. The experimental setup is supported by a system with 64 GB RAM and processors ranging from Core-i5 to Core-i9 11th generation, ensuring robust performance and efficiency in data processing and model training.

We have specifically worked with two EEG signal parameters from the vitalDB dataset: `BIS/EEG1_WAV` and `BIS/EEG2_WAV`. The results obtained from the analysis of these two parameters are provided below:

4.2 Experimentation using BIS/EEG1_WAV

The experiment was conducted on a dataset comprising 500 cases, with a sampling rate of 128 Hz. Cases with more than 30 minutes of data were selected, and a Bandpass filter with a low cutoff of 0.5 Hz, a high cutoff of 50.0 Hz, and an order of 4 was applied. Cases with a BIS value of 0 were excluded from the analysis.

We conducted two types of experiments: one utilizing only the operative time and the other incorporating preoperative, postoperative, and operative times. Each type of experimentation is discussed in detail below.

4.2.1 Preoperative, Postoperative and Operative Time

In this experimentation we considered the entire operation time from starting to the ending considering pre and post anesthetic period too. The Mean Absolute Error (MAE) was 4.96, the Mean Squared Error (MSE) was 46.10, the Root Mean Squared Error (RMSE) was 6.78, and the R2 Score was around 60.

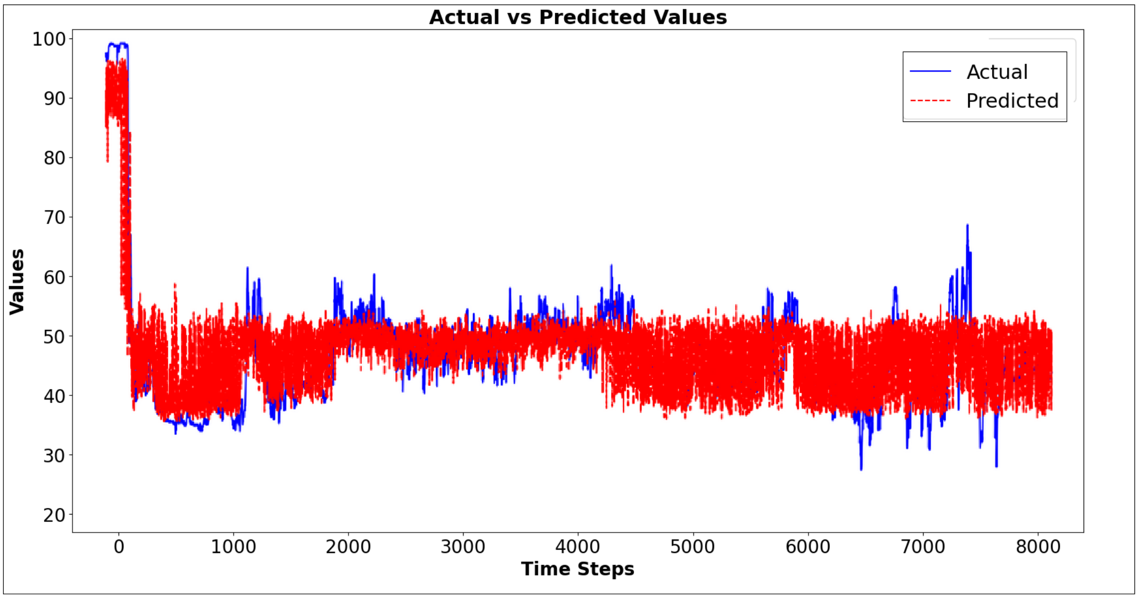

Figure 4.1: Fig: Actual vs Predicted BIS with 8000 time steps

Figure 4.1 presents the comparison between actual and predicted BIS values for the parameter BIS/EEG1_WAV over 8,000 time steps. Considering the entire period encompassing preoperative, intraoperative, and postoperative phases, the BIS value begins at 100, indicating that the patient is awake. After the administration of anesthesia, the BIS value decreases and stabilizes within the range of 40-60 during the anesthetic period, reflecting the sedative state of the patient. Following the conclusion of the operation, the BIS value returns to 100, signifying the patient's return to an awake state.

4.2.2 Only Operation Time

Experimentation Details: Similar to the previous experiment, but operation time was considered only without considering pre and post anesthetic period. Results: The Mean Absolute Error (MAE) was 4.05 (the best among all), the Mean Squared Error (MSE) was 28.90, the Root Mean Squared Error (RMSE) was 5.37, and the R2 Score was 0.60.

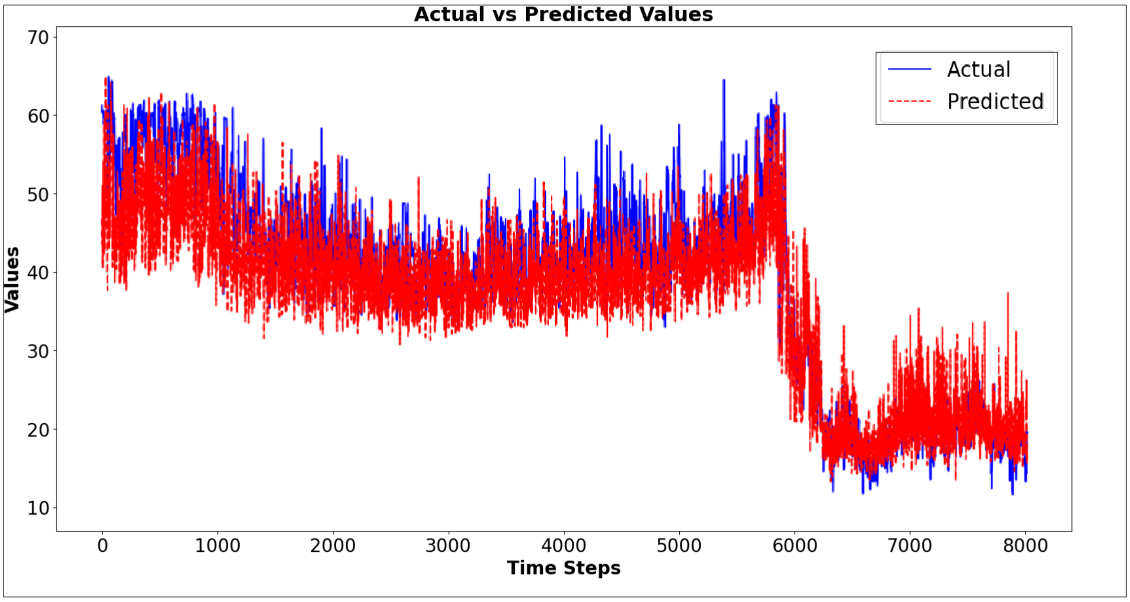

Figure 4.2: Fig: Actual vs Predicted BIS with 8000 time steps

Figure 4.2 illustrates the comparison between actual and predicted BIS values for the parameter BIS/EEG1_WAV over 8,000 time steps. In this experiment, only the operative time was considered, resulting in the BIS value starting at 70, indicating that the patient is already in an anesthetic state. During the anesthetic period, the BIS value remains within the range of 40-60, reflecting the sedative state. Since only the operative period is considered, the BIS value remains within this range throughout the time steps.

4.3 Experimentation using BIS/EEG2_WAV

The experiment was conducted on a dataset comprising 500 cases, with a sampling rate of 128 Hz. Cases with more than 30 minutes of data were selected, and a Bandpass filter with a low cutoff of 0.5 Hz, a high cutoff of 50.0 Hz, and an order of 4 was applied. Cases with a BIS value of 0 were excluded from the analysis.

We conducted two types of experiments with BIS/EEG2_WAV: one utilizing only the operative time and the other incorporating preoperative, postoperative, and operative times. Each type of experimentation is discussed in detail below.

4.3.1 Preoperative, Postoperative and Operative Time

In this experimentation we considered the entire operation time from starting to the ending considering pre and post anesthetic period too.The Mean Absolute Error (MAE) was 4.96, the Mean Squared Error (MSE) was 46.10, the Root Mean Squared Error (RMSE) was 6.78, and the R2 Score was 0.69 (the best among all).

The graph below is shown with only 8000 steps and for this it is looking less interesting with the actual pattern.

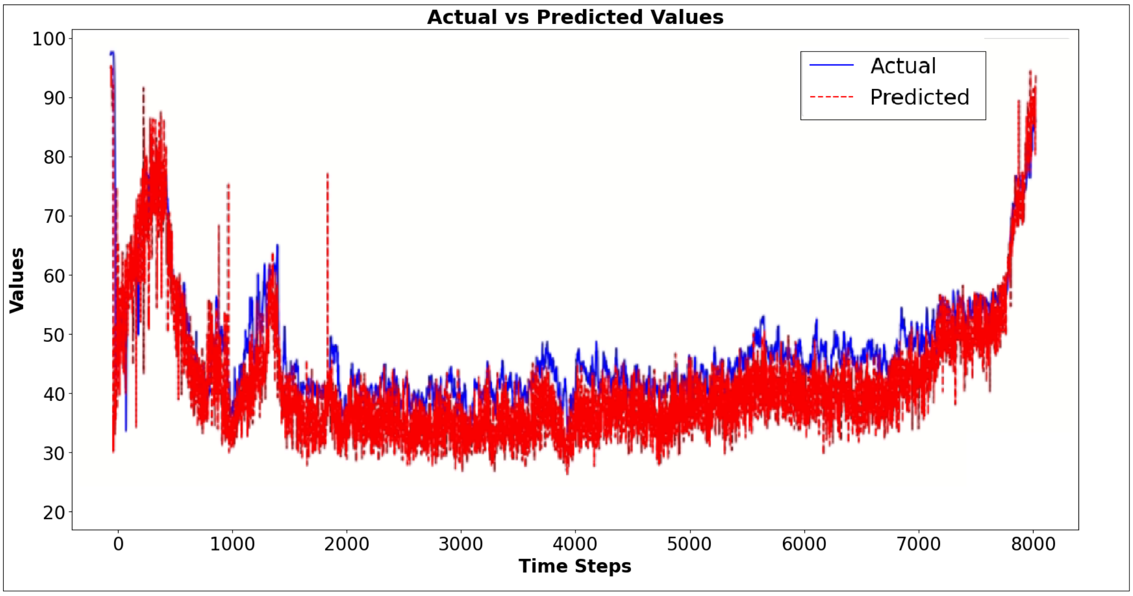

Figure 4.3: Fig: Actual vs Predicted BIS with 8000 time steps

Figure 4.3 presents the comparison between actual and predicted BIS values for the parameter BIS/EEG1_WAV over 8,000 time steps. Considering the entire period encompassing preoperative, intraoperative, and postoperative phases, the BIS value begins at 100, indicating that the patient is awake. After the administration of anesthesia, the BIS value decreases and stabilizes within the range of 40-60 during the anesthetic period, reflecting the sedative state of the patient. Following the conclusion of the operation, the BIS value returns to 100, signifying the patient's return to an awake state. Although similar to Figure 4.1, there is a slight gap between the actual and predicted lines in Figure 4.3.

4.3.2 Only Operation Time

Similar to the previous experiment, but operation time was considered only without considering pre and post anesthetic period. The Mean Absolute Error (MAE) was 4.69, the Mean Squared Error (MSE) was 38.79, the Root Mean Squared Error (RMSE) was 6.22, and the R2 Score was 0.49 (the lowest among all).

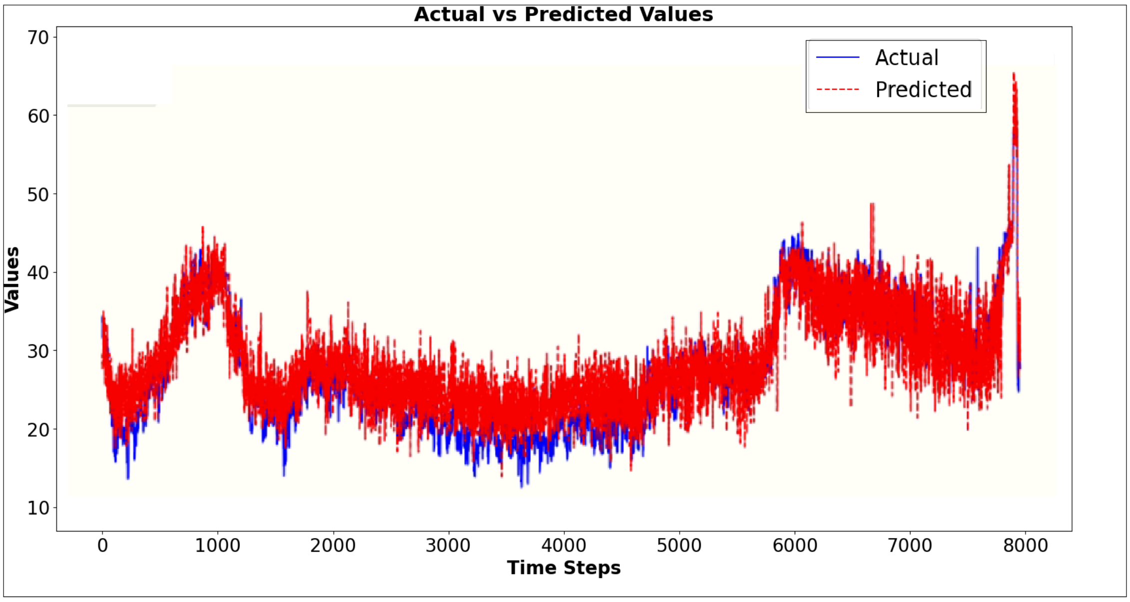

Figure 4.4: Actual vs Predicted BIS with 8000 time steps

Figure 4.4 illustrates the comparison between actual and predicted BIS values for the parameter BIS/EEG1_WAV over 8,000 time steps. In this experiment, only the operative time was considered, resulting in the BIS value starting at 40, indicating that the patient is already in an anesthetic state. During the anesthetic period, the BIS value remains within the range of 40-60, reflecting the sedative state. Since only the operative period is considered, the BIS value remains within this range throughout the time steps. Although there is a slight gap between the actual and predicted lines, it is more pronounced compared to Figure 4.2.

4.4 Classification

The analysis of EEG signals has provided valuable insights into the potential of these signals for predicting anesthesia levels. However, the realm of machine learning extends beyond mere prediction; it also encompasses the classification of data into distinct categories. Classification is a supervised machine learning method where the model is trained to predict the correct label of a given input data. It is a crucial aspect of machine learning, with applications spanning various domains, from email spam detection to medical diagnosis. This section delves into the classification outcomes of the models tested in this research, offering a deeper understanding of how these models perform in categorizing anesthesia levels based on EEG signals. The classification outcome levels are defined as follows: Class 0: Deep Anesthesia (DA, BIS: 0-40) Class 1: General Anesthesia (GA, BIS: 40-60) Class 2: Light Sedation (S, BIS: 60-80) Class 3: Awake (W, BIS: 80-100)

4.4.1 BiLSTM Model

The dataset obtained was imbalanced.We preprocessed the dataset and balanced it for cross comparison of results.The results in both cases are given below:
Imbalanced Data: The model achieved a test accuracy of 0.75, precision of 0.768, recall of 0.75, and an F1-score of 0.75.

Table 4.1: Confusion Matrix for BiLSTM Model on Imbalanced Data

	Class 0	**Class 1**	**Class 2**	**Class 3**
Class 0	176604	105973	156	12
Class 1	45833	331844	4247	80
Class 2	400	8091	6739	393
Class 3	16	99	362	374

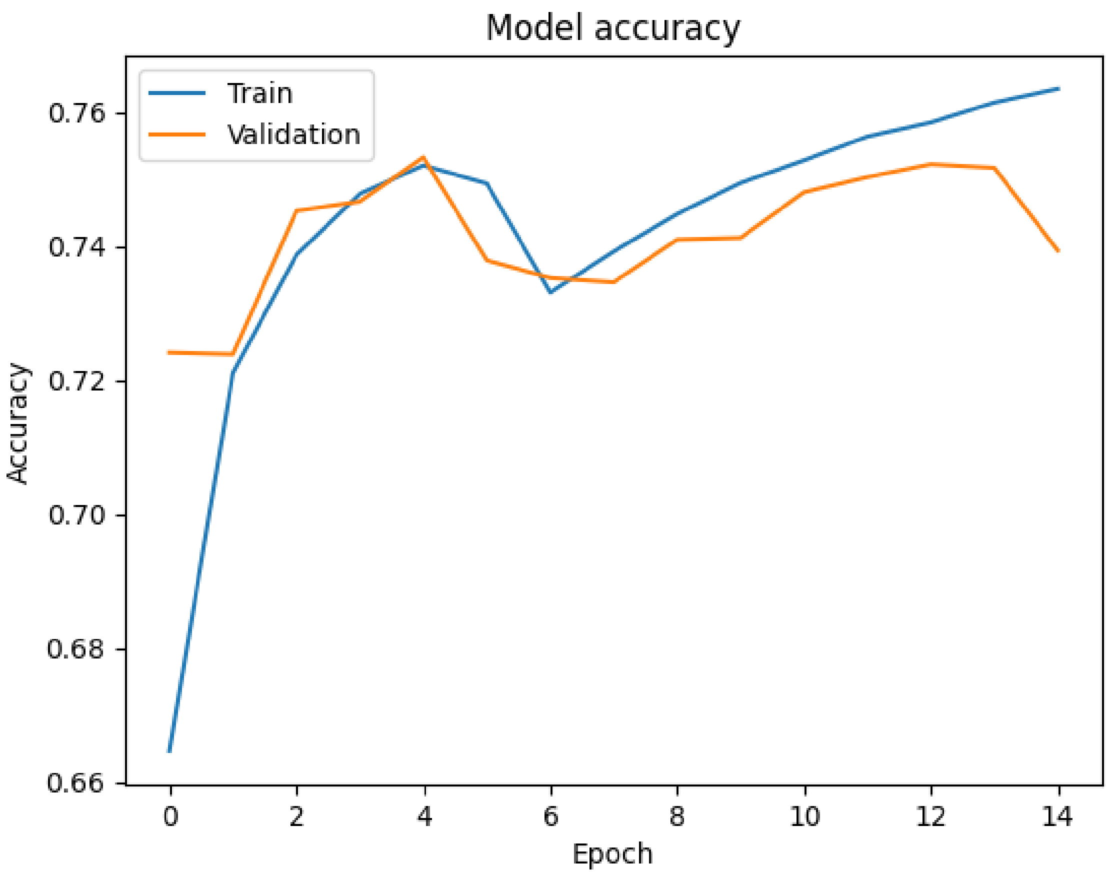

Figure 4.5: Fig: Accuracy of the Model during Training and Validation

In the graph of fig 4.5 the training accuracy appears to be increasing steadily, while the validation accuracy is relatively flat. This suggests that the model is still learning and has not yet begun to overfit.

Balanced Data: After applying SMOTE for class 2 and 3 and undersampling for classes 0 and 1, the model achieved a test accuracy of 0.69, precision of 0.71, recall of 0.71, and an F1-score of 0.70.

Table 4.2: Confusion Matrix for BiLSTM Model on Balanced Data

	Class 0	**Class 1**	**Class 2**	**Class 3**
Class 0	167682	97519	156	12
Class 1	45833	331844	4247	80
Class 2	400	8091	6739	393
Class 3	16	99	362	374

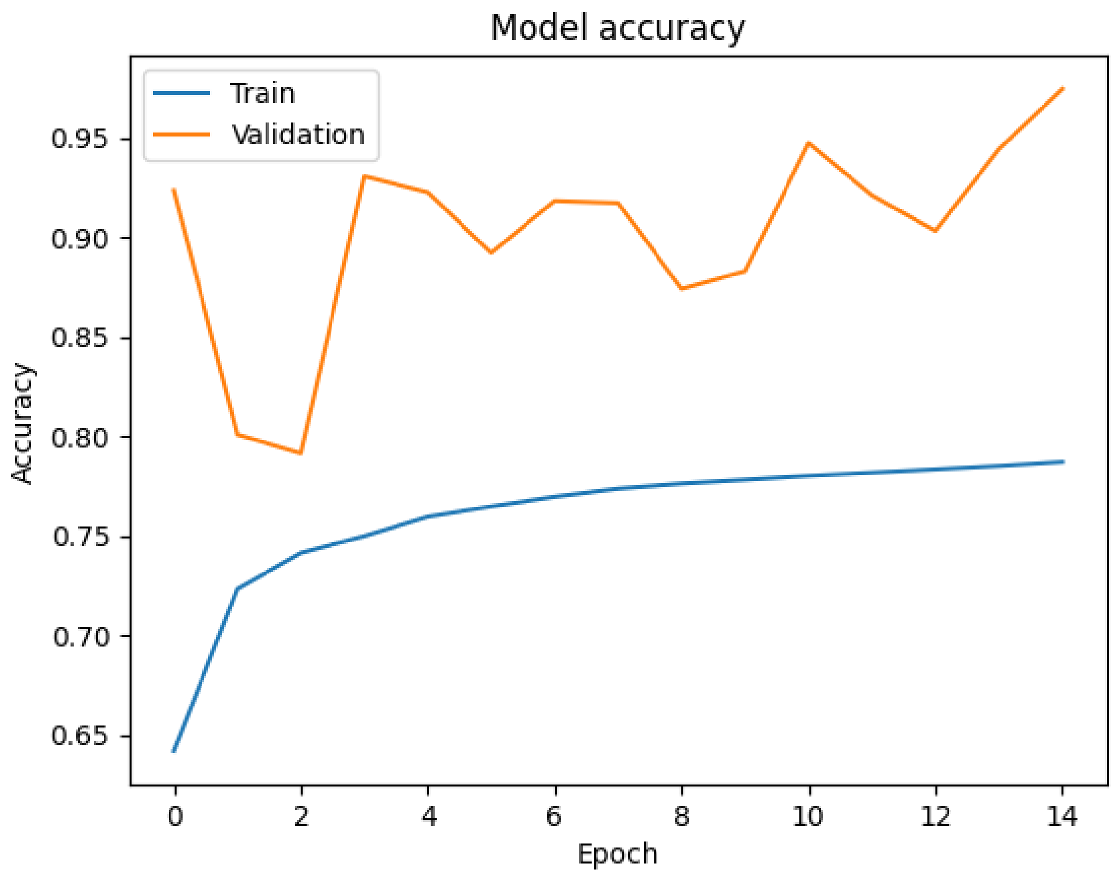

Figure 4.6: Fig: Accuracy of the Model during Training and Validation

In the Fig 4.6 the training accuracy appears to be increasing steadily, while the validation accuracy is relatively flat. This suggests that the model is still learning and has not yet begun to overfit. However, it is always possible to train a model for too long,

4.4.2 Resnet Model

The experimentation was cross checked using Resnet Model using both the balanced and imbalanced data.

Imbalanced Data: The model achieved a test accuracy of 0.71, precision of 0.71, recall of 0.71, and an F1-score of 0.70.

Table 4.3: Confusion Matrix for Resnet Model on Imbalanced Data

	Class 0	**Class 1**	**Class 2**	**Class 3**
Class 0	167682	386	2	71257
Class 1	7391	34	771	9106
Class 2	436	28	266	556

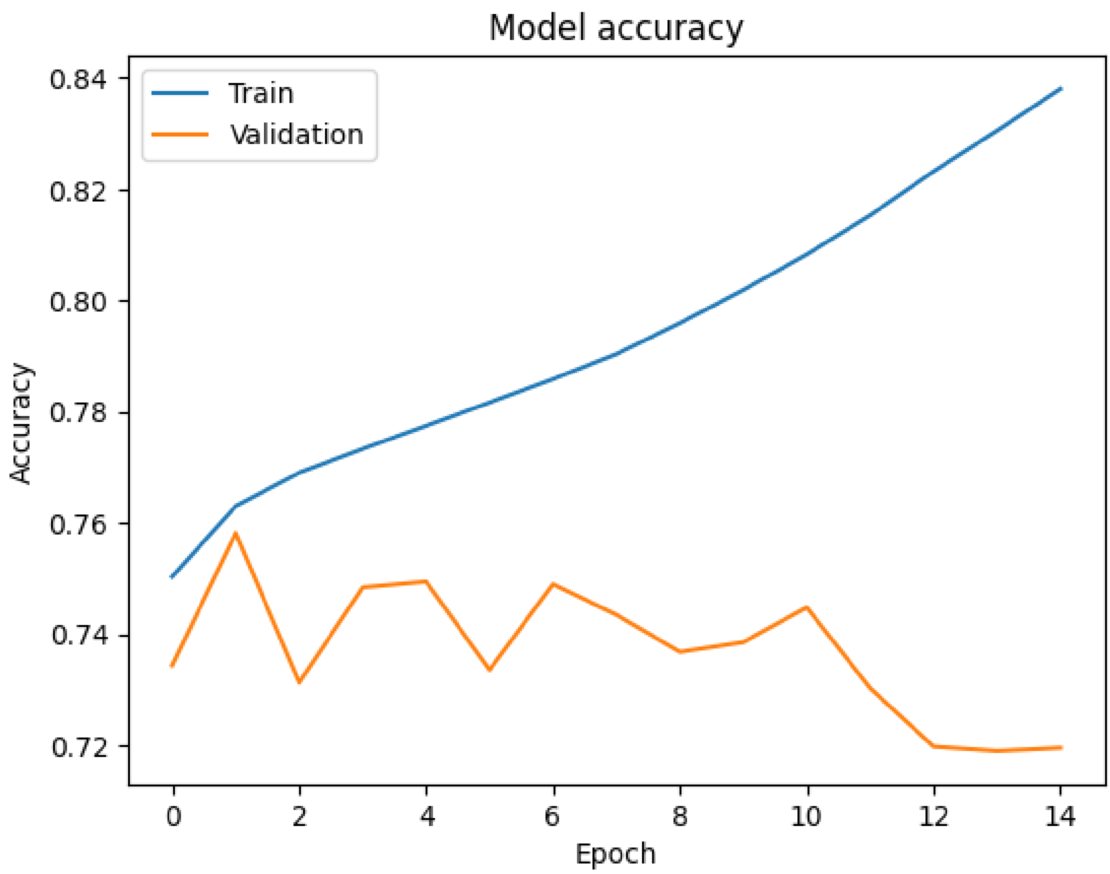

Figure 4.7: Fig: Accuracy of the Model during Training and Validation

In the Fig 4.7 the training accuracy is increasing, which is a good sign. The validation accuracy appears to be holding steady, which is also a good sign. This suggests that the model is still learning and generalizing well to unseen data.

Balanced Data: The model achieved a test accuracy of 0.69,precision of 0.71, recall of 0.71, and an F1-score of 0.70.

The results indicate that the combined model of CNN and LSTM performed better than the LSTM model alone, and the Resnet model provided a slightly lower R2 score. The application of SMOTE for balancing the dataset improved the performance of the BILSTM model, suggesting that the model's performance can be significantly influenced by the balance of the dataset.

Chapter 5

Discussions

The evaluation of various methods for predicting the Bispectral Index (BIS) from EEG signals is critical for understanding the advancements and effectiveness of different deep learning approaches in anesthesia monitoring. This section provides a comprehensive comparative analysis of several prominent studies alongside our proposed method, highlighting the performance metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) [16].

Shalbaf et al. [46] proposed an Artificial Neural Network (ANN) model for predicting BIS from EEG signals in 2013, demonstrating an MAE of 7.38, MSE of 98.83, and RMSE of 9.5. Liu et al. [32] introduced a CNN-based method in 2018 achieving an MAE of 8.44, MSE of 142.31, and RMSE of 11.44, indicating challenges in handling temporal dependencies in EEG signals related to BIS despite CNNs' ability to capture spatial features. A recent study by Afshar et al. [2] proposed a hybrid model combining neural network architectures, achieving improved performance with an MAE of 4.3, MSE of 32.44, and RMSE of 5.59. Building upon prior work, our research introduces a novel deep learning model integrating CNNs and Bi-directional Long Short-Term Memory (BiLSTM) networks for BIS prediction in 2024. Our method achieves an MAE of 4.05, MSE of 28.90, and RMSE of 5.37, demonstrating substantial improvement and addressing limitations observed in previous studies by incorporating operative time as an additional feature. By leveraging CNNs for feature extraction and BiLSTMs for temporal modeling, our approach offers a nuanced estimation of BIS, advancing the field of anesthesia monitoring.

The proposed method incorporates operative time (anesthetic state) as an additional feature, which contributes to the enhanced predictive accuracy. By leveraging the strengths of CNNs in feature extraction and BiLSTMs in temporal dependency modeling, the proposed approach offers a more nuanced and accurate estimation of BIS, thereby addressing the limitations observed in prior studies.

This comparative analysis underscores the evolution of BIS prediction methodologies from simple ANN models to more complex hybrid models that integrate multiple neural network architectures. Shalbaf et al.'s pioneering work with ANN models highlighted the potential of neural networks but also demonstrated significant prediction errors. Liu et al. advanced this approach with CNNs, yet the model struggled with the temporal dynamics of EEG data, resulting in relatively high error metrics. The hybrid model introduced by Sara Afshar et al. marked a significant advancement by combining different neural networks, leading to a substantial reduction in prediction errors. Our proposed method further refines this approach by integrating CNNs and BiLSTMs, achieving the lowest MAE, MSE, and RMSE among the compared methods. The inclusion of operative time as a feature enhances the model's ability to predict BIS accurately, reflecting the complex interplay of neural activity under anesthesia. Overall, the results demonstrate that hybrid deep learning models, particularly those incorporating both CNNs and BiLSTMs, are highly effective for BIS prediction from EEG signals. This advancement not only improves the accuracy of anesthesia monitoring but also contributes to safer and more personalized patient care during surgical procedures. The continued evolution and refinement of these models are expected to further enhance their predictive capabilities, offering valuable insights into the real-time monitoring of anesthesia depth.

Chapter 6

Conclusion

This research explored the efficacy of deep learning models, specifically those integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, for predicting the Bispectral Index (BIS) using EEG signals. The approach leveraged the complementary strengths of CNNs and LSTMs to capture both spatial and temporal features inherent in EEG data [4], [20], [43], providing a robust framework for predicting anesthesia depth. The individual capabilities of CNNs and LSTMs were first examined. CNNs are adept at extracting localized spatial features from sequential data through convolutional operations, pooling, and hierarchical feature learning. These capabilities enable CNNs to identify intricate patterns and relationships within the data [18], [42]. Conversely, LSTMs excel in capturing long-range dependencies and temporal dynamics due to their unique gating mechanisms that mitigate the vanishing gradient problem common in traditional RNNs. The proposed architecture combined these strengths by first applying CNN layers to extract spatial features from the EEG signals and then using bidirectional LSTM layers to capture temporal dependencies. This hybrid approach aimed to enhance the model's ability to predict BIS values accurately. The CNN layers focused on identifying localized patterns, while the LSTM layers ensured that temporal dependencies were effectively modeled, considering both past and future contexts through bidirectional processing. The experimental design involved using EEG signals from the vitalDB dataset[10], with specific preprocessing steps such as bandpass filtering and the exclusion of data points with a BIS value of zero. Various configurations were tested, including models with and without consideration of operation time and using different EEG signal channels. The analytical verdict of the experiments indicates that the CNN-LSTM model outperforms models that use either CNN or LSTM alone. The CNN layers extracted significant spatial features, while the bidirectional LSTM layers captured the temporal dependencies, leading to more accurate BIS predictions. The inclusion of operation time further improved the model's performance, highlighting the importance of contextual information in anesthesia depth prediction. Moreover, the results demonstrated that the BiLSTM model achieved better performance when the dataset was balanced using techniques such as SMOTE (Synthetic Minority Over-sampling Technique) [11] for classes with fewer samples. This balancing improved the model's ability to generalize across different BIS categories, leading to higher accuracy, precision, recall, and F1-scores. The research findings align with existing literature on deep learning for EEG signal analysis. Studies by Liu et al. [32] have highlighted the potential of hybrid models combining CNN and LSTM for various biomedical applications, including sleep stage classification and emotion recognition. This research contributes to this body of knowledge by specifically addressing the prediction of BIS for anesthesia monitoring, demonstrating the practical application of CNN-LSTM models in clinical settings. The CNN-LSTM model's superior performance underscores the value of integrating spatial and temporal feature extraction for complex sequential data like EEG signals. This approach not only improves prediction accuracy but also provides a comprehensive understanding of the underlying neural dynamics, which is crucial for reliable anesthesia monitoring. Additionally, this study emphasizes the importance of preprocessing steps such as bandpass filtering and the exclusion of outliers (e.g., BIS values of zero), which play a crucial role in enhancing model performance. The choice of preprocessing parameters, such as the cutoff frequencies and filter order, was guided by the need to retain critical EEG signal features while removing noise and irrelevant information. The incorporation of operation time as a feature further demonstrated its significance in improving prediction accuracy. Considering operation time allows the model to account for the varying contexts and stages of anesthesia, which can significantly influence BIS values. This finding suggests that incorporating additional contextual information related to the surgical procedure could further enhance the model's predictive capabilities. The comparison of different configurations, including models using EEG signals from different channels, highlighted the importance of selecting the most informative signals for analysis. While EEG signals from different channels may carry overlapping information, the choice of specific channels can impact the model's performance, emphasizing the need for careful selection and evaluation of input features. Furthermore, the application of SMOTE for balancing the dataset addressed the challenge of class imbalance, which is common in biomedical data. By generating synthetic samples for underrepresented classes, SMOTE improved the model's ability to learn and generalize across all BIS categories, leading to more robust and reliable predictions. In conclusion, the integration of CNN and LSTM networks offers a powerful approach for predicting BIS using EEG signals. The model effectively captures both spatial and temporal features, leading to more accurate and reliable anesthesia depth predictions. The research highlights the importance of balanced datasets and contextual information in enhancing model performance. These findings pave the way for further advancements in deep learning applications for biomedical signal analysis, with potential implications for improving patient care and clinical outcomes in anesthesia management. Future research could explore several avenues to build on the findings of this study. For instance, incorporating additional physiological signals such as heart rate and respiratory rate could provide a more comprehensive understanding of the patient's state, potentially leading to further improvements in BIS prediction accuracy. Moreover, investigating different deep learning architectures, such as attention mechanisms or Transformer models, could offer new insights into capturing complex patterns in EEG data. The implementation of real-time prediction systems in clinical settings represents another promising direction. By developing and validating models that can operate in real-time, healthcare providers could benefit from immediate feedback on anesthesia depth, leading to more precise and adaptive anesthesia management. This would require addressing challenges related to computational efficiency and latency, ensuring that the models can deliver accurate predictions with minimal delay. In summary, this research underscores the significant potential of deep learning models, particularly those integrating CNN and LSTM networks, for predicting BIS using EEG signals. The findings contribute to the growing body of knowledge on the application of deep learning in biomedical signal analysis, offering valuable insights for enhancing anesthesia monitoring and patient care.

By following this structure, you can ensure that your Conclusions chapter effectively encapsulates the essence of your research, its contributions, and its implications, providing a comprehensive closure to your thesis.

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