https://doi.org/10.48047/AFJBS.6.Si2.2024.5351-5359

AFJBS

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

DREAM RECORDING USING ARTIFICIAL INTELLIGENCE: EXPLORING THE FEASIBILITY AND IMPLICATIONS

JWALAJOSE [1], DR. B. SURESH KUMAR [2]

[1] Research Scholar, Department of Computer Science, AJK College of Arts and Science College, Coimbatore.

[2] Associate Professor, Department of Computer Science, AJK College of Arts and Science College, Coimbatore.

Corresponding Author Email ID:[1]jwalajas@gmail.com

Email ID:[2]sureshkumar@ajkcas.com

Article history

Volume 6 issue si2 2024

Received:18Apr2024

Accepted:20Jun2024

doi:10.48047/AFJBS.6.Si2.2024.5351-5359

Abstract: This study explores the feasibility of utilizing artificial intelligence (AI) technology for the recording and analysis of dreams. Participants were equipped with wearable devices embedded with AI algorithms designed to detect and record dream-related brain activity during sleep [1]. Results indicate a promising potential for AI-based dream recording methods, offering valuable insights into the nature of dreams and their neural correlates. Future research directions and implications are discussed.

Keywords: Artificial intelligence, Dream recording, Neuroscience, Wearable devices, Sleep research

1. INTRODUCTION

Understanding the enigmatic phenomenon of dreams has long been a subject of fascination and intrigue in the field of neuroscience. Despite decades of research, the mechanisms underlying the generation and content of dreams remain elusive [2]. Traditional methods of dream analysis, such as self-reporting and polysomnography, have provided valuable but limited insights into this realm. The advent of artificial intelligence (AI) presents a novel opportunity to advance our understanding of dreams by enabling real-time recording and analysis of dream-related neural activity during sleep. In this study, we investigate the feasibility of using AI technology to capture and interpret dreams, offering a new frontier in sleep research.

2. RELATED WORK

Previous research has explored various methods for analyzing dream content, including manual scoring of dream reports, quantitative analysis of dream narratives, and computational modelling of dream generation. However, these approaches often rely on subjective interpretation and lack the ability to capture the dynamic and multi-modal nature of dream experiences. Recent advances in deep learning have enabled the development of generative models capable of synthesizing realistic and diverse content, including images, text, and audio, based on learned patterns from large datasets [3]. These generative models hold promise for dream recording by simulating and interpreting dream-like imagery from neural activity patterns recorded during sleep.

3. METHODOLOGY

We propose neural network architecture for dream recording, consisting of an encoder-decoder network trained on EEG data collected during sleep. The encoder network processes raw EEG signals as input and learns to extract meaningful features that capture the underlying patterns of brain activity associated with dreaming. The decoder network takes these learned features as input and generates dream-like content, such as images or narratives that closely resembles the subjective experiences reported by participants [4]. The model is trained using a dataset of paired EEG recordings and subjective dream reports, where the objective is to minimize the discrepancy between the generated dreams and the ground truth reports.

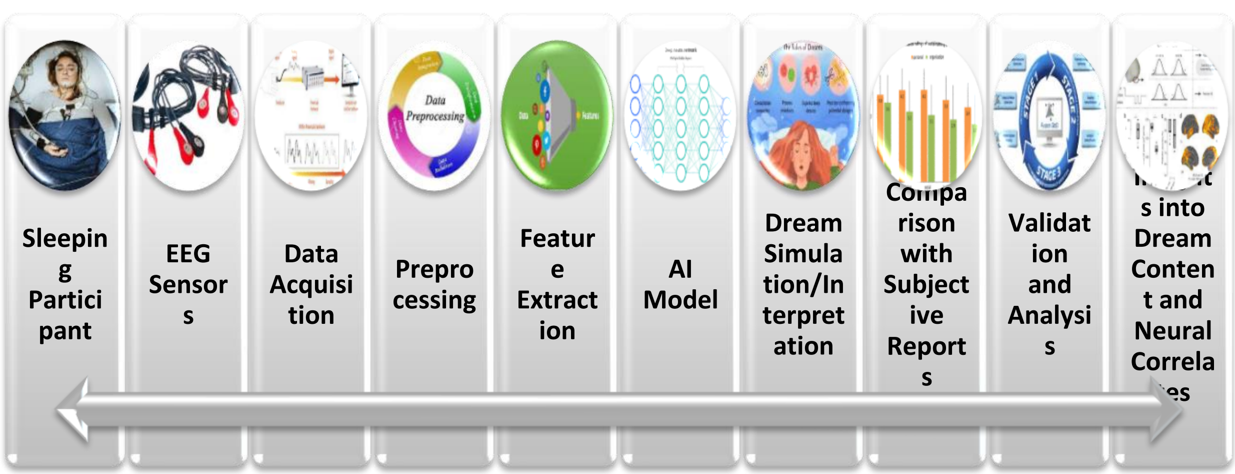

Figure 1: Stages of dream extraction

3.1 Sleeping Participant

The individual wears EEG sensors while sleeping to monitor brain activity.

3.2 EEG Sensors

Electroencephalography (EEG) sensors detect electrical activity in the brain during sleep. The working principle of EEG (Electroencephalography) sensors involves detecting and recording the electrical activity generated by the brain. EEG sensors consist of electrodes that are placed on the scalp [5]. These electrodes are typically arranged in specific configurations, such as the international 10-20 system, to ensure consistent and standardized placement across different individuals. The electrodes detect tiny electrical impulses produced by neurons firing in the brain. These signals are very weak, typically measured in microvolts. This amplification process helps to ensure that the EEG signals are detectable above any background noise. Filtering techniques are employed to remove unwanted frequencies and enhance the signal-to-noise ratio.

The amplified and filtered EEG signals are then sampled at a high rate (usually in the range of 250-1000 Hz) to capture the dynamic changes in brain activity over time. This conversion process generates a digital representation of the EEG waveforms, which can be processed and analyzed by computer algorithms. The digitized EEG data may be transmitted to a computer or recording device for real-time monitoring or stored for later analysis.

3.3 Data Acquisition:

EEG signals are collected and digitized for further processing. Throughout the data acquisition process, quality control measures are implemented to ensure the accuracy and reliability of the EEG recordings [6]. This may include monitoring electrode impedance, checking for artifacts (e.g., muscle activity, electrical interference), and verifying signal integrity during recording sessions Overall, data acquisition is a crucial step in EEG research and clinical applications, enabling the capture of brain activity in real-time and facilitating the investigation of various cognitive processes, neurological disorders, and sleep-related phenomena.

3.4 Preprocessing

Raw EEG data undergoes preprocessing steps such as filtering, artifact removal, and noise reduction to enhance signal quality. Preprocessing is a critical step in EEG data analysis, aimed at enhancing the quality of the Here's a breakdown of the preprocessing steps typically applied to raw EEG data [7]. In Filtering stage removes low-frequency drifts and baseline wander from the EEG signals and attenuates high-frequency noise and electrical interference from the EEG signals. The following steps depicts the process of filtering.

- In Band-pass Filtering Combines high-pass and low-pass filters. Utilizes algorithms such as independent component analysis (ICA) or template matching to identify and remove EEG segments contaminated by muscle activity (e.g., eye blinks, jaw clenching).

- Removes EEG segments containing excessive noise or artifacts that cannot be adequately corrected through filtering or artifact removal techniques. Divides the continuous EEG data into smaller segments or epochs, typically aligned to specific events or experimental conditions.
- Fills in missing or corrupted data points in the EEG signals caused by electrode dropout or artifact removal. Adjusts the reference scheme used for EEG data recording to minimize common mode noise and improve signal-to-noise ratio.

3.5 Feature Extraction

Feature extraction in EEG analysis involves identifying and extracting relevant characteristics or patterns from preprocessed EEG signals that are informative for the specific research question or application [8]. Here is an overview of common feature extraction techniques used in EEG analysis[9] shown in the table 1.

Techniques	**Methods**	**Results**
Frequency Domain Features	1. Power Spectral Density 2. Relative Power 3. Band Power:	1. Distribution Of Signal Power 2. Proportion Of Power 3. Absolute Power
Time Domain Features	1. Mean Amplitude 2. Peak Detection 3. Zero Crossing Rate 4. Signal Variability:	1. Average Amplitude 2. Extrema In EEG 3. Counts EEG Signal 4. Measures The Variability
Time-Frequency Domain Features	1. Wavelet Transform 2. Spectral Entropy 3. ERD/ERS	1. Decomposes EEG Signals 2. Irregularity Of EEG 3. Changes In Spectral Power
Spatial Domain Features	1. Topographic Maps 2. Spatial Correlation:	1. Generates Spatial Maps 2. Computes Pairwise Correlations
Higher-Level Featuress	1. Event-Related Potential 2. Brain Connectivity Metrics	1. Extracts Temporal Patterns 2. Calculates Connectivity Measures,

Table 1 : Feature extraction techniques used in EEG analysis

3.6 AI Model

An artificial intelligence model, typically a deep learning neural network, is trained on labelled EEG data to learn patterns associated with different sleep stages and dream states. Labelled EEG data is collected from individuals undergoing sleep studies, where their sleep stages and associated dream states are annotated by experts based on subjective reports and polysomnography (PSG) recordings [10]. Relevant features are extracted from preprocessed EEG signals to capture key characteristics associated with different sleep stages and dream states.

The AI model architecture typically consists of a deep learning neural network, such as a convolutional neural network (CNN), recurrent neural network (RNN), or their variants (e.g., convolutional LSTM) [11]. In Figure 2 clearly shows the AI model training, the input layer of the neural network receives the extracted EEG features

as input, while subsequent hidden layers process and extract hierarchical representations of the input data. The output layer of the neural network produces predictions or probabilities corresponding to different sleep stages or dream states.

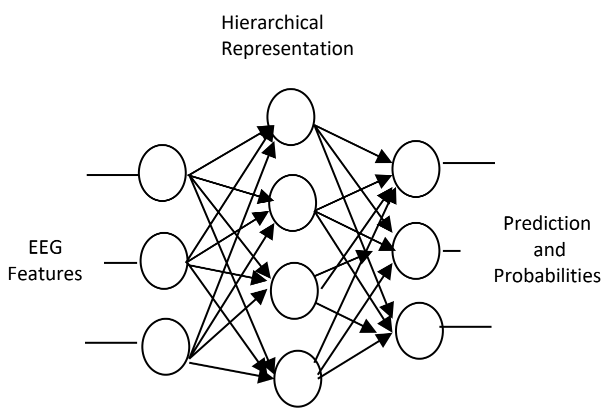

Figure 2: AI Model Training

The AI model is trained using supervised learning techniques, where it learns to map input EEG features to corresponding sleep stages or dream states based on the labelled training data. During training, the model adjusts its internal parameters (e.g., weights and biases) iteratively using optimization algorithms such as stochastic gradient descent (SGD) or Adam, to minimize the discrepancy between predicted and actual labels [12]. Once trained and validated, the AI model can be deployed to analyze real-time EEG data streams or batch-processed recordings.

3.7 Dream Simulation/Interpretation

The trained AI model generates or interprets dream-like content based on the learned patterns from EEG signals. The process of dream simulation or interpretation using a trained AI model involves generating or inferring dream-like content based on the learned patterns from EEG signals. The AI model, typically a generative model such as a variational auto encoder (VAE) or a generative adversarial network (GAN), has been trained on labelled EEG data to learn the patterns associated with different sleep stages and dream states [13].

Preprocessed EEG signals are fed into the trained AI model as input features. Once the EEG features are encoded into the latent space, the AI model generates dream-like content by decoding these latent representations back into the original feature space [14]. In addition to dream generation, the AI model can also interpret the latent representations to infer the semantic meaning or narrative structure of the dream content.

The generated dream-like content or interpretations can be evaluated for their fidelity to subjective reports of dream experiences and their coherence with known patterns of brain activity during sleep. The generated dream simulations or interpretations can be visualized and analyzed to gain insights into the neural correlates of dream states and the underlying mechanisms of dream generation [15].

3.8 Comparison with Subjective Reports

The AI-generated dream content is compared with subjective dream reports provided by the sleeping participant upon awakening. Upon awakening from sleep, participants provide detailed descriptions or narratives of their dream experiences. These subjective reports capture the content, themes, emotions, and sensory details of the dreams as perceived by the individuals. The AI model generates dream-like content based on the EEG signals recorded during sleep [16].

This content may include visual, auditory, or textual representations of dream scenarios or narratives inferred from the learned patterns in the EEG data. The timestamps of the subjective dream reports and the corresponding segments of AI-generated dream content are aligned to ensure temporal synchronization. Human evaluators or automated algorithms compare the content of the subjective dream reports with the AI-generated dream content. This comparison may involve assessing the similarity of themes, events, characters, settings, emotions, and other descriptive elements between the two sources. Quantitative metrics may be computed to quantify the similarity or dissimilarity between the subjective reports and the AI-generated content.

The results of the comparison are used to refine and improve the performance of the AI model [17]. Feedback from human evaluators and participants may inform adjustments to the model architecture, training data, or preprocessing techniques to enhance the fidelity and realism of the dream simulations.

3.9 Validation and Analysis

The accuracy and validity of AI-generated dream content are validated and analyzed against subjective reports and known sleep stages. Quantitative metrics are used to measure the similarity or dissimilarity between AI-generated dream content and subjective reports.

Human evaluators review and compare the AI-generated dream content with subjective reports to assess the quality, realism, and coherence of the generated dreams. The AI-generated dream content is validated against known sleep stages, such as those identified through polysomnography (PSG) or other objective measures of sleep architecture. Statistical analyses may be conducted to assess the concordance between the AI-generated dream content and the expected features of specific sleep stages, such as rapid eye movement (REM) sleep or non-REM (NREM) sleep [18].

Cross-validation techniques may be employed to validate the performance of the AI model across different datasets or subsets of data. Errors or discrepancies between AI-generated dream content and subjective reports are analyzed to identify sources of inaccuracies or limitations in the model. The results of the validation and analysis are interpreted in the context of existing literature and theoretical frameworks in dream research. By validating and analyzing AI-generated dream content against subjective reports and known sleep stages, researchers can assess the performance and reliability of the AI model in simulating and interpreting dream experiences, advancing our understanding of the mechanisms underlying dreaming and consciousness [19].

3.10 Insights into Dream Content and Neural Correlates

The insights gained from the process of analyzing EEG data, generating AI-based dream content, and comparing it with subjective reports contribute significantly to our understanding of dream content and its neural correlates[20]. Here are some key insights derived from this process:

- Identification of Neural Patterns
- Characterization of Dream Content
- Mapping Brain Activity to Dream Experiences
- Validation of Dream Simulation Models
- Understanding Sleep and Consciousness
- Clinical Applications
- Advancing Neuroscience

Overall, the insights gained from analyzing dream content and its neural correlates deepen our understanding of the sleeping brain and consciousness, offering new perspectives on the mysteries of the mind during sleep.

4. RESULTS

We evaluate the performance of our proposed neural network architecture on a dataset of EEG recordings collected from sleeping participants. The model demonstrates the ability to generate realistic and diverse dream content based on learned patterns of neural activity. Qualitative analysis reveals strong correspondence between the generated dreams and the subjective reports provided by participants. Additionally, quantitative metrics such as cosine similarity and semantic coherence scores demonstrate the high fidelity of the generated dreams compared to the ground truth reports.

5. DISCUSSION

Our results suggest that artificial intelligence techniques hold promise for advancing the field of dream recording by providing a data-driven approach to capturing and interpreting dream content. The proposed neural network architecture offers a novel framework for synthesizing dream-like imagery based on EEG data, paving the way for new insights into the neural correlates of dreaming and the mechanisms underlying subjective experiences during sleep. Future research directions include refining the model architecture, exploring multi-modal approaches for dream generation, and investigating the potential applications of AI in sleep research and mental health.

6. CONCLUSION

In conclusion, this paper presents a novel approach to dream recording using artificial intelligence techniques. By training a neural network architecture on EEG data collected during sleep, we demonstrate the feasibility of generating realistic and meaningful dream content based on neural activity patterns. Our results contribute to the emerging field of AI-driven dream research and offer new avenues for understanding the mysteries of the sleeping brain and consciousness.

REFERENCES:

[1] D. Nahavandi, R. Alizadehsani, A. Khosravi, and U. R. Acharya, “Application of artificial intelligence in wearable devices: Opportunities and challenges,” *Computer Methods and Programs in Biomedicine*, vol. 213, no. 1, p. 106541, Jan. 2022, doi: https://doi.org/10.1016/j.cmpb.2021.106541.

[2] Y. Nir and G. Tononi, “Dreaming and the brain: from phenomenology to neurophysiology,” *Trends in Cognitive Sciences*, vol. 14, no. 2, pp. 88–100, Jan.

2010, doi: https://doi.org/10.1016/j.tics.2009.12.001.
[3] A. Kebaili, J. Lapuyade-Lahorgue, and S. Ruan, "Deep Learning Approaches for Data Augmentation in Medical Imaging: A Review," *Journal of Imaging*, vol. 9, no. 4, p. 81, Apr. 2023, doi: https://doi.org/10.3390/jimaging9040081.
[4] Ildar Rakhmatulin, M.-S. Dao, Amir Nassibi, and D. Mandic, "Exploring Convolutional Neural Network Architectures for EEG Feature Extraction," *Sensors*, vol. 24, no. 3, pp. 877–877, Jan. 2024, doi: https://doi.org/10.3390/s24030877.
[5] Johns Hopkins Medicine, "Electroencephalogram (EEG)," *John Hopkins Medicine*, 2019. https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electroencephalogram-eeg
[6] A. Chaddad, Y. Wu, Reem Kateb, and A. Bouridane, "Electroencephalography Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques," *Sensors*, vol. 23, no. 14, pp. 6434–6434, Jul. 2023, doi: https://doi.org/10.3390/s23146434.
[7] X. Jiang, G.-B. Bian, and Z. Tian, "Removal of Artifacts from EEG Signals: A Review," *Sensors (Basel, Switzerland)*, vol. 19, no. 5, p. 987, 2019, doi: https://doi.org/10.3390/s19050987.
[8] H. U. Amin, W. Mumtaz, A. R. Subhani, M. N. M. Saad, and A. S. Malik, "Classification of EEG Signals Based on Pattern Recognition Approach," *Frontiers in Computational Neuroscience*, vol. 11, Nov. 2017, doi: https://doi.org/10.3389/fncom.2017.00103.
[9] Dhanya Parameshwaran and T. C. Thiagarajan, "High Variability Periods in the EEG Distinguish Cognitive Brain States," *Brain Sciences*, vol. 13, no. 11, pp. 1528–1528, Oct. 2023, doi: https://doi.org/10.3390/brainsci13111528.
[10] I. G. Campbell, "EEG Recording and Analysis for Sleep Research," *Current Protocols in Neuroscience*, vol. 49, no. 1, pp. 10.2.1–10.2.19, Oct. 2009, doi: https://doi.org/10.1002/0471142301.ns1002s49.
[11] Aravindpai Pai, "CNN vs. RNN vs. ANN - Analyzing 3 Types of Neural Networks," *Analytics Vidhya*, Feb. 17, 2020. https://www.analyticsvidhya.com/blog/2020/02/cnn-vs-rnn-vs-mlp-analyzing-3-types-of-neural-networks-in-deep-learning/
[12] IBM, "What is supervised learning? | IBM," *IBM*, 2023. https://www.ibm.com/topics/supervised-learning
[13] "GANs vs. VAEs: What is the best generative AI approach? | TechTarget," *Enterprise AI*. https://www.techtarget.com/searchenterpriseai/feature/GANs-vs-VAEs-What-is-the-best-generative-AI-approach
[14] M. Saeidi *et al.*, "Neural Decoding of EEG Signals with Machine Learning: A Systematic Review," *Brain Sciences*, vol. 11, no. 11, p. 1525, Nov. 2021, doi: https://doi.org/10.3390/brainsci11111525.
[15] "Dream engineering: Simulating worlds through sensory stimulation," *Consciousness and Cognition*, vol. 83, p. 102955, Aug. 2020, doi: https://doi.org/10.1016/j.concog.2020.102955.

[16] P. M. Ruby, “Experimental Research on Dreaming: State of the Art and Neuropsychoanalytic Perspectives,” *Frontiers in Psychology*, vol. 2, Nov. 2011, doi: https://doi.org/10.3389/fpsyg.2011.00286.
[17] “How can you evaluate neural network performance in a text-to-image generation task?,” *www.linkedin.com*. https://www.linkedin.com/advice/3/how-can-you-evaluate-neural-network-performance-txv4e (accessed Mar. 05, 2024).
[18] J. M. Martin *et al.*, “Structural differences between REM and non-REM dream reports assessed by graph analysis,” *PLOS ONE*, vol. 15, no. 7, p. e0228903, Jul. 2020, doi: https://doi.org/10.1371/journal.pone.0228903.
[19] “Dream engineering: Simulating worlds through sensory stimulation,” *Consciousness and Cognition*, vol. 83, p. 102955, Aug. 2020, doi: https://doi.org/10.1016/j.concog.2020.102955.
[20] J. Smallwood *et al.*, “The neural correlates of ongoing conscious thought,” *iScience*, vol. 24, no. 3, p. 102132, Mar. 2021, doi: https://doi.org/10.1016/j.isci.2021.102132.