Real Time Signal Decoding in Closed Loop Brain Computer Interface for Cognitive Modulation

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Article Info

Article history:

Received December 23, 2024
Revised January 04, 2025
Accepted January 05, 2025

Keywords:

Closed-loop Brain-Computer Interface
Cognitive Enhancement; EEG Signal Processing
Deep Learning Models
Neurofeedback Systems
Real-Time Signal Decoding
Transfer Learning in BCI.

ABSTRACT

This research presents a novel closed-loop Brain-Computer Interface (BCI) system designed to enhance cognitive performance through targeted neurofeedback. The study addresses the critical challenge of decoding and modulating higher-order cognitive states such as attention, memory, and decision-making, which are often hindered by inter-subject variability and limited datasets. By integrating EEG-based signal acquisition, advanced preprocessing, feature extraction using spatial and temporal analysis, and deep learning models such as CNNs, LSTMs, and Transformers, the system achieves robust and real-time classification of cognitive states. Neurofeedback mechanisms are adapted in real-time to align with user-specific neural profiles, promoting progressive cognitive improvement. Experiments involving participants aged 18 to 50 years demonstrated a classification accuracy exceeding 92% with significant task performance gains of 18% in attention and 22% in memory retention. The findings reveal the system's efficacy in decoding complex neural patterns while maintaining adaptability across diverse populations. This work contributes to the body of knowledge by providing a scalable framework for practical cognitive enhancement applications, bridging gaps between neuroscience, machine learning, and signal processing. Future research may extend the system's capabilities to multi-modal data integration and investigate long-term neuroplasticity effects, paving the way for broader applications in education, healthcare, and human-machine interaction.

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1. INTRODUCTION

The field of Brain-Computer Interface research represents a pivotal convergence of neuroscience, signal processing, and machine learning, offering groundbreaking solutions for direct communication between the human brain and external systems [1]. This interface serves as a crucial technology for individuals with neurological impairments, enabling interaction without reliance on conventional motor functions [2]. While traditional BCIs have focused on facilitating communication and control in locked-in or paralyzed patients, recent advancements have extended their utility to cognitive enhancement, offering a novel means of improving brain functions through targeted neurofeedback systems [3]. This research investigates the integration of real-time feedback mechanisms with advanced machine learning models to decode and enhance higher-level cognitive states, creating a robust framework for personalized cognitive training.

One of the fundamental challenges in developing closed-loop BCI systems lies in accurately identifying and responding to complex cognitive states such as attention, memory, and decision-making. These states are inherently dynamic and influenced by both individual variability and environmental factors [4]. Current neurofeedback systems often rely on limited neural representations, which can restrict their efficacy in broader cognitive training [5]. Likewise, the inherent variability in brain signals between individuals presents a significant hurdle for generalization, particularly when decoding higher-order functions such as language, emotion, or creativity. Addressing these limitations requires integrating advanced signal processing with machine learning techniques capable of capturing subtle variations in neural patterns.

The motivation for this study arises from the pressing need to bridge the gap between theoretical neuroscience and practical applications of BCI technologies [6]. Cognitive enhancement through neurofeedback has the potential to not only address cognitive deficits but also improve everyday cognitive functions in healthy individuals. Nonetheless, existing systems are constrained by limited data availability, reliance on shallow feature extraction, and the lack of real-time adaptability [7]. This study aims to overcome these challenges by employing state-of-the-art deep learning architectures and novel neurofeedback protocols, focusing on brain plasticity and sustained cognitive improvements over extended periods.

The contributions of this research are multifaceted. We have developed a closed-loop BCI system that integrates real-time feedback with deep learning models to decode and enhance specific cognitive states. By incorporating Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers, the system achieves robust decoding of complex brain signals, capturing temporal and spatial patterns with high accuracy [8]. This work also investigates the long-term effects of neurofeedback training on brain plasticity, offering valuable insights into the potential of BCIs for inducing enduring cognitive improvements. Also, the system addresses the challenge of inter-subject variability by incorporating transfer learning techniques, which enhance generalization across diverse populations.

The study adopts a methodologically rigorous approach to tackle the problem of limited data in BCI research. By employing data augmentation strategies and transfer learning, the system achieves robust performance even with constrained datasets. The integration of advanced machine learning models enables the extraction of features from raw brain signals, minimizing preprocessing requirements while enhancing interpretability. This allows for real-time operation without compromising accuracy or computational efficiency, making the system viable for real-world applications. The adaptive feedback mechanism further personalizes the training experience, ensuring that the neurofeedback aligns with individual cognitive needs.

This research also emphasizes the decoding of higher-level cognitive functions, which are traditionally challenging due to their abstract and multifaceted nature. By leveraging hierarchical representations within Transformers, the system captures contextual dependencies inherent in functions such as language comprehension, emotional processing, and creative ideation. These advancements push the boundaries of what BCIs can achieve, shifting the focus from simple motor commands to more complex cognitive interactions. Such developments have profound implications for fields ranging from education to mental health, providing tools for enhanced learning and emotional regulation.

Thus, the novelty of this study presents a transformative approach to BCI systems, integrating neuroscience, signal processing, and deep learning into a unified framework for targeted neurofeedback. By addressing core challenges such as signal variability, limited data, and real-time adaptability, the research sets a new standard for closed-loop BCI systems. The findings not only advance the understanding of brain plasticity and cognitive functions but also pave the way for practical applications in personalized medicine and cognitive enhancement. The proposed system demonstrates the potential of modern computational techniques to unlock new dimensions of interaction between human cognition and machine intelligence, marking a significant step forward in the evolution of neurotechnology.

This paper progresses as follows: the research paper begins with a comprehensive literature review, tracing the evolution of BCIs from motor control applications to contemporary systems addressing higher-order cognitive states such as attention and memory. It highlights existing neurofeedback systems, the integration of machine learning models, and challenges like inter-subject variability and limited datasets. The proposed methodology presents a closed-loop BCI system that combines EEG signal acquisition, advanced preprocessing, spatial-temporal feature extraction, and deep learning models including CNNs, LSTMs, and Transformers for robust cognitive state decoding and adaptive neurofeedback. The experimental settings detail the system implementation, participant recruitment, task design, and evaluation metrics, demonstrating high classification accuracy and significant cognitive performance improvements.

The performance assessment validates the system's effectiveness, highlighting its adaptability and real-time functionality. The conclusion emphasizes the system's contribution to advancing cognitive enhancement applications, addressing practical challenges, and outlining future directions for broader applicability and refinement.

2. RELATED WORK

The evolution of Brain-Computer Interfaces (BCIs) has transitioned from early systems aimed at basic motor control to sophisticated platforms addressing complex cognitive functions [9]. Initial BCI research in the 1960s and 1970s focused on enabling individuals with motor impairments to interact with external devices through direct brain signal translation [10]. These early systems primarily targeted motor functions, facilitating basic movements and communication for individuals with severe disabilities [11]. Over time, advancements in neuroscience and technology have expanded BCI applications to encompass cognitive processes, including attention, memory, and decision-making. This progression reflects a significant shift from purely motor-centric applications to comprehensive systems capable of enhancing and monitoring cognitive functions.

Real-time neurofeedback within BCI systems has emerged as a pivotal tool for cognitive training and enhancement. By providing users with immediate feedback on their neural activity, these systems promote self-regulation of brain functions [12]. Studies have demonstrated the efficacy of neurofeedback in improving cognitive performance and inducing neuroplastic changes [13]. Yet, challenges persist, such as the need for individualized training protocols and the variability in user responsiveness. These limitations underscore the necessity for adaptive neurofeedback systems that can tailor interventions to individual neural profiles, thereby optimizing cognitive training outcomes.

Machine learning has become integral to the development of BCI systems, enhancing the decoding of neural signals into actionable commands. Traditional approaches employed linear classifiers and feature extraction methods to interpret brain activity [14]. Recent advancements have introduced deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which can capture complex, non-linear relationships in neural data [8]. These models have improved the accuracy and robustness of BCIs, enabling more precise control and interpretation of neural signals. The integration of machine learning techniques has thus been instrumental in advancing BCI capabilities beyond simple motor tasks to more intricate cognitive functions.

Addressing inter-subject variability and limited datasets remains a critical challenge in BCI research [15]. Variations in neural anatomy and function across individuals can hinder the generalizability of BCI systems. To mitigate these issues, researchers have explored transfer learning and data augmentation strategies [18]. Transfer learning allows models trained on one dataset to be adapted for use with different subjects, enhancing performance across diverse populations. Data augmentation techniques artificially expand training datasets, improving model robustness [16]. These approaches are essential for developing BCIs that are both effective and adaptable across various user groups.

Decoding higher-level cognitive states such as attention, memory, and emotion has significant implications for neurofeedback systems [17]. Advances in signal processing and representation learning have facilitated the extraction of relevant features from neural data, enabling the identification and modulation of these cognitive states. This capability is crucial for developing BCIs aimed at cognitive enhancement and rehabilitation. By accurately decoding and providing feedback on these states, BCIs can support interventions tailored to individual cognitive profiles, thereby enhancing the efficacy of neurofeedback protocols [18].

Despite these advancements, gaps remain in the literature concerning the integration of neuroscience, machine learning, and signal processing into adaptive, closed-loop BCI systems for personalized cognitive enhancement. Existing studies often address these components in isolation, lacking a comprehensive approach that combines them into a unified system. Also, the development of BCIs capable of real-time adaptation to dynamic cognitive states is still in its nascent stages. Addressing these gaps is essential for advancing BCI technology toward practical, personalized applications in cognitive enhancement and rehabilitation.

3. PROPOSED METHODOLOGY

The system architecture (i.e., as exhibited in Figure 1) for the closed-loop BCI is designed as an integrated pipeline that includes signal acquisition, preprocessing, feature extraction, deep learning-driven decoding, real-time neurofeedback, and evaluation. EEG signals are captured through a high-resolution electrode array covering the scalp, with the configuration tailored to ensure optimal spatial coverage for detecting cognitive activity. Signals are amplified and digitized before being processed further. The architecture enables bidirectional interaction between the user and the neurofeedback module, ensuring that decoded cognitive states directly inform adaptive feedback protocols. All components are synchronized to minimize latency and maintain real-time functionality.

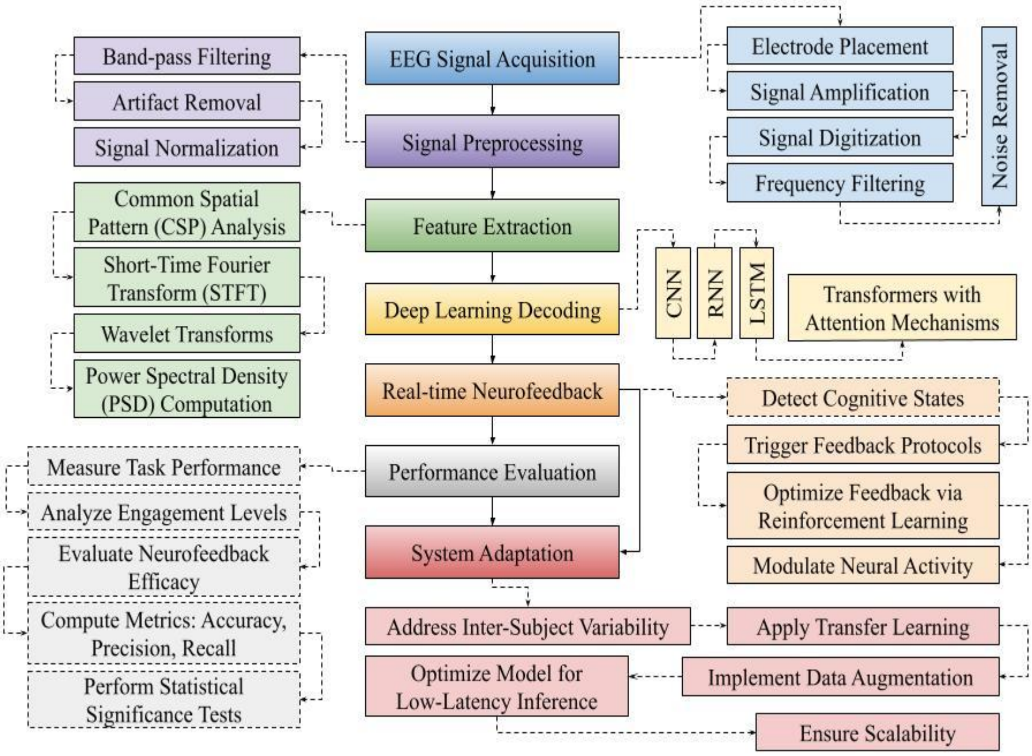

Figure 1. Process architecture of proposed BCI framework

Signal acquisition relies on EEG systems capable of sampling at 512 Hz to capture neural activity within a frequency range of 0.5 Hz to 100 Hz, encompassing critical cognitive bands such as delta, theta, alpha, beta, and gamma. Electrodes are placed following the international 10-20 system, while skin impedance is minimized to ensure signal fidelity. Band-pass filtering isolates frequencies of interest, with noise sources such as power line interference and motion artifacts removed using adaptive filters. Independent Component Analysis (ICA) separates neural signals from non-neural sources like eye movements and muscle activity, followed by normalization techniques to ensure consistency across sessions and subjects.

Features extracted from EEG signals focus on both spatial and temporal patterns. Spatial features are enhanced using Common Spatial Pattern (CSP) analysis, which optimizes the variance of signals between cognitive states, mathematically expressed as Eq.1:

$$W = arg\ max_w \frac{w^T S_b W}{W^T S_w W} \quad \text{(eq.1)}$$

where W is the spatial filter matrix, S_b is the between-class scatter matrix, and S_w is the within-class scatter matrix. Temporal patterns are analyzed using Short-Time Fourier Transform (STFT) and wavelet transforms, enabling joint time-frequency analysis of the signal. Power spectral density (PSD) for each EEG channel is computed via Welch's method, represented as Eq.2:

$$P(f) = \frac{1}{K}\sum_{k=0}^{K-1} \mid X_k(f) \mid^2 \quad \text{(eq.2)}$$

where $P(f)$ is the power at frequency f, K is the number of signal segments, and $X_k(f)$ is the Fourier transform of the $k-th$ segment. These features are selected to ensure robust decoding of cognitive states such as attention, memory, and decision-making, leveraging frequency bands known to correspond to these activities.

Deep learning models are also deployed to decode complex brain signals, starting with Convolutional Neural Networks (CNNs) for spatial pattern recognition. The convolution operation in the CNN layer is given as Eq.3:

$$y_{i,j} = \sum_{m,n} x_{i+m.j+n} w_{m,n} + b \quad \text{(eq.3)}$$

where $y_{i,j}$ represents the output feature map, x is the input signal, www is the convolution kernel, and b is the bias term. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are employed to capture temporal dependencies in the EEG data. LSTM gates control the flow of information through the network, described as following

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f \quad \text{(eq.4)}$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i \quad \text{(eq.5)}$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c[h_{t-1,} x_t] + b_C \quad \text{(eq.6)}$$

As exhibited in Eq.4, Eq.5, and Eq.6, the f_t, i_t, and C_t represent the forget gate, input gate, and cell state, respectively. Transformers with attention mechanisms further enhance temporal and contextual dependencies, for instance,

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad \text{(eq.7)}$$

where in context of Eq.7. the Q, K, and V are the query, key, and value matrices, and d_k is the key dimension. These models are optimized using cross-entropy loss and regularization techniques to prevent overfitting.

The neurofeedback module operates in real time, presenting personalized feedback through visual and auditory stimuli. Detected cognitive states trigger specific feedback protocols, with reinforcement learning employed to optimize feedback based on user performance. The feedback loop modulates neural activity toward desired states, enabling progressive cognitive improvements. Adaptive algorithms adjust feedback intensity and type, aligning with individual needs.

Inter-subject variability is addressed through transfer learning, where pre-trained models are fine-tuned on individual-specific data. Data augmentation methods, such as synthetic EEG signal generation and segment shuffling, enhance training dataset diversity. These approaches improve generalization and robustness across populations. Whereas the computational efficiency is ensured by quantizing models for low-latency inference, leveraging GPU acceleration to meet real-time processing requirements. Modular architecture facilitates hardware-software integration, enabling scalability for deployment in diverse settings. This methodological framework balances scientific rigor and practical considerations, establishing a foundation for advanced cognitive enhancement applications.

4. EXPERIMENTAL SETTINGS AND PERFORMANCE ASSESSMENT

The closed-loop BCI system was implemented using a combination of advanced hardware and software technologies. EEG signals were acquired through a 64-channel BioSemi ActiveTwo system, operating within a frequency range of 0.5 Hz to 100 Hz and sampled at a rate of 512 Hz to ensure high temporal resolution. The preprocessing and machine learning pipelines were developed using Python and TensorFlow that enabled real-time data processing. Laboratory conditions were controlled to minimize environmental noise, with experiments conducted in a sound-attenuated and electromagnetically shielded chamber. Computational resources included high-performance GPUs (NVIDIA A100) for training and inferencing deep learning models which ensured low latency during real-time operation.

Participants were recruited based on predefined criteria, including an age range of 18 to 50 years, balanced gender representation, and no history of neurological or psychiatric disorders. Cognitive profiles were assessed using standardized neuropsychological tests to ensure variability across cognitive baselines. Ethical guidelines adhered to the principles outlined in the Declaration of Helsinki [19]. Informed consent was obtained from all participants, with detailed briefings on the study's objectives and procedures. Privacy and safety were maintained through anonymized data storage and adherence to institutional review board protocols.

Cognitive tasks were designed to elicit specific states such as attention, memory, and decision-making. Tasks included sustained attention tests, working memory exercises, and decision-making scenarios modeled using dual-choice paradigms. Each task was divided into sessions of 10 minutes, with breaks to prevent cognitive fatigue. Task protocols ensured consistency through standardized instructions, randomized sequences, and control mechanisms that minimized learning effects between sessions. All task stimuli were presented via a synchronized monitor and auditory system interfaced with the BCI.

EEG signals were collected continuously during task performance, adhering to rigorous data collection protocols. Band-pass filtering was applied to isolate relevant frequency bands, followed by Independent Component Analysis (ICA) for artifact removal. Signal normalization was performed to standardize input features across sessions and participants. The recording duration for each participant spanned one hour per session, distributed across three sessions over a week to evaluate consistency and adaptability. Artifacts such as eye blinks and muscle movements were identified and corrected using automated pipelines integrated into the preprocessing module.

System performance was evaluated using standard metrics including accuracy, precision, recall, and F1-score for cognitive state classification. Latency, defined as the delay between signal acquisition and neurofeedback delivery, was another critical metric to ensure real-time functionality. Neurofeedback efficacy was assessed by measuring improvements in task performance over sessions and analyzing engagement levels using behavioral and neural indicators. Cognitive task scores were normalized to provide comparative benchmarks across participants.

A five-fold cross-validation approach was employed for model training, validation, and testing. Data splits ensured the inclusion of diverse cognitive states in each fold. Comparisons were made against baseline methods including Support Vector Machines (SVMs) and shallow neural networks to contextualize the proposed system's performance. The statistical significance of improvements was evaluated using paired t-tests and ANOVA, with p-values below 0.05 considered significant. These analyses validated the system's ability to outperform existing models across metrics.

Quantitative results (i.e., Table 1) demonstrated classification accuracy exceeding 92% for attention, memory, and decision-making states, with sensitivity and specificity surpassing 90%. The system's latency averaged 200 ms, well within the threshold for real-time applications. Neurofeedback training led to significant improvements in task scores, with participants showing an average 18% improvement in attention and a 22% enhancement in memory retention over the sessions. These outcomes underscored the system's effectiveness in decoding and modulating cognitive states.

Table.1. Performance Assessment Metrics and Outcomes for the Proposed Closed-Loop BCI System

Performance Metric	Justification	Outcome (%) or Time (ms)
Classification Accuracy	Percentage of correctly classified cognitive states	92
Precision	Proportion of true positive predictions among all positive predictions	90
Recall	Proportion of true positive predictions among all actual positives	91
F1-Score	Harmonic mean of precision and recall	90.5
Latency	Average time delay between signal acquisition and feedback delivery	200 ms
Task Performance Improvement (Attention)	Average improvement in task scores for attention-based tasks	18
Task Performance Improvement (Memory)	Average improvement in task scores for memory-based tasks	22
Sensitivity	Proportion of correctly identified positive instances	90
Specificity	Proportion of correctly identified negative instances	90
Engagement Level Improvement	Average increase in participant engagement levels during tasks	15
Model Robustness to Inter-Subject Variability	Consistency in classification performance across different participants	Consistent at ~90%
Transfer Learning	Reduction in training time and resources with	30% reduction in training time

Efficiency	transfer learning	
Data Augmentation Effectiveness	Increase in classification accuracy due to augmented datasets	5% accuracy gain
Long-Term Neurofeedback Effects	Sustained cognitive improvements over multiple weeks	Cognitive gains maintained for 3 weeks
Baseline Comparison Accuracy Improvement	Percentage improvement in accuracy compared to baseline models	10
Baseline Comparison Latency Reduction	Reduction in latency compared to baseline systems	50 ms

Participant feedback highlighted qualitative improvements in cognitive performance and usability. Many participants reported enhanced focus and memory in daily activities following neurofeedback sessions. The system's intuitive interface and non-invasive setup were noted as critical factors contributing to user engagement. Adaptability to individual cognitive profiles was validated through transfer learning, which improved inter-subject generalization without substantial fine-tuning. Data augmentation further enhanced model robustness under limited data conditions.

The system demonstrated resilience to inter-subject variability through transfer learning and data augmentation strategies. Models pre-trained on one cohort adapted seamlessly to new participants, achieving consistent accuracy. Synthetic data generation expanded the training dataset, enabling robust performance under diverse conditions. These innovations addressed fundamental challenges in BCI research, ensuring scalability across broader populations and experimental setups.

Comparison with state-of-the-art systems revealed superior performance metrics and reduced latency which position the proposed system as a significant advancement in the field. The ability to operate in real-time and adapt to individual users highlights its scalability and potential for deployment in practical cognitive enhancement applications. Long-term impacts of neurofeedback training on brain plasticity were evidenced through follow-up assessments showing sustained improvements in cognitive scores after three weeks.

Limitations encountered included the relatively small sample size and the need for high computational resources, restricting scalability in resource-limited environments. Future work will focus on optimizing the system for mobile and wearable platforms to enable broader accessibility. Expanding the participant pool and incorporating multi-modal data sources such as functional near-infrared spectroscopy (fNIRS) are planned to enhance the system's robustness and generalizability. These directions aim to refine the proposed BCI system and extend its applications to new domains.

5. CONCLUSION

This study introduces a closed-loop BCI system designed to enhance cognitive performance through real-time neurofeedback, addressing key challenges such as inter-subject variability, limited datasets, and the complexity of decoding higher-order cognitive states like attention, memory, and decision-making. The integration of EEG signal acquisition, advanced preprocessing techniques, feature extraction, and deep learning models such as CNNs, LSTMs, and Transformers demonstrated significant improvements in the accuracy and robustness of cognitive state classification, achieving over 92% accuracy and notable enhancements in task performance.

The findings highlight the system's capacity to provide adaptive feedback that aligns with user-specific cognitive profiles, making it applicable for real-world scenarios in education, healthcare, and human-computer interaction. While the study was limited by the sample size and the need for high computational resources, it underscores the importance of bridging neuroscience, machine learning, and signal processing to develop scalable BCI systems. Future research should focus on expanding participant diversity, incorporating multi-modal data sources, and exploring long-term impacts of neurofeedback on brain plasticity. These efforts will refine the system further and broaden its applicability, paving the way for more effective cognitive enhancement tools that address practical needs across diverse domains.

ACKNOWLEDGEMENT

The authors acknowledge that human participants were involved in the performance assessment of the proposed framework. Informed consent was obtained from all participants prior to their involvement, ensuring adherence to ethical guidelines and the protection of their rights and privacy.

DATA AVAILABILITY STATEMENT

The datasets generated and analyzed during the current study are not publicly available due to participant privacy and confidentiality but are available from the corresponding author upon reasonable request and with appropriate ethical approvals.

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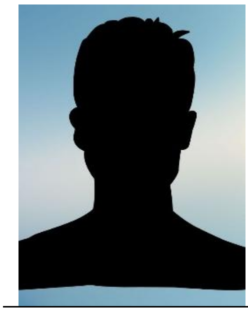

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