Targeted Brain Computer Interface Utilisation by Employing Endogenous EEG Frameworks

[1]Srivinay, [2]Swetha Parvatha Reddy Chandrasekhara, [3]Amogh Pramod Kulkarni and [4]Sneha S Bagalkot
[1,2]Department of Information Science and Engineering, B.M.S. College of Engineering, Bengaluru, Karnataka, India.
[3]Department of Machine Learning, B.M.S. College of Engineering, Bengaluru, Karnataka, India.
[4]Department of Computer Science and Engineering, B.M.S. College of Engineering, Bengaluru, Karnataka, India.
[1]srivinay.ise@bmsce.ac.in, [2]swethapc.ise@bmsce.ac.in, [3]amoghpramod.mel@bmsce.ac.in, [4]snehasb.cse@bmsce.ac.in

Correspondence should be addressed to Srivinay : srivinay.ise@bmsce.ac.in

Article Info
Journal of Machine and Computing (https://anapub.co.ke/journals/jmc/jmc.html)
Doi : https://doi.org/10.53759/7669/jmc202505028
Received 02 July 2024; Revised from 30 September 2024; Accepted 25 November 2024.
Available online 05 January 2025.

Abstract – Brain-computer interfaces (BCI) establish a direct communication link between the brain and computers or other external devices. These interfaces enhance human capabilities by either supplementing or replacing peripheral functions, with potential applications in fields like rehabilitation, affective computing, robotics, gaming, and neuroscience. Significant global research efforts have led to standardized platforms that address the challenges of complex, non-linear brain dynamics, feature extraction, and classification. However, time-varying psycho-neurophysiological fluctuations and their impact on brain signals present additional challenges in translating BCI technology from controlled laboratory settings to everyday use. This review provides an overview of recent advancements in the BCI field and outlines key challenges. In this paper, we propose a conceptual framework for personalized BCI applications, aimed at improving the user experience by tailoring services to individual needs and preferences based on endogenous electroencephalography (EEG) paradigms, including motor imagery (MI), speech imagery (SI), and visual imagery. The framework comprises two core components: user identification and intention classification, which allow for personalized services by identifying users and recognizing their intended actions through EEG signals. We validate the framework's feasibility with a private EEG dataset from eight subjects, utilizing the ShallowConvNet architecture to decode EEG features. Experimental results show that user identification achieved an average classification accuracy of 0.996, while intention classification reached 0.55 accuracy across all paradigms, with MI showing the best performance. These results suggest that EEG signals can effectively support personalized BCI applications, offering strong user identification and reliable intention decoding, particularly for MI and SI.

Keywords - Brain-Computer Interfaces, Electroencephalography, Psycho-Neurophysiology, Brain Feature Extractions, Personalized BCI.

I. INTRODUCTION

Brain-Computer Interface (BCI) technology represents a cutting-edge field that bridges the gap between the human brain and external devices, enabling direct communication and control through neural activity. BCIs operate by capturing electrical signals from the brain, decoding them, and translating them into commands that can control devices such as computers, robotic limbs, or even assistive technologies [1]. This technology has enormous potential, particularly for individuals with neurological impairments or disabilities, as it offers a way to restore lost functionalities, such as movement or communication, without the need for conventional physical interfaces like hands or speech.

Neurological and neuroanatomical injuries and disorders impact millions of people globally, often resulting in movement impairments and the loss of the ability to perform daily activities such as communicating, reaching, and grasping independently. People who have experienced neurological injuries, such as spinal cord injury (SCI), amyotrophic lateral sclerosis, or stroke, can regain partial functionality through cortical prosthetic systems [2]. A cortical prosthesis is an end effector device that receives action commands via a brain-computer interface (BCI), which records cortical activity and decodes information related to the intended action. These end effectors can range from virtual communication systems for typing to robotic arms and hands, or even the reanimation of a person's limb through functional electrical stimulation (FES).

BCIs can be classified into invasive and non-invasive types, with invasive BCIs involving implanted electrodes to record neural signals with higher precision, while non-invasive BCIs utilize external methods, such as electroencephalography (EEG), to monitor brain activity. Despite the technological advancements, non-invasive BCIs remain more widely used due to their lower risk, although they often face challenges in signal clarity, resolution, and processing speed [3].

The application of BCIs spans a wide range of fields, from medical and rehabilitation to communication and entertainment. In healthcare, BCIs are being used to help individuals with conditions like paralysis, stroke, or amyotrophic lateral sclerosis (ALS) regain some degree of control over their environment [4]. BCIs are also integral to neuroprosthetics, which allow users to control robotic limbs or other assistive devices directly with their thoughts, offering the possibility of restoring lost mobility and independence.

Non-invasive brain imaging techniques, such as electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI), have been applied in simpler BCI systems, such as low-throughput communication tools for spelling. However, these non-invasive methods often face limitations, including slow processing speeds (e.g., fMRI), low spatial resolution, limited signal bandwidth (e.g., EEG), and susceptibility to external artifacts [5]. Consequently, they are not ideal for complex, real-time applications like high-performance communication, control of multidimensional robotic limbs, or reanimation of paralyzed limbs for coordinated reaching and grasping. In contrast, invasive BCIs, which offer higher resolution and greater signal bandwidth, provide the potential for individuals with neurological injuries to naturally control more advanced systems and restore more intricate functions.

Electroencephalography (EEG) is a neurophysiological signal generated by neural activity in the brain, providing insights into an individual's mental states and intentions. For decades, researchers have sought to decode EEG signals to understand these mental states and intentions. Recent advancements in deep learning have significantly enhanced the performance of EEG decoding [6]. Consequently, EEG-based brain-computer interface (BCI) technology, which enables the control of external devices based on a user's mental state or intention, has been extensively explored across various domains, showing promising potential for real-world applications [7].

Despite these advancements, research on personalized BCI applications that cater to an individual's specific interests remains limited. Most existing BCI systems rely on generalized models that inadequately address individual differences in interests, habits, and lifestyles, thus limiting their convenience and user experience. However, variations in EEG patterns among individuals present an opportunity to leverage this user-specific information to develop personalized BCI systems tailored to the unique characteristics and needs of each user.

To address this gap, we propose a conceptual framework for personalized BCI applications, utilizing user-specific information through tasks such as user identification and intention classification. We further demonstrate the feasibility of this framework through preliminary experiments using a private endogenous EEG paradigm dataset.

II. WORK IN THIS AREA

BCI technology has diverse applications in both clinical and non-clinical fields such as medicine, entertainment, education, and psychology, offering solutions to various health issues like cognitive decline, slow processing speed, memory impairment, and reduced movement ability in the elderly [8]. These issues can negatively impact the quality of life and mental health of older individuals. Over the past decade, several BCI applications have been developed to help seniors maintain a healthy lifestyle and sense of well-being.

BCIs can be categorized based on the type of electrodes used to measure brain activity: non-invasive BCIs, where electrodes are placed on the scalp (e.g., EEG-based BCIs), and invasive BCIs, where electrodes are implanted directly into the brain (e.g., ECoG or iEEG). EEG-based BCIs are widely used for both synchronous and asynchronous control and communication. Non-invasive EEG-based BCIs are further classified into "evoked" BCIs, which rely on brain responses to external stimuli (e.g., P300, SSVEP), and "spontaneous" BCIs, which analyze brain activity during mental tasks performed by the user voluntarily [9].

BCIs typically consist of several components: signal acquisition, preprocessing, feature extraction, classification, translation into commands, and user feedback. Open-source software tools like BCI2000, EEGLab, and FieldTrip have been developed to aid the processing and analysis of brain data, incorporating advanced signal processing and AI techniques [10]. Despite these advancements, BCIs face challenges such as low classification accuracy, limited degrees of freedom, and long training times.

To improve performance, hybrid BCIs (hBCIs) combining multiple modalities (e.g., P300 with SSVEP or MI) have been explored. These systems leverage the advantages of different brain activity signatures or combine brain signals with non-brain signals, such as eye movements (EOG), muscle activity (EMG), or heart signals (ECG). Closed-loop BCIs, which provide real-time feedback, offer potential therapeutic benefits, such as enhancing cognitive abilities in elderly patients through biofeedback, potentially inducing cerebral plasticity and facilitating rehabilitation [11].

One major challenge is developing non-invasive BCI technologies for paralyzed patients, as non-invasive methods can suffer from weaker signals and lower signal-to-noise ratios. However, advanced techniques like deep learning can help address these issues by improving the decoding and extraction of relevant information from EEG signals. EEG-based BCIs have promising applications in motor control, psychological therapies, and monitoring conditions like smoking or alcohol abuse [12]. They are also being used in therapies for autism, memory capacity tests, and cognitive assessments.

The brain, which consists of the central nervous system (brain and spinal cord) and peripheral nervous system, has specialized regions that control various functions. BCIs leverage these brain regions to facilitate communication and control, offering hope for individuals with neuromuscular disorders. BCIs can restore or replace lost functions due to conditions such as ALS, cerebral palsy, stroke, or spinal cord injuries. Research continues to explore their potential for controlling prosthetic devices, robotic arms, and aiding rehabilitation, with the goal of improving quality of life for those with disabilities [13].

III. COMPONENTS OF BCI

The components of BCI systems are broadly categorized into four main parts: signal acquisition, processing, output, and feedback. The effectiveness of a BCI system largely depends on the signal acquisition module, which is crucial for detecting and recording brain signals. This module is the primary focus of this paper.

The processing component analyses the recorded brain activity using specialized methods and algorithms to interpret the user's intended actions. It includes pre-processing techniques such as independent component analysis and decoding methods that integrate machine learning approaches like support vector machines [14]. Recent advancements also emphasize algorithms like canonical correlation analysis for steady-state visually evoked potentials and deep learning for paradigm-agnostic solutions [15]. **Fig 1** shows the components of a brain computer interface.

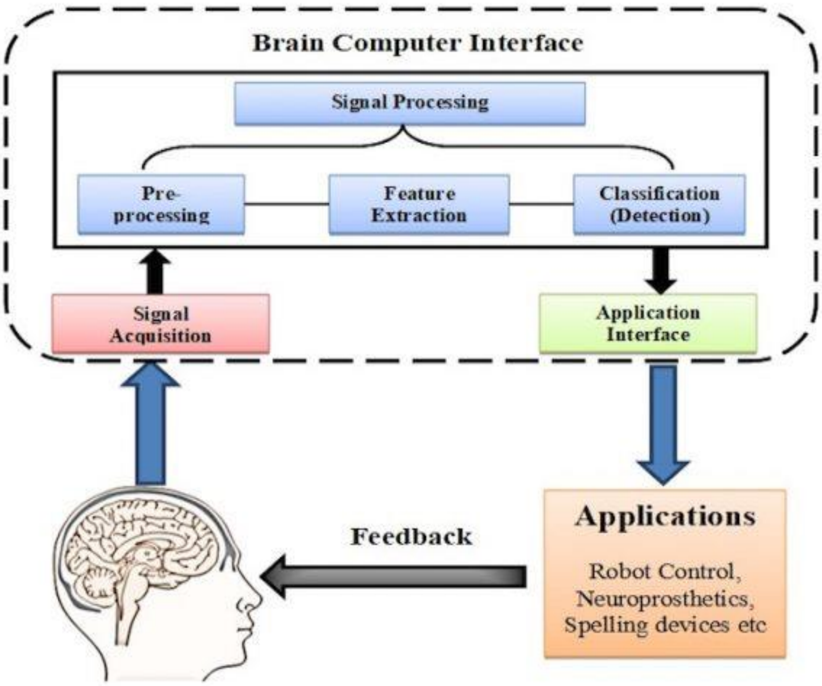

Fig 1. Components of a Brain Computer Interface. [18]

Feature Extraction identifies meaningful patterns or features from the signals (e.g., time, frequency, or spatial features). Feature Classification decodes extracted features into user intentions using machine learning or statistical methods [16, 17]. The output component translates the user's intended actions into real-world results, such as controlling a robotic arm or operating a speller, based on the processed information. The feedback component provides the user with information about the system's interpretation of their intended actions and the final execution results, using sensory feedback methods like visual or auditory cues.

IV. APPLICATIONS OF BCI

Brain-Computer Interface (BCI) technology is a rapidly advancing field with transformative potential to enhance human life, particularly in medicine. It enables individuals with physical disabilities to control machines through thought, restoring capabilities and independence. Collaboration between scientists and engineers is crucial to overcoming challenges and developing innovative applications. Beyond medicine, BCI has shown promise in industries like mining and education and is expected to drive advancements in robotics and neurophysiology. Additional applications include thought decoding, memory enhancement, telepathic communication, automation, and targeted medical treatments.

Interpretation of Thoughts

The human brain regulates thoughts and various physiological functions, some of which manifest externally, like anger, while others remain internal and inaccessible. Current technologies cannot accurately interpret individual thoughts, but BCI holds promise in scenarios like criminology, where it could enhance polygraphs by integrating artificial intelligence.

BCI's future potential includes translating thoughts into text, mapping imaginations into tangible objects, decoding dreams, and creating wearable devices for monitoring thoughts or sleep patterns. It may also enable individuals, particularly those with disabilities, to control machines like drones or vehicles using their thoughts [19].

However, as BCI technology advances, concerns about security and privacy will grow, necessitating universal regulatory standards. Further research and development are required to explore these possibilities fully.

Enhancement of Human Memory

Stephen Hawking proposed the idea of uploading the human mind into a computer, raising the question of whether Brain-Computer Interface (BCI) technology could make this possible by extracting and decoding memory signals for storage in a computer. If successful, this could enable faster processing, retrieval, and transmission of information, as well as control of external devices.

Recent BCI advancements show that brain signals can be converted into data reflecting human intentions, with future research exploring the extraction of behaviours and traits for scientific study. However, ethical guidelines must be followed in this research. If brain data can be accurately harvested, it could be stored and retrieved from external devices, such as portable storage drives [20]. For example, a psychologist could use a BCI device to gain insights into a person's behaviour, providing more informed counselling. Achieving this goal would require extensive multidisciplinary research.

Mind-To-Mind Communication

Rao et al. showed that BCI, in combination with the computer-brain interface (CBI), could enable telepathic communication, allowing individuals to communicate without physical or sensory channels. The integration of BCI and CBI forms a brain-to-brain interface, which is still in early stages of development. Future research may expand telepathic communication across various fields and explore how human brains can be connected through the Internet of Things (IoT) for better information exchange [21]. Although some studies have investigated BCI-IoT interfacing, establishing brain-IoT connectivity remains a significant challenge. Further exploration of mind-to-mind and mind-to-machine interfaces is also needed to enhance human-machine-human communication, with ethical considerations remaining central to these advancements.

Automated Control Systems

Advancements in BCI technology are showing promise for automation and control industries, including home automation, where it helps people with physical disabilities perform daily tasks independently. As BCI continues to develop, it is expected to positively impact industrial manufacturing, particularly through integration with secure wireless networks for automation. With rapid progress in sensor technology, BCI could also be applied in non-contact control and automation systems [22]. However, further research is needed to overcome BCI's limitations and ensure effective interaction with intelligent sensors.

Knowledge Exchange

BCI, combined with CBI, could potentially enable brain reprogramming and intelligence sharing between individuals. While this concept may seem like science fiction, the principles behind the technology suggest it could be possible. However, achieving this requires a thorough understanding of brain function, which current scientific knowledge has not yet fully developed [23].

Brain Power Extraction

The human brain, despite constituting only 2% of the body's mass, uses about 20% of the body's total energy, making it the third most energy-intensive organ. It is suggested that BCI technology, in conjunction with other advanced technologies, could harvest some of this energy to power low-energy external devices [24]. However, more research is needed to assess how much energy a typical BCI system could extract from the brain.

Bounded Brain–Computer Interface

In BCI systems, electrodes capture all brain signals in their vicinity, leading to a large amount of noise and making signal processing difficult. By localizing the system to focus on specific brain signals for a targeted body part, such as placing it near speech-related areas in individuals with speech impairments, the system's performance could improve, and its size could be reduced [25].

V. DIFFICULTIES

Neurological and Psychophysiological Difficulties

Emotional, mental, neurophysiological, and neurological factors significantly impact BCI performance, leading to variability both within and between individuals. Psychological factors such as attention, memory load, fatigue, and motivation, as well as personal traits like lifestyle, gender, and age, influence brain dynamics and BCI performance. For instance, individuals with lower empathy tend to generate higher P300 wave amplitudes than those with greater empathy. Additionally, resting-state physiological parameters, such as heart rate variability and brain network dynamics, also affect BCI performance.

BCI performance is linked to neuroanatomical and psychological factors, such as gray matter volume in sensorimotor cortical areas, and physiological predictors like spectral entropy from EEG recordings. Around 15–30% of individuals struggle to produce strong enough brain signals to operate a BCI, which may be influenced by both neurophysiological and technological factors. Adaptive machine learning approaches could help reduce BCI illiteracy by considering both physiological and psychological traits.

Case-specific research is needed to address challenges like BCI illiteracy and to improve stroke rehabilitation using customized BCI systems that account for individual brain function. Although current neuroimaging techniques can identify lesion sites, tailored BCI designs are necessary for effective rehabilitation, but this individualized approach limits broader implementation.

Technical Difficulties

Event-related potentials (ERP), steady-state visual evoked potential (SSVEP), auditory evoked potential (AEP), steady-state somatosensory evoked potential (SSSEP), and motor imagery (MI) are used to detect cognitive signatures in BCIs, but none work universally for all applications. ERPs and SSVEPs depend on external stimuli and may not be effective for individuals with impaired visual processing, whereas auditory-based ERPs could be an alternative. SSVEP offers high information transfer but suffers from visual fatigue and non-intuitive control signals. MI-based BCIs are slower, limiting their use in real-time environments like virtual reality.

Hybrid BCIs combining different signatures (e.g., SSVEP/ERP, SSVEP/MI) offer improved performance, but asynchronous BCIs still struggle. Brain dynamics' inherent instability complicates BCI systems, which rely on signal acquisition, processing, and effector devices. EEG-based systems, though cost-effective and portable, have low spatial resolution. High-density EEG improves resolution but increases computational demands. Combining EEG with other methods like fNIRS enhances performance, but fNIRS alone is inadequate. MEG offers better spatiotemporal resolution but is more expensive. Classifier design in BCIs faces challenges like dimensionality issues, bias-variance trade-offs, and covariate shifts, which can be addressed through adaptive methods and transfer learning.

VI. PROPOSED METHODOLOGY

Duties of The Tailored BCI Application

The primary objective of the proposed framework is to deliver personalized BCI applications for each individual user. To accomplish this, we propose that the application should possess two key capabilities: i) user identification to assess user preferences, and ii) intention classification to carry out the user’s intended action.

User Identification to Assess User Preferences

User identification involves determining the individual using the application, which serves as an initial step in understanding their preferences. Similar to other bio signals, EEG signals exhibit subject variability, meaning that EEG features can differ between individuals, even when they are in the same mental state or performing identical tasks. By capitalizing on this variability, user-specific EEG features can be extracted and used for identification, enabling the BCI application to adjust to the unique characteristics of each user.

Intention Classification to Carry Out the User’s Intended Action

User identification involves determining the individual using the application, which serves as an initial step in understanding their preferences. Similar to other bio signals, EEG signals exhibit subject variability, meaning that EEG features can differ between individuals, even when they are in the same mental state or performing identical tasks. By capitalizing on this variability, user-specific EEG features can be extracted and used for identification, enabling the BCI application to adjust to the unique characteristics of each user.

Personalized BCI Application Framework

Fig 2 illustrates the overall workflow of the proposed framework, designed to deliver personalized user-intended services through the BCI application. When a user interacts with the system using an endogenous EEG paradigm, the corresponding EEG signals serve as input for processing.

The user identification model extracts user-specific information from the database, analysing preferences. Simultaneously, the intention identification model deciphers the user’s intended action and triggers the relevant application programming interface (API) tied to that action. By combining the user’s preferences with the identified API, the framework delivers a personalized BCI service.

The user identification and intention classification model processes EEG signals as input and provides personalized BCI services based on the user's information and detected intention.

This process is mathematically expressed as follows:

$$p(s) = f(x) \tag{1}$$

$$p(c) = g(x) \tag{2}$$

$$p(cs) = h(p(p(c)|p(s))) \quad (3)$$

Here, x represents the input EEG signal; f(·) and p(s) denote the user identification model and the predicted user class, respectively. Similarly, g(·) and p(c) correspond to the intention classification model and the predicted intention class. The function h(p(p(c)|p(s))) represents the API-calling process, conditioned on the predicted user class. Finally, p(cs) represents the output, delivering the personalized action result for the BCI application.

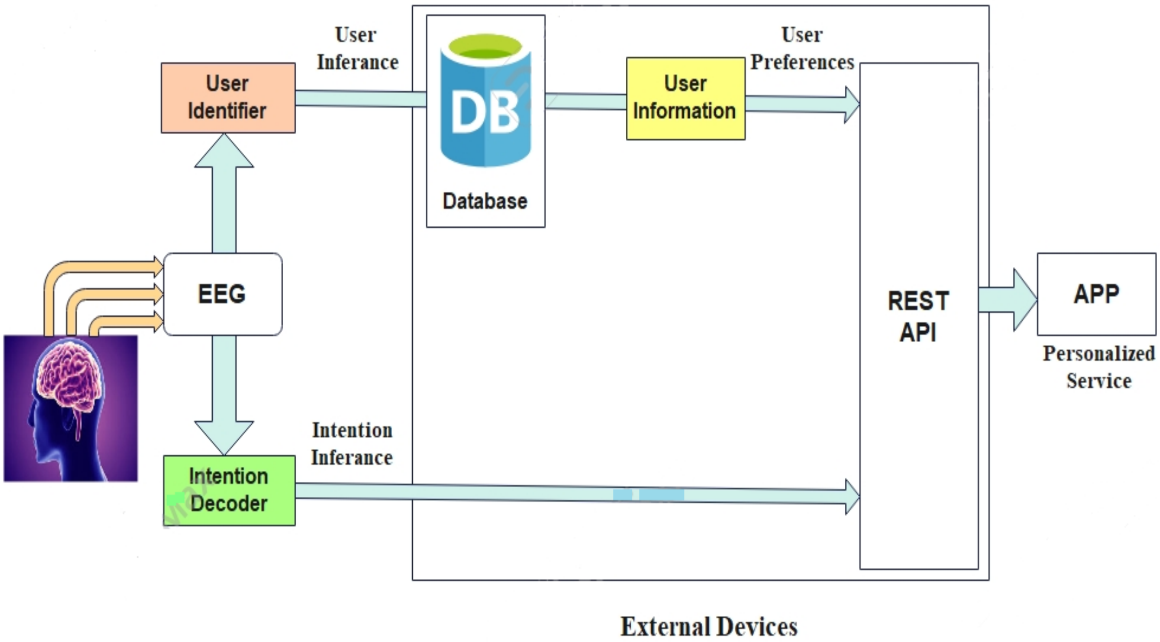

Fig 2. Overview of The Proposed Framework.

VII. EXPERIMENTAL ANALYSIS AND RESULTS

To assess the feasibility of the proposed framework, we conducted experiments to evaluate the reliability of its two primary tasks—user identification and intention classification—using a private dataset.

Acquisition Of EEG Data

We gathered EEG signals from eight participants (four males and four females, aged 26.4 ± 1.7 years) using three types of endogenous EEG paradigms—Motor Imagery (MI), Somatosensory Imagery (SI), and Visual Imagery (VI)—to create a private dataset for our experiments. All participants were healthy with no history of neurophysiological disorders and voluntarily took part in the study, which was reviewed and approved by the Institutional Review Board of Korea University [KUIRB–2024–0065–01]. During the experiment, participants were instructed to perform the three types of endogenous EEG paradigms based on prompts displayed on a monitor. Each trial involved presenting a target imagery class and paradigm for two seconds, followed by a two-second fixation cross to stabilize EEG responses. Participants then imagined the target class for three seconds during a blank screen, with a final two-second fixation cross to clear residual EEG activity.

Models For EEG Decoding

ShallowConvNet [24] architecture was used as the EEG decoding model for user identification and intention classification tasks, leveraging its versatility in decoding EEG features. The model was trained to identify subjects for user identification and classify signals into four imagery classes for intention classification, with cross-entropy loss used for optimization in both tasks.

Model Training

The training dataset for the user identification task was created by shuffling all EEG trials from all subjects and splitting them into 70% training, 10% validation, and 20% test sets. For the intention classification task, EEG trials from six subjects were used for training, with the remaining trials from two subjects used for validation and testing. Both models were trained with a learning rate of 0.001, weight decay of 0.001, batch size of 64, and the Adam optimizer for 100 epochs. To prevent overfitting, the models were validated at each epoch using the validation set.

Table 1. Accuracy of User Identification by Endogenous Paradigms

Subject	**Paradigm**			
	MI	**SI**	**VI**	**Overall**
S1	0.999	0.998	0.999	0.999
S2	0.998	0.999	0.998	0.998
S3	0.998	0.994	0.997	0.997
S4	0.994	0.997	0.999	0.998
S5	0.995	0.996	0.995	0.996
S6	0.997	0.995	0.994	0.995
S7	0.994	0.998	0.995	0.995
S8	0.994	0.994	0.994	0.996
Mean	**0.99613**	**0.99638**	**0.99638**	**0.99675**

Table 2. Accuracy of Intention Classification by Endogenous Paradigms

Subject	**Paradigm**			
	MI	**SI**	**VI**	**Overall**
S1	0.46	0.47	0.38	0.39
S2	0.47	0.39	0.39	0.39
S3	0.45	0.55	0.39	0.40
S4	0.95	0.81	0.67	0.70
S5	0.51	0.45	0.77	0.61
S6	0.63	0.46	0.47	0.55
S7	0.95	0.87	0.59	0.80
S8	0.68	0.65	0.68	0.57
Mean	**0.6375**	**0.58125**	**0.5425**	**0.55125**

Assessment Method

The model's performance for each task was evaluated using average classification accuracy. For the user identification model, performance was assessed by combining EEG trials from all subjects and applying five-fold cross-validation. For the intention classification model, performance was evaluated using five-fold cross-validation for each subject with a subject-dependent BCI configuration.

VIII. FINDINGS AND ANALYSIS

Efficacy of User Identification

The experimental findings for user identification tasks are shown in **Table 1**. With an average classification accuracy of 0.996, the user identification performance was consistently dependable across all subjects and EEG paradigms, as the table illustrates. These findings suggest that by utilising unique EEG characteristics that are personal to each person, EEG signals can be a reliable method for determining user-specific information and preferences.

Efficacy of Intention Classification

The experiment's findings for the intention categorisation task are shown in **Table 2**. All paradigms combined had an overall classification accuracy of 0.58. With a mean performance of 0.64, MI outperformed SI and VI among the three endogenous paradigms, even though it used a straightforward ShallowConvNet model as the decoding model with no task-specific techniques or fine-tuning.

The mean accuracy for VI was 0.54, the lowest performance for SI, which had a mean performance of 0.58. According to these findings, MI and SI may be trustworthy endogenous paradigms for expressing user intention as a natural mode of communication. Subject 6 performed the best among the participants in each of the three paradigms. Despite having a worse performance in VI, Subject 4 also demonstrated consistent performance in MI and SI. Although they did not perform as well as subjects 6 and 4, subjects 1, 2, 3, 5, 7, and 8 nevertheless showed promise for employing endogenous EEG paradigms with accuracies higher than chance levels.

IX. CONCLUSION

In this research, we propose a conceptual framework for a personalised BCI application that uses endogenous paradigms to identify users and provide customised services depending on user input. Additionally, using experiments on private datasets, we show that the two main goals in our framework—user identification and intention classification—are feasible. Recommendation algorithms could be improved and more accurate and dependable personalisation could be achieved by combining user feedback mechanisms with additional bio signals, such EMG, and past user activity data. Our upcoming research will concentrate on improving classification performance using sophisticated EEG decoding models, adding task-specific optimisations, and putting the suggested framework into practice as a real-time BCI application. We will also integrate user feedback and leverage user data to improve personalisation.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Srivinay, Swetha Parvatha Reddy Chandrasekhara, Amogh Pramod Kulkarni, Sneha S Bagalkot; **Methodology:** Swetha Parvatha Reddy Chandrasekhara, Amogh Pramod Kulkarni; **Data Curation:** Srivinay, Swetha Parvatha Reddy Chandrasekhara; **Writing- Original Draft Preparation:** Srivinay, Swetha Parvatha Reddy Chandrasekhara, Amogh Pramod Kulkarni, Sneha S Bagalkot; **Visualization:** Amogh Pramod Kulkarni, Sneha S Bagalkot; **Validation:** Amogh Pramod Kulkarni, Sneha S Bagalkot; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding agency is associated with this research.

Competing Interests

There are no competing interests

References

[1]. M. Abu-Alqumsan and A. Peer, “Advancing the detection of steady-state visual evoked potentials in brain–computer interfaces,” Journal of Neural Engineering, vol. 13, no. 3, p. 036005, Apr. 2016, doi: 10.1088/1741-2560/13/3/036005.
[2]. L. Acqualagna, L. Botrel, C. Vidaurre, A. Kübler, and B. Blankertz, “Large-Scale Assessment of a Fully Automatic Co-Adaptive Motor Imagery-Based Brain Computer Interface,” PLOS ONE, vol. 11, no. 2, p. e0148886, Feb. 2016, doi: 10.1371/journal.pone.0148886.
[3]. A. Agarwal et al., “Protecting Privacy of Users in Brain-Computer Interface Applications,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 8, pp. 1546–1555, Aug. 2019, doi: 10.1109/tnsre.2019.2926965.
[4]. R. Alomari, M. V. Martin, S. MacDonald, A. Maraj, R. Liscano, and C. Bellman, “Inside out - A study of users’ perceptions of password memorability and recall,” Journal of Information Security and Applications, vol. 47, pp. 223–234, Aug. 2019, doi: 10.1016/j.jisa.2019.05.009.
[5]. P. Arpaia, L. Duraccio, N. Moccaldi, and S. Rossi, “Wearable Brain–Computer Interface Instrumentation for Robot-Based Rehabilitation by Augmented Reality,” IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 9, pp. 6362–6371, Sep. 2020, doi: 10.1109/tim.2020.2970846.
[6]. Y. Song, Q. Zheng, B. Liu, and X. Gao, “EEG Conformer: Convolutional Transformer for EEG Decoding and Visualization,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 710–719, 2023, doi: 10.1109/tnsre.2022.3230250.
[7]. G. Kong, C. Li, H. Peng, Z. Han, and H. Qiao, “EEG-Based Sleep Stage Classification via Neural Architecture Search,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 1075–1085, 2023, doi: 10.1109/tnsre.2023.3238764.
[8]. J. M. Rosenow, “Anatomy of the Nervous System,” Neuromodulation, pp. 25–39, 2018, doi: 10.1016/b978-0-12-805353-9.00003-6.
[9]. C. C. McIntyre, “Patient-Specific Modeling of Deep Brain Stimulation,” Neuromodulation, pp. 129–135, 2018, doi: 10.1016/b978-0-12-805353-9.00012-7.
[10]. C. Chen et al., “Efficacy Evaluation of Neurofeedback-Based Anxiety Relief,” Frontiers in Neuroscience, vol. 15, Oct. 2021, doi: 10.3389/fnins.2021.758068.
[11]. J. P. Donoghue, “Brain–Computer Interfaces,” Neuromodulation, pp. 341–356, 2018, doi: 10.1016/b978-0-12-805353-9.00025-5.
[12]. Y. Sun, F. P.-W. Lo, and B. Lo, “EEG-based user identification system using 1D-convolutional long short-term memory neural networks,” Expert Systems with Applications, vol. 125, pp. 259–267, Jul. 2019, doi: 10.1016/j.eswa.2019.01.080.
[13]. D. Wu, Y. Xu, and B.-L. Lu, “Transfer Learning for EEG-Based Brain–Computer Interfaces: A Review of Progress Made Since 2016,” IEEE Transactions on Cognitive and Developmental Systems, vol. 14, no. 1, pp. 4–19, Mar. 2022, doi: 10.1109/tcds.2020.3007453.
[14]. S. P. R. Chandrasekhara, M. G. Kabadi, and Srivinay, “A Novel SIFT-SVM Approach for Prostate Cancer Detection,” Journal of Computer Science, vol. 16, no. 12, pp. 1742–1752, Dec. 2020, doi: 10.3844/jcssp.2020.1742.1752.
[15]. Srivinay, M. B. C., M. G. Kabadi, N. Naik, and S. P. R. Chandrasekhara, “Stock Price Classification Based on Hybrid Feature Selection Method,” Journal of Computer Science, vol. 19, no. 2, pp. 274–285, Feb. 2023, doi: 10.3844/jcssp.2023.274.285.
[16]. S. P. R. Chandrasekhara, M. G. Kabadi, and S. Srivinay, “Wearable IoT based diagnosis of prostate cancer using GLCM-multiclass SVM and SIFT-multiclass SVM feature extraction strategies,” International Journal of Pervasive Computing and Communications, vol. 20, no. 1, pp. 19–37, Sep. 2021, doi: 10.1108/ijpcc-07-2021-0167.
[17]. Srivinay, B. Manujakshi, M. Kabadi, and N. Naik, “A Hybrid Stock Price Prediction Model Based on PRE and Deep Neural Network,” Data, vol. 7, no. 5, p. 51, Apr. 2022, doi: 10.3390/data7050051.
[18]. “Emerging role of fNIRS in brain-computer interface applications”, The Society for functional Near Infrared Spectroscopy, by mari in News on September 30, 2017.
[19]. T. O. Zander and C. Kothe, “Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general,” Journal of Neural Engineering, vol. 8, no. 2, p. 025005, Mar. 2011, doi: 10.1088/1741-2560/8/2/025005.
[20]. J. R. Wolpaw et al., “Brain-computer interface technology: a review of the first international meeting,” IEEE Transactions on Rehabilitation Engineering, vol. 8, no. 2, pp. 164–173, Jun. 2000, doi: 10.1109/tre.2000.847807.
[21]. S. Soman and B. K. Murthy, “Using Brain Computer Interface for Synthesized Speech Communication for the Physically Disabled,” Procedia Computer Science, vol. 46, pp. 292–298, 2015, doi: 10.1016/j.procs.2015.02.023.
[22]. M. P. Orenda, L. Garg, and G. Garg, “Exploring the Feasibility to Authenticate Users of Web and Cloud Services Using a Brain-Computer Interface (BCI),” New Trends in Image Analysis and Processing – ICIAP 2017, pp. 353–363, 2017, doi: 10.1007/978-3-319-70742-6_33.

[23]. U. Hoffmann, J.-M. Vesin, T. Ebrahimi, and K. Diserens, "An efficient P300-based brain–computer interface for disabled subjects," Journal of Neuroscience Methods, vol. 167, no. 1, pp. 115–125, Jan. 2008, doi: 10.1016/j.jneumeth.2007.03.005.
[24]. G. Goodman, R. R. Poznanski, L. Cacha, and D. Bercovich, "The Two-Brains Hypothesis: Towards a guide for brain–brain and brain–machine interfaces," Journal of Integrative Neuroscience, vol. 14, no. 03, pp. 281–293, Sep. 2015, doi: 10.1142/s0219635215500235.
[25]. V. K. K. Shivappa, B. Luu, M. Solis, and K. George, "Home automation system using brain computer interface paradigm based on auditory selection attention," 2018 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), pp. 1–6, May 2018, doi: 10.1109/i2mtc.2018.8409863.