
Tackling Challenges of Electroencephalogram on an Android Smartphone for Natural Environment Experimentation

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By

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Dedicated to

My beloved parents

Mati Ram Hazarika and Khiroda Hazarika

for their blessings, love and encouragement.





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Declaration

I hereby declare that the findings presented in this thesis are the result of original research conducted by me in the Department of Biosciences and Bioengineering at the Indian Institute of Technology Guwahati, Assam, India, under the guidance of Dr. Cota Navin Gupta.

In accordance with standard academic practices, appropriate acknowledgements have been provided wherever the work of other researchers has been referenced in this thesis.

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Certificate

This is to certify that the thesis entitled "**Tackling Challenges of Electroencephalogram on an Android Smartphone for Natural Environment Experimentation**", submitted by **Doli Hazarika** (196106008), a research scholar in the *Department of Biosciences and Bioengineering, Indian Institute of Technology Guwahati*, for the award of the degree of **Doctor of Philosophy**, is a record of an original research work carried out by him under our supervision and guidance. The thesis has fulfilled all requirements as per the regulations of the institute and has reached the standard needed for submission. The results embodied in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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Abstract

Electroencephalogram (EEG) is a non-invasive technique used to measure brain activity and has applications in cognitive studies, neuroscience, and clinical diagnostics. Traditional EEG experiments are often lab-confined, requiring stationary setups with multiple electrodes, which limits the mobility of human subjects and real-world applicability. Mobile EEG systems have emerged as a flexible alternative that enables brain activity monitoring of human subjects in natural settings using lightweight and portable equipment. Among these, smartphone-based mobile EEG offers a promising solution by combining portability, affordability, and real-time signal acquisition with computational capabilities. However, challenges such as artifact removal, data processing, and brain state classification on smartphones must be addressed for effective deployment. This research aims to address these gaps by developing smartphone-based EEG analysis frameworks with three major contributions.

The first contribution validates CameraEEG, an Android application developed to capture synchronized brain and video data in natural settings. The occurrence of artifacts or exact experimental stimuli can be identified by viewing the recorded camera video data. Built using Android SDK version 28 and integrated with the Smarting Mobi SDK from mBrainTrain, the app is compatible with Android devices running Android version 5.0 (Lollipop) or higher. CameraEEG allows users to mark audio-visual events of interest during data recording, enhancing contextual analysis. The application was evaluated using data collected from four individuals performing eyes-open and eyes-closed tasks in a resting state seated posture. EEG recordings from the occipital and parieto-occipital sites revealed a prominent alpha-band peak during eyes-closed, aligning with established neurophysiological patterns for healthy subjects. Importantly, the synchronized video and EEG recordings confirmed the temporal precision of the system.

The second contribution involves the development of Embedded-ASR (E-ASR), an innovative framework designed to extend the capabilities of the Artifact Subspace Reconstruction (ASR) algorithm to single-channel EEG data. While conventional ASR techniques typically rely on multichannel recordings, E-ASR overcomes this limitation by employing a dynamical embedding strategy for a single channel. Specifically, it constructs an embedded matrix using delay vectors from the single-channel EEG signal,

enabling effective artifact removal through ASR and subsequent signal reconstruction. The method was implemented and tested using EEG recordings from frontal electrodes acquired via the CameraEEG Android application. Evaluations carried out in semi-simulated and real EEG datasets confirmed E-ASR's ability to suppress common artifacts, particularly eye blinks, while preserving the underlying neural signal. Although E-ASR has not yet been implemented in the Android app, it demonstrates strong potential. We speculate that this framework could support the development of mobile EEG solutions with minimal hardware requirements, making it well-suited for real-world, resource-constrained environments.

The third contribution builds upon previous developments by integrating machine learning models into mobile EEG analysis. A streamlined pipeline was created to support offline EEG classification directly on Android devices using TensorFlow lite. EEG signals, acquired via the CameraEEG app and preprocessed using the E-ASR algorithm, were used to extract power spectral features. A Support Vector Machine (SVM) classifier was trained on data from a single occipital electrode to distinguish between eyes-open and eyes-closed states. The trained model was successfully deployed in the EEG Classifier app, which enables offline EEG state prediction on smartphones with limited computational capacity. This demonstrates the feasibility of deploying lightweight machine learning EEG classifiers on mobile platforms for practical applications in natural environments.

Keywords: Electroencephalogram (EEG), Smartphone, Android application, Artifact removal, Artifact subspace reconstruction (ASR), Single-channel, Eye-blink, TensorFlow lite, Classification, Support vector machine (SVM).

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List of Abbreviations

EEG	Electroencephalogram
BCI	Brain-computer interface
Mobile-EEG	Portable electroencephalography
VR	Virtual reality
AR	Augmented reality
fNIRS	Functional near-infrared spectroscopy imaging
CMI	Cognitive-motor interference
IAF	Individual alpha-frequency
AR	Augmented reality
AAD	Auditory attention decoding
ERP	Event-related potentials
SME	Subsequent memory effect
SSVEP	Steady-state visual evoked potential
SPI	Serial peripheral interface
ADC	Analog-to-digital converter
BLE	Bluetooth low energy
ECG	Electrocardiogram
ILAE	International league against epilepsy
IFCN	International federation of clinical neurophysiology
ASR	Artifact Subspace Reconstruction
rASR	Riemannian Artifact Subspace Reconstruction
SBS	Smartphone Brain Scanner
FFT	Fast fourier transform
CSP	Common spatial pattern
ICA	Independent component analysis

List of Abbreviations

PSD	Power spectral density
LSL	Lab streaming layer
AFEx	Audio feature extraction
IC	Integrated circuit
RMS	Root mean square
SCALA	Signal ProCessing and CLassification on Android
LSTM	Long short-term memory
GPU	Graphics processing unit
BERT	Bidirectional encoder representations from transformers
NLP	Natural language processing
DAE	Deep autoencoder
TF	TensorFlow
tflite	TensorFlow lite
CNN	Convolutional neural network
ADHD	Attention Deficit Hyperactivity Disorder
PSG	Polysomnography
GMM	Gaussian mixture model
RF	Random forest
ROI	Regions of interest
E-ASR	Embedded artifact subspace reconstruction
SVM	Support vector machine
JDK	Java development kit
SDK	Software development kit
API	Application programming interface
GUI	Graphical user interface
DFT	Discrete fourier transform
ENBW	Equivalent noise bandwidth
RBW	Resolution bandwidth
PCA	Principal component analysis
SSA	Singular spectrum analysis
SNR	Signal-to-noise ratio

AF	Adaptive filter
TCP	Transmission control protocol
EOG	Electrooculogram
RRMSE	Relative root mean square error
CC	Correlation coefficient
MCC	Matthews correlation coefficient
TP	True positive
TN	True negative
FP	False positive
FN	False negative
LOSO-CV	Leave-one-subject-out cross validation
EO	Eyes open
EC	Eyes closed



List of Symbols

Hz	Hertz: unit of frequency
f_s	Sampling frequency
f_{Nyquist}	Nyquist frequency
L	Lag
f_L	Lowest frequency of interest
M	Embedding dimension
M_C	Mixing matrix
V_C	Eigen vectors
D_C	Eigen values
Y_C	Principal component space
z	z-score
μ	Mean
k	Cut-off parameter
σ	Standard deviation
w	Weight
b	Bias
C	Regularization parameter
s	Seconds



1

Introduction and Literature Review

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1.1 Introduction

The electroencephalogram (EEG) is a pivotal tool in neuroscience and medicine, allowing researchers and clinicians to measure electrical activity in the brain through electrodes placed on the scalp [1]. Its origins trace back to the early 20th century when German psychiatrist Hans Berger first recorded human brain waves in 1924 [2], publishing his findings in 1929 after years of experimentation with patients and his own children. Berger's groundbreaking work built on earlier discoveries, such as Richard Caton's 1875 [3] observation of electrical activity in animal brains. He introduced the term "elektroenkephalogramm" to describe these rhythmic patterns, like alpha waves, which he linked to states of rest.

EEG signals are composed of various frequency bands, each associated with distinct cognitive and physiological states. Delta waves (0.5 – 4 Hz) are typically observed during deep sleep, while theta waves (4 – 8 Hz) appear during drowsiness, meditation, and light sleep. Alpha waves (8 – 13 Hz), first noted by Berger, are linked to relaxed wakefulness, especially with eyes closed [4]. Beta waves (13 – 30 Hz) dominate during active concentration and mental engagement, whereas gamma waves (> 30 Hz) are associated with high-level cognitive processes such as attention, learning, and memory. These oscillatory patterns offer valuable insight into the functional states of the brain and are fundamental to both clinical diagnostics and cognitive research [4]. Since then, EEG has evolved from a rudimentary diagnostic method into a sophisticated technology, widely used today to study brain function, diagnose epilepsy [5], explore consciousness [6], and enhance the detection of neural responses such as visual-evoked potentials in brain-computer interface applications [7]. Berger's innovation laid the foundation for modern neurophysiology, establishing EEG as an indispensable tool for exploring the human mind and enabling detailed investigation of brain regions and functions [4].

The human brain is anatomically divided into four primary lobes-frontal, parietal, temporal, and occipital-each with distinct roles that EEG studies have helped illuminate (Figure 1.1). The frontal lobe, located at the brain's anterior region, governs executive functions like decision-making, planning, and motor control, with its prefrontal cortex being critical for personality and cognitive behavior [8]. The parietal lobe, positioned superior to the occipital lobe, processes sensory information such as touch and spa-

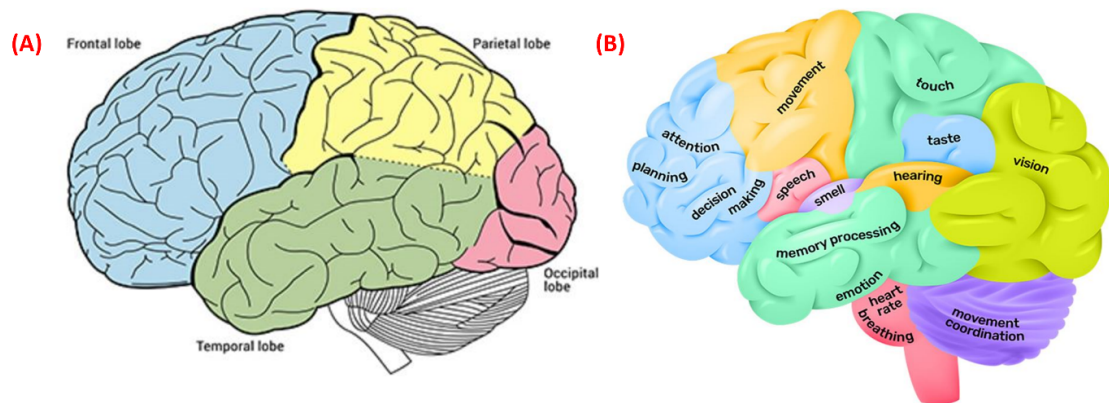


Figure 1.1: (A) Anatomical illustration of the human brain showing four major lobes- frontal, parietal, temporal, and occipital. (B) Functional mapping of the brain highlights cognitive and sensory processes like attention, memory, and vision. This helps relate EEG signals to brain activity across key functional areas. Figure adapted from <https://qbi.uq.edu.au/brain/brain-anatomy/lobes-brain>.

tial awareness, integrating inputs to form a coherent perception of the body's environment [9]. The temporal lobe, on the lateral sides, is essential for auditory processing, language comprehension, and memory formation, notably through structures like the hippocampus [10]. Lastly, the occipital lobe, located at the back of the brain, serves as the hub for visual processing, translating signals from the eyes into meaningful images [11]. While EEG has limited spatial resolution, it has been instrumental in studying brain function by capturing dynamic patterns of electrical activity during tasks such as problem-solving or rest. These patterns provide valuable insights into both healthy brain function and neurological disorders.

The 10-20 system is a standardized method for positioning electrodes on the scalp to record EEG signals, ensuring consistency and precision across studies and clinical applications (Figure 1.2). Introduced by Herbert Jasper in 1958 [12], the 10-20 system defines 21 standard electrode positions; 19 active scalp sites plus 2 reference points (typically A1 and A2)-by dividing the scalp into proportional distances of 10% and 20% between key anatomical landmarks like the nasion (bridge of the nose) to inion (base of the skull) [12]. Each electrode site is labeled with a letter indicating the lobe (e.g., F for frontal, T for temporal) and a number denoting its position, allowing researchers to target specific brain regions, such as the occipital lobe for visual activity or the frontal lobe for cognitive tasks [4]. The 10-20 system has become a foundational standard in neurology and research due to its reliability in mapping electrical activity to anatomical structures

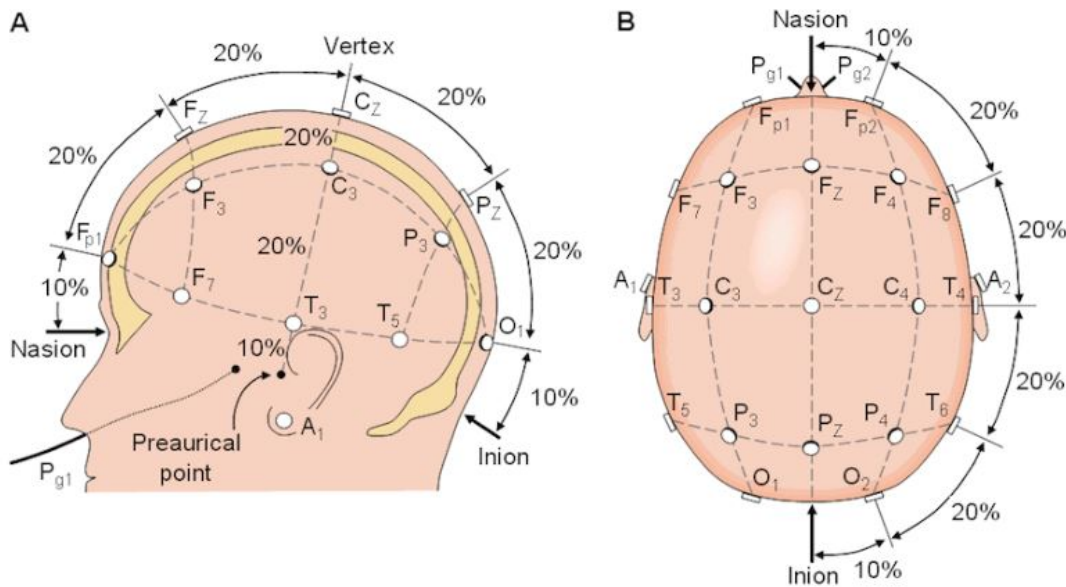


Figure 1.2: (A) Side view and (B) top view of the International 10-20 System for EEG electrode placement. The system uses anatomical landmarks such as the nasion, inion, and preauricular points to position electrodes at intervals of 10% or 20% of the total head circumference, ensuring standardized and reproducible electrode locations across individuals for capturing brain electrical activity. Figure adapted from (<https://www.tmsi.artinis.com/blog/the-10-20-system-for-eeeg>)

[13] [14]. Its influence extends to emerging applications, including smartphone-based EEG technologies, which will be explored in the following section.

1.2 Trends in Smartphone-based Electroencephalogram

As EEG technology evolves, the focus is shifting from traditional lab-based systems to smartphone-based mobile EEG, replacing bulky wires with wearable, wireless designs. This evolution enhances participant mobility and increases the flexibility of experimental design, enabling real-time, natural environment experiments outside the constraints of a laboratory. As illustrated in Figure 1.3, EEG experimentation is transitioning from controlled laboratory environments to natural settings, incorporating new experimental paradigms, alternative electrode types, and smartphone-based preprocessing and classification strategies [15]. The reduction in amplifier size and the transformation of wired electrodes into wireless wearables and even beyond wearables have made it possible for participants to move freely, thereby allowing more ecologically valid experiments [16]. Smartphone-based mobile electroencephalography (mobile EEG) is a non-invasive, portable, and affordable next-generation neuroscientific technique for

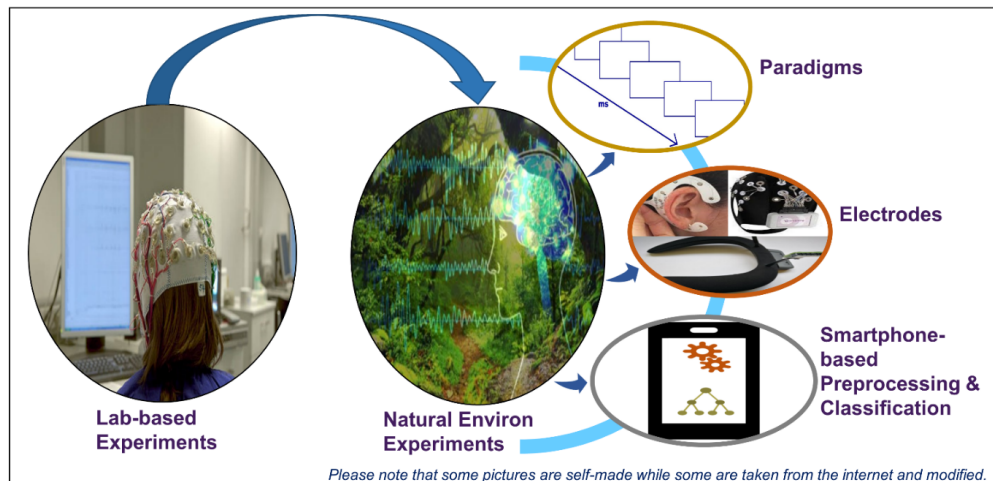


Figure 1.3: Transition from lab-based EEG experiments to smartphone-based EEG acquisition in natural environments. The figure illustrates the evolution of EEG systems from wired, high-density lab setups to flexible, wearable systems suitable for real-world experimentation. It also highlights key components such as experimental paradigms, electrode types, and on-device preprocessing and classification strategies essential for natural environment EEG applications.

studying brain activity in real time. Additionally, minimizing the number of electrodes helps participants behave more naturally, promoting authentic behavioral data collection. EEG-based experimentation in natural environments using smartphones is now an active and rapidly growing area of research.

Despite these advantages, smartphone-based mobile EEG introduces new challenges. A significant concern is the presence of artifacts, which often contaminate the EEG signals of interest. These include biological artifacts such as heartbeats, eye and muscle movements, and electrical artifacts such as motion of the electrode or wire and line noise [17]. Natural environment studies involving whole-body movement further amplify the likelihood of such disturbances. Implementing a suitable and robust preprocessing algorithm is critical for isolating the neural signals of interest. Once clean signals are obtained, integrating them with a classifier can yield meaningful insights into brain function. Existing studies have addressed these challenges using diverse experimental paradigms, carefully designed smartphone apps, compatible hardware solutions, and on-device signal processing and classification methods, as reviewed below.

1.2.1 Paradigms/Experiments in Natural Environment

Electroencephalography has traditionally been confined to laboratory settings due to its sensitivity to noise and movement artifacts. However, advancements in mobile EEG

technology have enabled researchers to study brain activity in more naturalistic, everyday environments. This has facilitated novel investigations into brain function in real-world contexts, introducing experimental paradigms with enhanced ecological validity.

- **Mobile EEG and Virtual Reality (VR):** Integrating mobile EEG with VR creates immersive, controlled environments for recording brain activity, simulating real-world scenarios. This approach has been proven feasible for studying neural responses to dynamic stimuli, such as spatial navigation or attention, with head-mounted augmented reality (AR) enhancing cognitive research in natural settings [18].
- **Ambulatory EEG and Real-World Tasks:** Ambulatory EEG captures brain activity during everyday activities like walking or social engagement, offering insights into adaptive neural processing. Studies have successfully adapted classical paradigms, such as attention or memory tasks, to outdoor environments using mobile EEG, demonstrating real-world applicability [19].
- **Hyperscanning and Social Interaction:** Hyperscanning simultaneously records EEG from multiple individuals during social interactions, revealing neural dynamics of social cognition. While functional near-infrared spectroscopy imaging (fNIRS) has been used, EEG-based hyperscanning has similarly explored brain synchrony in naturalistic dialogues [20] [21].
- **EEG-Based Brain-Computer Interfaces (BCIs) in Natural Settings:** Research on BCIs in natural environments assesses their real-world usability, employing paradigms like the auditory oddball task to decode brain signals. Such studies highlight mobile EEG's potential for practical applications such as real-life environmental studies [22].

Table 1.1 describes some more mobile-EEG studies in terms of experimental paradigms used and their significance.

Table 1.1: Electroencephalogram Paradigms used in Mobile EEG experiments

Study	No. of Participants	Mobile EEG Amplifier Used	Experimental Paradigm	Significance
Rosenkranz et al., 2024 [23]	22	SMARTING	The study employed a simulated laparoscopic surgery task combined with a memory task to study cognitive demand.	By combining cognitive and motor tasks in real-world auditory distractions, the research provides insights into how environmental sounds impact cognitive load and performance in high-stress settings.
Klapprott et al., 2024 [24]	11	SMARTING Pro	The study employed a cognitive-motor interference (CMI) paradigm to investigate the feasibility of recording brain activity using mobile EEG during a full-body motion task like swimming	The study establishes that mobile EEG is feasible in aquatic environments, opening new possibilities for studying brain activity during complex, real-world motor tasks.

Study	No. of Participants	Mobile EEG Amplifier Used	Experimental Paradigm	Significance
Papin et al., 2024 [25]	18	SMARTING	They employed the CMI paradigm, a dual-task approach designed to assess how simultaneous cognitive and motor tasks impact brain functions.	The study demonstrated that mobile EEG can effectively track brain activity during complex real-world tasks like slacklining, highlighting how the brain manages simultaneous cognitive and motor demands.
Sidelinger et al., 2023 [26]	18	MUSE 2	The authors employed a resting-state EEG paradigm to assess the stability of individual alpha-frequency (IAF) over multiple days	The authors validated the use of consumer EEG systems for robust, repeated measurement of a key cognitive biomarker (IAF).
Krugliak et al., 2022 [18]	8	LiveAmp	The study employed a face inversion paradigm across three distinct conditions to assess the feasibility of combining mobile EEG with augmented reality (AR).	They have demonstrated that mobile EEG combined with AR can effectively capture cognitively relevant neural signals, such as the face inversion effect, in real-world environments.

Study	No. of Participants	Mobile EEG Amplifier Used	Experimental Paradigm	Significance
Straetmans et al., 2022 [27]	19	SMARTING	The authors used a two-competing speaker paradigm.	The authors showed the feasibility of decoding auditory attention from EEG in natural, real-world conditions.
Hölle et al., 2022 [28]	1	SMARTING	The authors used three auditory paradigms, i.e., piano oddball, piano freeplay, and home-office soundscape conditions.	The authors developed two Android apps (AFEx and Record-a) for understanding sound perception in a real-world situation.
Kutafina et al., 2021 [29]	24	Emotiv EPOC+	They used the N-back task, which is a working memory paradigm, commonly used to examine mental workload modulation.	The authors demonstrated that mobile EEG systems can reliably monitor mental workload outside of traditional laboratory settings.
Jaeger et al., 2020 [30]	21	BrainAmp	Used a two-competing speaker paradigm.	The authors developed an auditory attention decoding (AAD) pipeline for detecting the level of attention.

Study	No. of Participants	Mobile EEG Amplifier Used	Experimental Paradigm	Significance
Lin et al., 2020 [31]	40	Emotiv EPOC	Performed high-pressure learning tasks indoors and simulated outdoor conditions.	They studied the emotional changes in urban space caused by common behaviours.
Hölle et al., 2020 [32]	21	SMARTING	They performed auditory oddball tasks within the lab and office environment.	Auditory attention in everyday contexts was investigated using an everyday environmental situation.
Blum et al., 2020 [33]	20	BrainAmp	The authors used three paradigms, i.e., auditory oddball, vibrotactile oddball, and sentence processing task in a laboratory environment.	They presented flex printed EEG electrodes that can be used for clinical, laboratory, and mobile EEG settings.
Reiser et al., 2019 [19]	29	LiveAmp	Used an auditory stimulus detection task during standing, walking, and obstacle crossing conditions at the institute's lawn area.	They demonstrated behavioural and electrophysiological changes during the tasks, thus explaining the feasibility of EEG paradigms in outdoor conditions.

Study	No. of Participants	Mobile EEG Amplifier Used	Experimental Paradigm	Significance
Scanlon et al., 2019 [34]	12	Brain Products v-Amp 16 channel	Used auditory oddball paradigm while sitting on a bike in indoor and outdoor conditions.	The authors demonstrated methods for recording mobile event-related potential (ERP) data.
Ladouce et al., 2019 [35]	59	ANT-neuro	Used auditory oddball paradigm to measure P300 ERP during a walking task in a natural environment.	They studied the neural activity affected during the presentation of external stimuli in a real-world situation.
Salvidegoitia et al., 2019 [36]	25	SMARTING	Used subsequent memory paradigm while walking outdoors in a familiar university campus.	They demonstrated episodic memory research using smartphone EEG.
Leong et al., 2017 [37]	36	-	Used gaze synchronization experimental paradigm.	They demonstrated that direct gaze strengthens the infant-adult connection in both directions.
Griffiths et al., 2016 [38]	29	-	They used a behavioural paradigm for episodic memory encoding in the real world.	The authors have identified the oscillatory subsequent memory effect (SME) in a realistic environment and examined it with in-lab factors.

Study	No. of Participants	Mobile EEG Amplifier Used	Experimental Paradigm	Significance
Zink et al., 2016 [39]	15	SMARTING	Three-class auditory oddball task while pedalling on a fixed bike and cycling freely around.	The cognitive paradigm results in realistic scenarios are changing by increasing cognitive load due to an unconstrained environment.
Debener et al., 2015 [40]	10	SMARTING	Used an auditory oddball paradigm in an office environment.	They introduced cEEGrid electrodes for a smartphone-based mobile EEG system to acquire long-lasting recordings in a natural environment.
Aspinall et al., 2015 [41]	12	Emotiv EPOC	A walking task was carried out in an urban shopping street, green space (open lawn), and a busy commercial street.	The authors studied the electrophysiological changes in EEG data as the participants walked through the three environments.

1.2.2 Smartphone Applications

Advancements in mobile EEG have led to the development of smartphone-integrated systems, enabling real-time brain activity monitoring in naturalistic settings. The Smartphone Brain Scanner [42], for instance, combines low-cost wireless EEG sensors with smartphones to offer real-time 3D EEG imaging, demonstrating the feasibility of mobile neuroimaging in everyday contexts. Similarly, applications like NeuroPhone [43] utilize P300 signals to allow users to dial phone numbers via smartphones, showcasing the integration of EEG functionalities into mobile devices for practical communication tasks. Early systems, such as the Nokia phone-based BCI setup [44], employed visual stimulators and wireless EEG headbands to facilitate number dialing through Steady-State Visually Evoked Potential (SSVEP) paradigms, highlighting the potential of mobile devices in EEG applications.

Further developments led to fully smartphone-operated EEG systems, integrating signal processing within a single device, though challenges remained due to reliance on single paradigms and proprietary communication protocols [45]. Blum et al. [46] introduced a multi-app framework combining data acquisition, EEG processing, and stimulus presentation on Android smartphones, offering flexibility in paradigms and sensor compatibility, despite practical challenges associated with running multiple applications concurrently. The TinnitusSense application [47] consolidated previous functionalities into a single platform, enabling real-time EEG data recording and visualization, thereby facilitating real-world EEG experiments by simplifying user interfaces and operational workflows. Additionally, applications like AFEx and Record-a, developed by Hölle et al. [28], allowed simultaneous acquisition of EEG data and audio features on Android platforms, aiming to enhance the understanding of auditory perception in real-world environments.

Extending these advancements, Bateson et al. [48] introduced a custom-built, low-cost, 19-channel EEG system featuring wireless data transmission via Wi-Fi to a smartphone. Leveraging ADS1299-based hardware and a Unity game engine-based mobile application, they validated the platform through resting-state and auditory oddball experiments, demonstrating performance comparable to clinical-grade EEG systems and further advancing the feasibility of mobile, real-world neurophysiological research. Building on these advancements, the DreamMachine system [49] utilizes the EEGDroid Android

application, specifically designed to work with the device. The app enables real-time recording and monitoring of EEG signals, provides visual feedback on signal quality and electrode placement, and allows users to adjust key parameters such as channel selection, gain, sampling rate (250 Hz or 167 Hz), and filtering options. Data is transmitted via Bluetooth Low Energy (BLE) for seamless communication between the device and smartphone, and recordings are saved in .csv format for easy analysis.

Additionally, the BrainCapture EEG system [50], a low-cost, 27-channel EEG platform, is designed to enable non-expert users to conduct EEG recordings through a smartphone-based application. Unique to BrainCapture, the system provides real-time feedback on signal quality and electrode placement, assisting users in the recording process. After data acquisition, the recordings are uploaded to a secure cloud platform for remote diagnosis, enhancing telemedicine applications in countries with limited healthcare resources. This marks a significant step towards democratizing EEG technology, enabling individuals in underserved areas to access neurophysiological diagnostics. These advancements underscore the progression toward more accessible and versatile mobile EEG systems, leveraging the ubiquity and computational capabilities of smartphones to facilitate real-world EEG applications.

1.2.3 Electrodes/Hardware Compatible with Smartphone-based EEG

The first and foremost step for natural environment EEG experimentation is selecting appropriate hardware and electrodes for the study. The data acquisition system should be chosen based on the task, participants' nature, and the research question. The selection of the electrodes can be decided based on factors such as the type of electrode (wired or wireless), cost, signal fidelity, and the setup time to put the electrodes. Table 1.2 presents some commercially available EEG amplifiers/electrodes that have been used in many studies. Apart from these, task design and data storage play a significant role in a smartphone-based EEG study.

Scanlon et al. compared active and passive electrode configurations during standing and walking conditions [51]. Their main takeaway was that regardless of whether the electrode type is active or passive, the signal quality for both experiments remained the same. Thus, using passive electrodes offers participants a hassle-free investigation with greater freedom of movement for outdoor experiments. Bleichner et al. developed

cEEGrid electrodes to capture EEG signals around the ear used for auditory attention studies [16]. These electrodes are lightweight, comfortable to wear, easy to set up, and concealable.

With the development of mobile EEG hardware, Bleichner and Emkes [52] created the nEEGlance, a modified version of the Smarting amplifier for beyond-the-lab trials. They tested it with the previously developed smarting and presentation app. Furthermore, Hölle et al. also used the Smarting app and cEEGrid electrodes to study auditory perception in daily life situations [32]. Lin et al. [53] developed a cost-efficient custom-made electrode holder assembly with replaceable montage using a 3D printer, tested using dry electrodes. When comparing ear-EEG with scalp-EEG data for auditory attention tasks, Meiser et al. [54] concluded that ear-EEG captured equivalent signal quality with strong event-related potentials (ERPs).

Beyond the LiveAmp and SmartingMobi amplifiers used in the previous studies, Smarting Pro and Smarting Pro X are the recent additions to the mobileEEG amplifiers, providing high-density EEG recordings. Electrodes are a critical component of any data acquisition system, and selecting the appropriate electrodes is vital. For smartphone-based EEG experiments, selecting the optimal electrode setup for data acquisition is crucial, depending on the type of application and compatibility with the smartphone.

Complementing these developments, Bateson et al. [48] introduced a mobile EEG system that enhances portability and functionality for beyond-the-lab applications. The system utilizes three interconnected ADS1299 Integrated Circuits (ICs), each offering 24-bit resolution and 250Hz sampling frequency, creating 24 differential channels for EEG measurements. These ICs are connected to an LPC1769 ARM processor via a Serial Peripheral Interface (SPI) bus, allowing individual channel control for precise signal acquisition. Wireless data transmission to a smartphone is enabled through an RN131 wireless LAN module connected to the microcontroller via RS232, with an omnidirectional antenna ensuring stable Wi-Fi connectivity. The system is powered by a lithium-ion battery, and housed in a durable aluminum case to withstand mobile use, weighing just 338g. The system's embedded software, developed in C programming language using FreeRTOS, facilitates real-time task scheduling and efficient control of the EEG system. The software supports SPI and RS232 communication protocols and provides a command-line interface for system management [48].

Table 1.2: Commercially available wireless EEG hardware/electrodes

Company	Product Name	Channels	Bluetooth enabled?	en- Battery Life (if applicable)	Compatible with Smartphones?	Smartphone Compatible App
Brain Products	LiveAmp	8, 16, 24, 32	Yes	>3 hrs wireless, No >4.5 hrs on memory card	-	-
Emotiv	EPOC X	14	Yes	<9 hrs	No	EMOTIV App
	EPOC+	14	Yes	<6 hrs	Yes	
	INSIGHT	5	Yes	<4 hrs	Yes	
NeuroSky	MindWave Mobile 2	1	Yes	8 hrs	Yes	MindWave Mobile 2 App
Advanced Brain Monitoring	B-Alert X Series	Upto 20	Yes	<8 hrs	No	-
	Stat X Series	Upto 20	Yes	<8 hrs	No	-
g.tec	g.Nautilus PRO	8, 16, 32	Yes	<10 hrs	6 hrs (64 ch), 10 hrs (8, 16, 32 ch)	-
	g.Nautilus RE-SEARCH	8, 16, 32, 64	Yes	<10 hrs		
	g.Nautilus Multi-Purpose	8, 16, 32, 64	Yes	6 hrs (64 ch), 10 hrs (8, 16, 32 ch)		

Company	Product Name	Channels	Bluetooth enabled?	en- Battery Life (if applicable)	Compatible with Smartphones?	Smartphone Compatible App
	g.Nautilus PRO	8, 16, 32	Yes	<6 hrs (64 ch),	No	
	FLEXIBLE			<10 hrs (8, 16, 32 ch)		
Neuroelectrics	Enobio®	8, 20, 32	Yes	<20 hrs	No	
InteraXon	Muse S	1	Yes	<10 hrs	Yes	Muse App
	Muse 2	1	Yes	<5 hrs		
Cognitionics	Quick-20m	20	Yes	6 hrs	No	-
	Quick-20rv2	21	Yes	8 hrs		
	Quick-32r	32	Yes	8 hrs wireless		
	Mobile Series	72, 128	Yes	4 hrs wireless, 10 hrs with micro-SD card		
mBrainTrain	SMARTING mobi	24	Yes	<5 hrs	Yes	SMARTING App
	Smarting PRO	32	Yes	<12 hrs		
	SMARTING	24	Yes	<15 hrs		
	SLEEP					
	Smartphones	11	Yes	-		

Company	Product Name	Channels	Bluetooth enabled?	en-	Battery Life (if applicable)	Compatible with Smartphones?	Smartphone Compatible App
Wearable Sensing	DSI 24	24	Yes		Continuous		
	DSI 7	7	Yes		(hot-swappable batteries) <12 hrs		
	DSI 7 Flex	7	Yes		<12 hrs	No	-
	VR 300	7	Yes		<12 hrs		
	NeuSenW	8-64	Yes		4 hrs		
	NeuroCube	8	<2 hrs				
TMSi	cEEGrid	10	Yes	(Smarting compatible)	<5 hrs	Yes	Can be used with SMARTING App
imec	EEG Headset	8	Yes		8 hrs	No	
BrainCapture	BC-1	27	Yes		<22 hrs	Yes	BC Android App

In addition to the systems described above, the DreamMachine EEG system [49] offers a highly specialized solution for mobile EEG monitoring, designed for portability and advanced functionality in real-world applications. Similar to the mobile EEG systems discussed earlier, the DreamMachine uses high-resolution components to capture EEG signals. It incorporates three AD7779ACPZ Analog-to-Digital Converters (ADCs), each providing 24-bit simultaneous sampling for eight channels, allowing for a total of 24 differential EEG channels. This configuration ensures precise and high-quality signal acquisition, even in dynamic mobile environments. The device also utilizes a common reference electrode and employs a ground regulator to mitigate noise interference, ensuring clean signal acquisition in mobile settings. For digital communication, the DreamMachine uses a BC832 chip to handle data preprocessing and transmission via Bluetooth Low Energy (BLE), enabling wireless data transfer to smartphones. The system is powered by a 3.7V lithium-polymer battery, providing up to six hours of continuous operation with all channels engaged. Additionally, it features a robust power management system that allows for connection to an external power bank, ensuring extended usage. With its lightweight design, efficient power consumption, and dedicated Android app for system management, the DreamMachine is a promising tool for EEG monitoring in natural environments. It is useful in areas such as perception, learning, memory, language, decision-making, and neural connectivity mapping [49].

Furthermore, the BrainCapture EEG system [50] offers another cost-effective solution for EEG data acquisition. This system features a 27-channel EEG amplifier that samples and streams data to a mobile app via Bluetooth, with Electrocardiogram (ECG) included in the recordings. The BrainCapture EEG system employs two multiplexers, each handling 16 channels, significantly reducing the number of required A/D converters, making the system more affordable. The multiplexers enable the system to handle 32 channels with only two A/D converters, streamlining the design and minimizing costs. The processed data offers a high-quality 256 Hz sampling rate, complying with international standards set by the International League Against Epilepsy (ILAE) and the International Federation of Clinical Neurophysiology (IFCN). This system operates on battery power for up to 22 hours, making it a reliable solution for extended outdoor EEG experiments. With its efficient design and long battery life, BrainCapture EEG system [46] serves as an excellent option for mobile EEG studies, particularly in natural envi-

environments requiring portable, low-cost systems for EEG data acquisition.

1.2.4 Preprocessing/Feature Extraction Implemented on Smartphone

Natural environment experimentation attracts multiple biological and non-biological artefacts that can often mislead the smartphone-based EEG system's objective. Selecting a suitable smartphone preprocessing algorithm is a challenging task. Artifact Subspace Reconstruction (ASR) [55] is a widely used technique for reducing eye and muscle artefacts in EEG data. Riemannian ASR (rASR), developed by Blum et al. [56], builds upon ASR and has been shown to outperform it in both online and offline analyses. They used MATLAB and EEGLAB for the comparison and analysis. However, ASR is present on the Smarting Pro application (<https://mbraintrain.com/smarting-pro-line/>). Similarly, the Smartphone Brain Scanner (SBS) framework [42] supports hardware-agnostic EEG data acquisition and modular, packet-based signal processing. It includes basic preprocessing features such as filtering (via Sbs2Filter), Fast Fourier Transform (FFT), and spatial filtering using Common Spatial Patterns (CSP). EEG data packets are dispatched asynchronously to various processing modules, which can record data, extract features, or stream results over a network. While not all processing is strictly real-time, the architecture supports extensible, frame-based workflows suitable for real-time applications [42]. The DreamMachine's EEGDroid app offers filtering within the microcontroller and not on the smartphone app. The smartphone app is used primarily for configuration and visualization of the processed data [49]. Bleichner et al. [57] put forward an independent component analysis (ICA) based automated artifact detection technique to study the artefacts' nature and distribution in cEEGrid data. However, its implementation in a smartphone app is yet to be realized. Mehdi et al. put forward a preprocessing pipeline for the Smartphone-based EEG applications [58]. The pipeline offered a 3rd order Butterworth filter for high pass filtering, a Bandstop filter for line noise removal, and PREP's re-referencing algorithm [59] to detect bad channels. The Audio Feature Extraction (AFEx) app was developed for calculating acoustic features such as audio capture, Power Spectral Density (PSD), Root Mean Square (RMS), acoustic onset detection, etc., to study real-world sound perception [28] [60]. The app ran together with the Record-a app (for Lab Streaming Layer data streaming) and the Smarting app. The feasible option available at this time is to select a preprocessing algorithm that would be

suitable for the hardware, power, and battery of a smartphone.

1.2.5 Classifiers on Smartphone

Integrating classifiers into an EEG Android app is crucial for enabling real-time cognitive state recognition and decision-making directly on the device. This facilitates autonomous, context-aware applications in naturalistic settings without relying on external computational resources. Blum et al. [46] presented a simple classifier in the SCALA (Signal ProCessing and CLassification on Android) app using a template matching procedure inspired by Choi et al. [61] and Bleichner et al. [16]. The classifier was capable of distinguishing between left attended and right attended trials.

Long Short-Term Memory (LSTM), a type of recurrent neural network, has also shown promise in classifying different patterns within the same cognitive task [62]. However, its slower computational speed and reliance on high-end graphics processing units (GPU) pose challenges for smartphone-based EEG applications. Pre-trained models such as BERT (Bidirectional Encoder Representations from Transformers) have demonstrated strong performance in EEG-based Natural Language Processing (NLP) tasks [63], but their high computational demands limit their deployment on mobile platforms. A compact version, MobileBERT- developed using TensorFlow Lite for mobile devices offers task-agnostic capabilities and has outperformed the BERT_{BASE} model in several NLP tasks [64], suggesting potential for mobile EEG applications.

Xing et al. [65] proposed a Deep AutoEncoder (DAE) neural network for real-time artifact removal from single-channel EEG signals on Android smartphones using TensorFlow Lite and delegate-based acceleration. The DAE model demonstrated effective removal of ocular, motion, and muscular artifacts, achieving high correlation with ground-truth EEG data. It processed 4-second EEG windows in under 5 milliseconds, significantly outperforming traditional methods such as FastICA [65]. This work validates the feasibility of low-latency, mobile EEG preprocessing for portable BCI systems. A lightweight Convolutional Neural Network (CNN) framework was also proposed for real-time attention deficit hyperactivity disorder (ADHD) detection using EEG signals on Android smartphones via TensorFlow Lite [66], achieving over 98% accuracy on two public datasets. In another effort, Koushik et al. [67] integrated a single-channel EEG system with a smartphone to perform real-time sleep staging using deep learning, offer-

ing a more accessible alternative to traditional polysomnography (PSG).

Beyond EEG applications, TensorFlow Lite has also proven effective in other mobile health domains, such as detecting malignant tumors in breast ultrasound [68] and classifying monkeypox from skin lesion images [69], highlighting its versatility for real-time, on-device medical diagnostics. Classification algorithms such as Random Forest (RF) have also been implemented in a voice-activity detection app for Android and iOS to enable real-time, on-device noise classification [70], yielding better results than Gaussian Mixture Model (GMM). Sehgal and Kehtarnavaz [71] extended this approach by applying a deep learning algorithm, CNN, designed to act as a switch for noise reduction in hearing device signal processing pipelines. Similarly, Majumder et al. [72] applied deep neural networks for real-time detection of diabetic retinopathy. From the existing literature, it is evident that TensorFlow Lite is widely used for deploying classification models into Android apps across various application domains. Its compatibility with deep neural networks makes it a powerful tool for on-device, real-time inference. However, since TensorFlow Lite primarily supports deep learning models, which typically require large datasets for effective training, the choice of classifier must be carefully considered based on the specific application and the availability of annotated data.

1.3 Challenges

A smartphone-based mobile EEG system using an Android app opens new avenues for real-world brain monitoring but also introduces several challenges. One key requirement is motion tolerance, enabling EEG recordings to be conducted seamlessly in various settings, whether indoors or outdoors [16]. The app must be capable of detecting and classifying external artifacts within the acquired signals. Although low-power artifact removal algorithms and efficient classifiers integrated into mobile platforms are active areas of research, further advancements are necessary [73].

Progress in these domains could lead to reliable, portable EEG systems for applications such as mindfulness training [74]. Moreover, lightweight and wireless acquisition devices will facilitate hassle-free experimentation in any environment [51]. For practical use, the entire system should be discreet and comfortable, allowing users to carry out daily tasks without drawing attention [16].

Recording EEG in naturalistic environments offers the opportunity to assess brain activity in more comfortable and less conscious settings, enabling the study of environmental influences on human behavior [75]. Such systems also show promise for clinical applications. For instance, EEG-based monitoring is being explored for patients with Alzheimer's disease [76], and future work could extend such approaches to high-risk infant populations, such as those born to cocaine-addicted mothers [77].

There is growing interest in understanding the psychological and cognitive impacts of excessive smartphone use, which has been linked to decreased workplace productivity [78]. Integrating EEG into such studies could offer deeper insights into the underlying neural correlates, including associations with mental health conditions such as depression and anxiety [79]. Additionally, EEG has been used to investigate brain connectivity patterns influenced by different musical genres [80], highlighting the potential benefits of mobile, user-friendly EEG systems for studying diverse cognitive and affective phenomena in naturalistic settings.

From a practical standpoint, using a minimal number of electrodes, focused on specific regions of interest (ROIs), can reduce data size and speed up analysis. Selecting electrodes based on prior knowledge and classification performance can also reduce test error. Importantly, electrode usability can be prioritized without sacrificing signal quality, as it remains consistent regardless of the amplifier type (active or passive) [51]. Finally, rigorous evaluation of preprocessing and classification algorithms using standard metrics is crucial for developing a robust smartphone-based EEG application.

1.4 Contributions of this Thesis

Driven by the current trends and challenges illustrated above, this thesis seeks to address key limitations associated with smartphone-based EEG systems for experimentation in natural environments. The main contributions of the work are as follows:

- Conventional lab-based EEG setups often limit participant mobility. To address this, the CameraEEG Android application was validated for enabling synchronized recording of EEG and video data during real-world activities [S. Madhavan, M.Tech Thesis, IIT Guwahati, 2020]. In a pilot study, four participants performed eyes-open and eyes-closed tasks during the resting state. EEG signals recorded via

the CameraEEG app from occipital and parieto-occipital sites exhibited a distinct alpha peak during the eyes-closed condition. The data confirmed accurate synchronization between EEG and video recordings, highlighting the app's potential for EEG experiments in natural environments [81].

- A novel framework is introduced for applying the ASR algorithm to single-channel EEG data. While ASR is effective in removing artifacts such as eye blinks and motion, it typically requires multichannel input. The proposed method, Embedded ASR (E-ASR), overcomes this limitation by employing a dynamical embedding approach; constructing a delay-embedded matrix from single-channel EEG data, followed by ASR application and signal reconstruction. EEG recordings were obtained from four participants (eyes open) using two frontal electrodes via the CameraEEG Android application. The E-ASR algorithm was evaluated on both semi-simulated and real EEG data, demonstrating strong performance across both datasets. This framework shows promise for artifact removal in smartphone-based EEG applications conducted in natural environments with minimal electrode setups [82].
- Traditional deep learning models for EEG classification are accurate but require large datasets and significant computational resources. Converting these models to TensorFlow Lite enables deployment on mobile devices, though data limitations remain a challenge. To address this, a lightweight machine learning pipeline was developed for EEG classification on Android using limited training data. As a case study, EEG signals recorded via the CameraEEG app were used to classify eye states (eyes open vs. eyes closed) after preprocessing with the E-ASR algorithm and extraction of power spectral features. A high-accuracy single-channel Support Vector Machine (SVM) model was trained and deployed on Android smartphones. This study demonstrates the feasibility of deploying machine learning-based EEG classifiers on smartphones, contributing to scalable and accessible EEG-based monitoring for research and clinical use.

1.5 Organization of the Thesis

The organization of the thesis is as follows. **Chapter 2** presents the validation of the CameraEEG Android application, designed to enable synchronized acquisition of EEG and video data in real-world settings. The chapter details a pilot study in which the app was used to record eyes-open and eyes-closed tasks from participants in a resting state condition. **Chapter 3** introduces a novel Embedded Artifact Subspace Reconstruction (E-ASR) framework for artifact removal in single-channel EEG data. This chapter discusses the limitations of conventional ASR in low-channel setups and presents an embedding-based solution tailored for minimal electrode configurations. Evaluation using both semi-simulated and real EEG data demonstrates the effectiveness of the method, establishing its potential for mobile EEG applications. **Chapter 4** focuses on the design and implementation of a lightweight machine learning pipeline for on-device EEG signal classification. The approach addresses the challenge of limited training data by combining E-ASR preprocessing with power spectral feature extraction and a single-channel Support Vector Machine (SVM) classifier. The trained model was successfully deployed on Android smartphones, validating the pipeline's suitability for mobile EEG-based monitoring. Finally, **Chapter 5** concludes the thesis with a summary of key findings and a discussion of future directions.



2

Validation of the CameraEEG Android Application

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2.1 Introduction

Recent developments in cognitive psychology emphasize the importance of studying brain responses in real-world environments where individuals engage in natural activities [28] [83]. This shift from controlled laboratory setups to ecologically valid settings has encouraged the use of smartphones for recording brain activity, addressing long-standing concerns about the external validity of traditional lab-based neuroimaging approaches [84] [85]. Several studies have explored how neural responses vary when individuals are exposed to limited but ecologically relevant stimuli [86] [87], demonstrating significant differences in cognitive processing between controlled and natural environments [35] [88]. Observing this shift toward ecological validity, one key advancement enabling this transition is the integration of Electroencephalogram (EEG) technology with smartphones, which allows brain activity to be monitored in mobile and dynamic contexts [46] [89]. Mobile EEG systems have been applied in a range of studies, including those focusing on attention in classroom settings [90] [91], social behavior, [92], and even human responses to existential experiences such as mortality [93]. In a notable example, smartphone-supported hyperscanning was used to observe neural synchrony among musicians during interaction [94]. These applications demonstrate the value of synchronizing EEG data with contextual cues, particularly video, which can help identify meaningful events more accurately.

Beyond cognitive research, in clinical contexts, portable EEG devices are now used for long-term monitoring in individuals with epilepsy and neurodevelopmental disorders [95] [96], with a recent study showing comparable accuracy to traditional hospital-based systems for seizure detection [97]. Additionally, smartphones are being explored for video-based seizure detection [98] [99]. In parallel, mobile apps are developed for sleep monitoring, combining data from low-cost sensors and built-in smartphone capabilities [100] [101]. These technological advances are complemented by growing evidence supporting the clinical validity of mobile neuroimaging approaches [102].

To enable these real-world data collection efforts, the CameraEEG Android application was originally developed as part of an M. Tech thesis project by Srihari Madhavan at IIT Guwahati (2020). The app records EEG signals and video streams simultaneously and is specifically designed for studies conducted in natural settings. It enables

synchronized data collection using a Smarting EEG device (mBrainTrain), an EasyCap EEG headcap or concealed ear-EEG electrodes, and the smartphone's rear camera. The phone can be placed in a transparent wearable pouch, allowing hands-free video recording and easy access to the screen. The technical specifications and architecture of the CameraEEG application are summarized in Table 2.1. This includes details on the development platform, EEG integration, video module, and camera resource handling mechanisms.

Table 2.1: Technical Specifications of the CameraEEG Application

Component	Details
Development Platform	Android Studio using Java Development Kit (JDK)
EEG Integration	Manufacturer's Software Development Kit (SDK), version 2019 integrated; compatible only with Smarting devices (mBrainTrain)
Video Module	Developed using Android's Camera2 API
Video Resolution	480p, 30fps
Display Adjustment	Custom AutofitTexture class for maintaining aspect ratio
Camera Resource Handling	Binary semaphore used for smooth camera resource management

CameraEEG saves EEG data in .bdf format and video in .mp4. The user interface includes buttons for connecting to the EEG device, starting/stopping synchronized recording, marking events, and tracking duration with a chronometer. The application is freely available online at: <https://github.com/NeuralLabIITGuwahati/CameraEEG>. A demo video of the app is available at: <https://www.youtube.com/watch?v=NWJN9obgwXk>. Figure 2.1 shows the graphical user interface of the CameraEEG Android app.

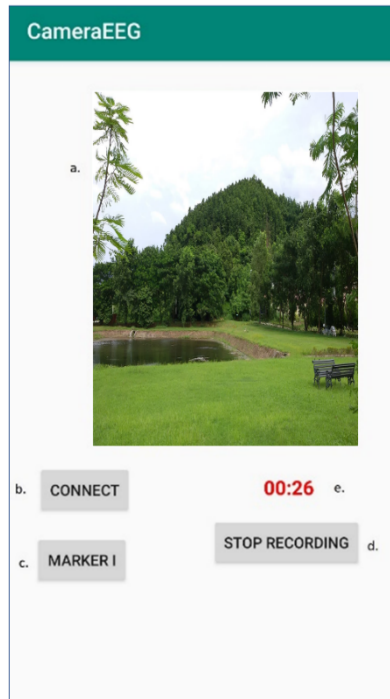
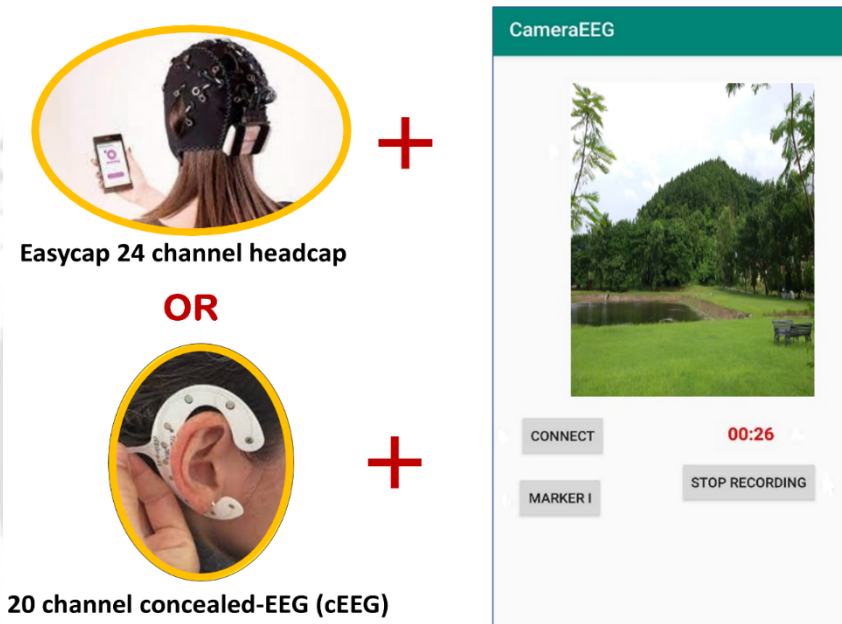


Figure 2.1: Graphical User Interface of the CameraEEG App: a) Preview of video recording, b) Button for Connecting/Disconnecting to the EEG device, c) Button to Mark Events, d) Start/Stop Record Button for Video-EEG, e) Chronometer - For tracking the recording time

2.2 Data Acquisition using the CameraEEG Android Application

To validate the functionality of the CameraEEG application, data collection was conducted on four individuals (three males and one female) with a mean age of 25 years and a standard deviation of 2.16. Ethical approval for the study was granted by the Institutional Ethics Committee of IIT Guwahati. Written informed consent was obtained from all participants prior to the EEG and video recording sessions. Participants were informed about the nature of the recordings, the purpose of the study, and the handling of the collected data. EEG signals were recorded using the Smarting device (mBrainTrain) with a 24-channel EasyCap headcap (<https://mbraintrain.com/smarting-mobi/>). The application is also compatible with a 20-channel concealed-EEG (cEEGrid) electrode system [103]. Figure 2.2 shows the experimental setup of the CameraEEG android application. Prior to data acquisition, electrode impedance levels were verified using the SMARTING mobile application provided by the manufacturer. EEG data were acquired from two electrode sites: an occipital (O2) channel and a parieto-occipital (POz) chan-

nel, at a sampling frequency of 500 Hz. The application's performance was evaluated by recording EEG data while participants performed eyes open and eyes closed tasks in a resting state sitting position, each lasting approximately five minutes. This task was chosen to verify the presence of alpha waves, which are typically prominent during the eyes closed condition and suppressed during eyes open [104]. Detecting this expected difference served as a validation of the EEG signals recorded using the app. Although the app includes an event marker feature to log specific events during recordings, this functionality was not utilized in the current study.



Please note that some pictures are self-made while some are taken from the internet and modified.

Figure 2.2: Experimental setup for the CameraEEG android application

2.3 Power Spectral Analysis

To evaluate the EEG data collected through the app, power spectral analysis was performed on signals recorded during eyes-closed and eyes-open conditions. Previous studies have reported increased alpha wave (8–13 Hz) activity during resting-state eyes-closed conditions compared to eyes-open conditions [105]. This activity is particularly prominent in the occipital region [104]. Although each recording session lasted approximately 10 minutes, 6-second EEG segments were selected for spectral analysis based on previous studies demonstrating that alpha rhythm activity can be reliably identified within short stationary EEG epochs [104]. The power spectral density (PSD) was then

estimated from these segments. These segments improve the reliability of PSD estimation while minimizing contamination from non-stationary artifacts that may occur during longer recordings.

We employed the syntax `pspectrum(x,fs)`, where `fs` denotes the sampling frequency (<https://in.mathworks.com/help/signal/ref/pspectrum.html>) and `x` represents the 6-second segment of the EEG signal. The `pspectrum` function was applied to the 6-second EEG segment using a Kaiser window to reduce spectral leakage [106] [107]. The signal was first multiplied by the window function, resulting in Equation 2.1:

$$x_w[n] = x[n] \cdot w[n], \quad 0 \leq n \leq N - 1 \quad (2.1)$$

where $x[n]$ denotes the discrete EEG signal of length N , and $w[n]$ is the Kaiser window applied to the signal. The frequency-domain representation of the windowed signal was obtained by computing the Discrete Fourier Transform (DFT) using the Fast Fourier Transform (FFT) algorithm [106], which efficiently calculates the DFT for long time series as in Equation 2.2:

$$X(f) = \sum_{n=0}^{N-1} x[n] \cdot w[n] \cdot e^{-j2\pi f n / f_s} \quad (2.2)$$

The power spectral density (PSD) was then estimated by normalizing the squared magnitude of the DFT (Equation 2.3):

$$P_{xx}(f) = \frac{1}{N f_s} |X(f)|^2 \quad (2.3)$$

where f_s is the sampling frequency. The resulting spectral estimate offers a time-frequency characterization of the EEG signal, enabling the investigation of nonstationary dynamics such as variations in alpha band activity.

2.4 Results

The synchronized EEG and video recordings were examined to evaluate potential data loss or misalignment. The application reliably recorded video in 480p resolution at 30 fps in .mp4 format, which was stored on the smartphone's internal storage. Furthermore, the total number of recorded EEG samples consistently matched the corresponding

video recording duration across all sessions, indicating stable and reliable synchronized acquisition.

The EEG recordings were stored in .bdf format on the internal memory of the smart-phone. The EEG time series obtained during the two experimental tasks were divided into segments using MATLAB (Version 2021a) and EEGLAB (Version 2021.1) for subsequent processing. To carry out offline analysis, custom scripts were implemented for both tasks. Given that alpha waves are predominantly observed in the occipital region of the brain, one occipital and one parieto-occipital electrode were chosen from the 24-channel EEG configuration used in the study. The variations in alpha activity were then examined, following the methodologies outlined in prior research [104] [108] [109].

The PSD plots from the O2 channel (Figure 2.3) show a clear increase in alpha band power (8-13 Hz) during the eyes-closed condition across all four subjects, with distinct alpha peaks around 10 Hz. This activity significantly diminishes when the subjects open their eyes, consistent with known patterns of visual-induced alpha suppression. Subject 3 displays the highest alpha power during eye closure. These results confirm the O2 channel's effectiveness in capturing alpha modulation related to visual input.

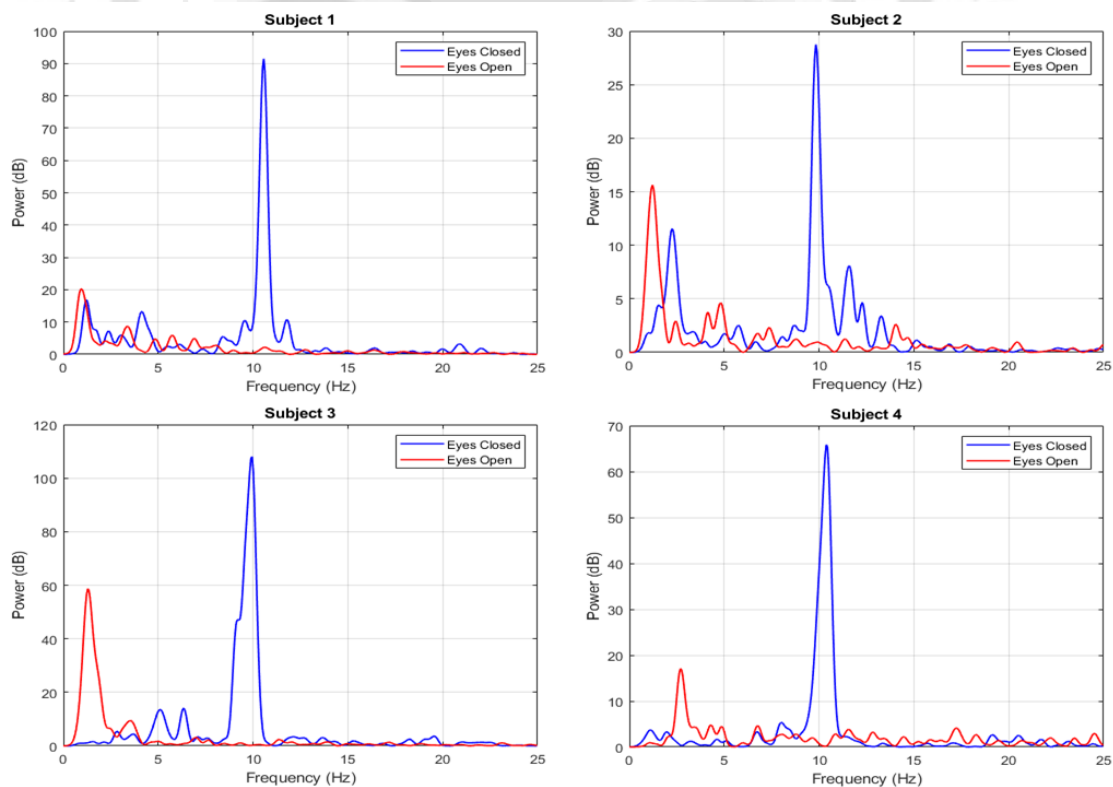


Figure 2.3: Raw PSD plots of EEG signals recorded from the O2 channel for four subjects during eyes-closed (blue) and eyes-open (red) conditions

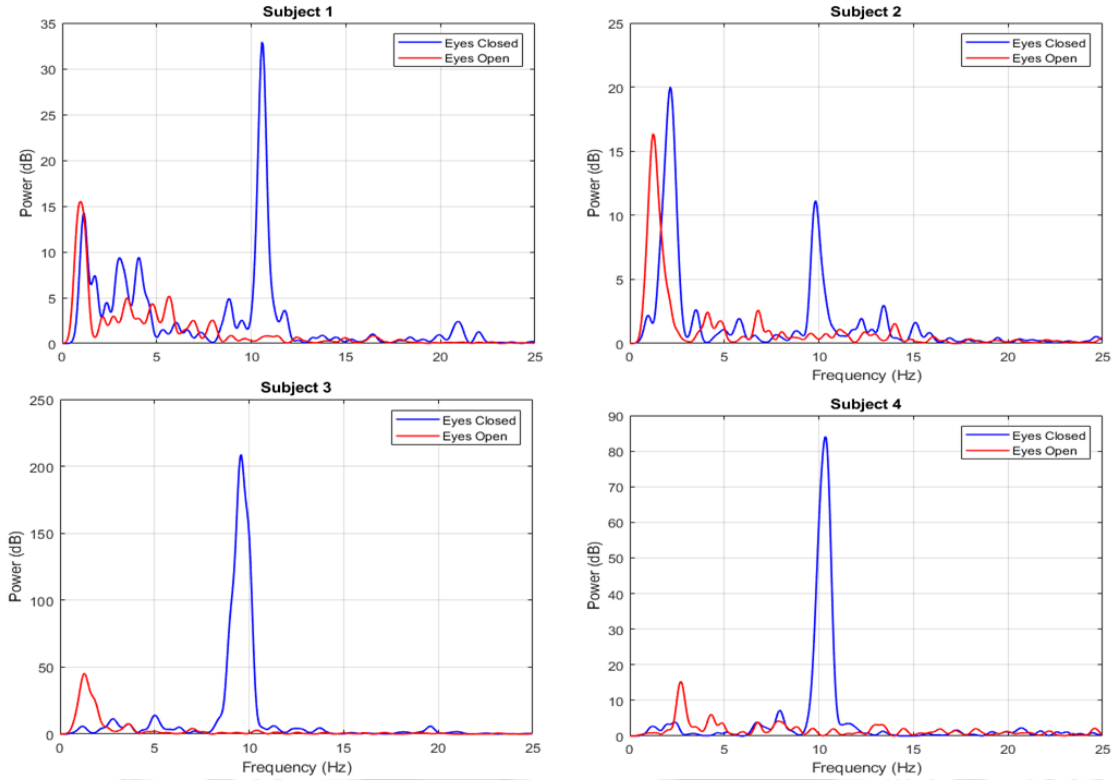


Figure 2.4: Raw PSD plots of EEG signals recorded from the POz channel for four subjects during eyes-closed (blue) and eyes-open (red) conditions

Similarly, PSD plots from the POz channel (Figure 2.4) exhibit increased alpha activity during eyes-closed periods in all subjects, with particularly strong peaks in Subjects 3 and 4, where power exceeds 200 dB and 80 dB, respectively. Upon eye opening, a notable reduction in alpha power is observed across all subjects, underscoring the impact of visual engagement. These findings reinforce the involvement of the occipital and parieto-occipital regions in the generation of the alpha rhythm and its regulation by sensory input, confirming the overall quality of the collected EEG data.

2.5 Discussion

To verify the performance of the developed CameraEEG application, we conducted eyes closed and eyes open recording sessions, a standard approach in previous EEG studies [104] [48] [52]. The presence of a prominent alpha peak in the eyes-closed condition confirms that the Android-based CameraEEG application accurately captured EEG signals. Specifically, recordings from the O2 and POz electrodes showed a marked increase in alpha activity (8-13 Hz) during eye closure across all four subjects, with al-

pha peaks around 10 Hz. Subject 3 demonstrated the strongest alpha power during this condition. On eye opening, alpha power significantly declined in both channels, reflecting the well-established phenomenon of visual-induced alpha suppression [104]. These results reinforce the physiological accuracy of the app in capturing meaningful brain activity.

The CameraEEG application integrates EEG and video recording within a single Android app, unlike many existing solutions that rely on multiple apps or complex setups [46] [34]. This streamlined configuration minimizes system load and can be easily adapted for different use cases by incorporating new modules. The app uses EEG device-specific libraries, making it compatible with mBrainTrain devices only, which limits its use with other EEG hardware.

Since the CameraEEG framework involves synchronized EEG and video acquisition, participant privacy and data security are important considerations. In the present implementation, all EEG and video recordings were stored locally on the smartphone and used solely for research purposes under controlled experimental conditions. The framework does not require cloud-based transmission during acquisition, thereby reducing potential privacy risks associated with remote data transfer. Nevertheless, future large-scale real-world deployments will require additional privacy-preserving mechanisms, secure data management strategies, and user-controlled consent procedures.

Synchronization between EEG and video streams was also evaluated for reliability. The CameraEEG application successfully recorded 480p video at 30 fps in .mp4 format, stored locally on the smartphone. Synchronization between the EEG and video streams was achieved using Lab Streaming Layer (LSL, <https://labstreaminglayer.org/#/>), which performs timestamp-based alignment of multimodal data streams. The video timestamps were consistently matched with the corresponding EEG sample points across all sessions, with no observable synchronization drift during the recordings, indicating stable and reliable synchronized acquisition between the EEG and video streams. Given the 30 fps video acquisition rate used in the present work, the synchronization granularity corresponds approximately to the duration of a single video frame (33 ms). This level of temporal resolution is generally sufficient for behavioral monitoring and naturalistic EEG studies where behavioral events occur over relatively slower timescales. Conventional laboratory EEG-video systems commonly employ hardware-trigger-based

synchronization mechanisms to obtain high temporal precision between modalities, particularly for applications involving rapid neural responses such as event-related potential (ERP) studies [110] [111]. EEG experiments involving event-related analyses require accurate temporal alignment because timing jitter and drift can distort stimulus-locked neural responses [112]. In contrast, the current CameraEEG implementation uses software-level synchronization within a single Android application environment, providing a portable and practical framework for naturalistic mobile EEG recordings. The CameraEEG framework has also been employed in several other mobile EEG investigations. One such study involved the real-time evaluation of EEG activity elicited by live Indian classical vocal performances with therapeutic relevance [113]. These studies further demonstrate its applicability in naturalistic neurophysiological experiments. Nevertheless, the present validation was conducted on a limited cohort of four participants and did not include dedicated quantitative measurements of synchronization latency or jitter. In addition, although the application was successfully tested on multiple Android smartphones released after 2020, comprehensive benchmarking across a wider range of Android versions and hardware configurations was not systematically performed. The absence of larger-scale validation studies and dedicated quantitative synchronization assessment, therefore, remains a limitation of the present work, which may affect the broader generalizability of the proposed framework across diverse recording conditions and hardware configurations.

Although the initial recordings served as a primary validation, longer-duration sessions were also recorded successfully, confirming the app's reliability during extended use. During extended recording sessions on smartphones released after 2020, specifically the Redmi Note 7 Pro (4 GB RAM) and Realme 5 Pro (6 GB RAM), no noticeable overheating or performance degradation was observed under the tested recording conditions. In contrast, older devices may face thermal management issues during prolonged sessions. To maintain smooth operation, recordings were conducted at 480p resolution, which balanced performance and resource usage. While higher resolutions can improve visual quality, they may place additional strain on system resources.

Overall, the CameraEEG app enables robust, synchronized EEG and video recordings in natural settings, making it particularly suitable for capturing rare or subtle social behaviors [114]. It has also been employed in the real-time dynamic analysis of EEG

responses to live Indian classical vocal stimuli [113], highlighting its potential in therapeutic and music-based interventions. In the future, integrating real-time EEG processing features such as artifact removal and task classification may extend its utility to more advanced mobile neuroimaging applications, including low-cost epilepsy monitoring in home environments [115].





3

Development of an Electroencephalogram Artifact Reduction Algorithm for Smartphone Applications using Single Channel

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3.1 Introduction

In recent years, portable EEG devices with a single recording channel have gained popularity in non-laboratory and non-clinical environments due to their practicality and ease of use [116] [117]. These single-channel systems have been successfully applied across various domains, including brain-computer interface (BCI) research, driver fatigue detection, and the investigation of neurological and psychological disorders [118] [119] [120].

EEG signals are often affected by artifacts. Non-biological artifacts may arise due to high electrode impedance, malfunctioning sensors, or interference from nearby electrical devices. Biological artifacts such as blinks, eye movements, muscle activity, and cardiac signals present a major challenge in EEG analysis and are a key focus for artifact removal [121] [122]. Eye-related activity, including blinks and saccades, causes noticeable amplitude shifts, especially in the prefrontal electrodes (Fp1 and Fp2). As one moves from the frontal to the posterior regions of the scalp, the strength of these blink-related signals typically decreases. These artifacts often have amplitudes around 500 microvolts and occur below 20 Hz [121] [122], similar to signals generated by upper-limb movements [123] [124] [125]. Muscle-related movements such as jaw clenching, swallowing, or facial expressions also produce large variations in the EEG signal. If not properly filtered, these artifacts can distort both the temporal and spectral content of the EEG, possibly leading to the loss of vital information and reducing the reliability of EEG-based applications in a natural environment.

The Artifact Subspace Reconstruction (ASR) algorithm, introduced and patented by C.A.E. Kothe and T.P. Jung in 2016 [126], is an adaptive spatial filtering approach designed to remove artifacts from EEG recordings. It utilizes a sliding window mechanism to perform Principal Component Analysis (PCA) on EEG data. Initially, ASR derives reference segments directly from the raw EEG signal by analyzing the distribution of signal variance. Based on this, it calculates thresholds for detecting artifact components, where the threshold is set as a multiple of the standard deviation of the principal components, scaled by a user-defined parameter k . Within each window, ASR identifies components that exceed this threshold and excludes them from reconstruction. The signal is then reconstructed using only the retained, non-artifactual components [55]. As noted by [127], the choice of k controls how aggressively noisy data is removed;

lower values of k lead to stricter artifact rejection. A modified version, known as Riemannian ASR, incorporates manifold-based computations of covariance matrices and has demonstrated effective artifact removal performance [56]. In a study involving motor imagery EEG [128], ASR with default parameters was found to outperform both Independent Component Analysis (ICA) and PCA. The method's efficacy for automatically cleaning EEG data collected during attention-demanding tasks, such as simulated driving, was demonstrated in [55]. Furthermore, its applicability to EEG signals recorded during activities like fast-paced walking and single-leg stance was discussed in [129]. ASR has also been integrated into the Smarting Pro mobile platform, providing real-time multi-channel artifact removal (<https://mbraintrain.com/smarting-pro-line/>). Nonetheless, ASR's effectiveness diminishes when applied to recordings with very few channels and is currently unsuitable for single-channel EEG applications [55].

The potential of Singular Spectrum Analysis (SSA) for removing eye-blink artifacts from single-channel EEG recordings was investigated in [130]. SSA is designed to decompose a single time-series signal into its low-frequency, oscillatory, and noise components [131]. A key challenge with traditional SSA lies in selecting the appropriate signal eigenvectors, which are essential for accurately reconstructing the clean signal. To address this, new criteria for eigenvector selection were proposed in [131]. Later, SSA was incorporated into the Adaptive Filter (AF) framework to improve artifact suppression performance, as shown in [132]. In other work, Independent Component Analysis (ICA) has also been applied to single-channel EEG signals after SSA pre-processing [133]. More recently, SSA has been utilized as a smoothing filter to suppress Electrooculogram (EOG) artifacts in EEG signals [134]. A hybrid method combining SSA-ICA with wavelet thresholding was explored in [135] for EOG artifact elimination in single-channel EEG. Additionally, [136] proposed a flexible artifact removal framework using wavelet-based techniques that adaptively adjust coefficients in a data-driven manner to suppress various artifact types in single-channel EEG data. Despite these advancements, the integration of SSA-based artifact removal methods into Android smartphone applications remains largely unexplored.

Most of the previously discussed methods for removing eye-blink artifacts are designed for offline processing. However, applications such as EEG monitoring in natural settings or epilepsy detection require real-time signal processing. In such cases, the

artifact removal algorithm must be capable of operating in real time. First, the algorithm should function automatically, without manual adjustments. Second, it is important to use the fewest possible electrodes during recordings in natural environments. This minimizes discomfort and is more practical for long-term use. Single-channel EEG offers a key advantage in this context due to its simplicity. It reduces setup time and equipment needs. It is also cost-effective, making it suitable for researchers with limited resources. Despite having only one channel, it has been successfully used to detect mental states such as driver drowsiness [137], and conditions like depression and anxiety [138]. Finally, for integration into smartphone applications, the algorithm must have low computational complexity. This helps ensure real-time performance without causing processing delays [15].

The concept of using dynamical embedding for applying ICA to single-channel EEG was first presented in [139] for removing ocular artifacts. In this approach, a pseudo-multichannel dataset, known as the embedding matrix, is constructed from delayed segments of the single-channel EEG over a few seconds. This matrix is then used as input to the ICA algorithm. Embedding is a core component of SSA, enabling the extraction of artifact components from single-channel EEG data [131]. ASR has already been implemented in real-time on Android smartphones using multichannel EEG input (<https://mbraintrain.com/smaring-pro-line/>). However, no existing studies have examined the use of ASR on single-channel EEG signals. To address this gap, our work aims to explore the use of embedding as a method to adapt ASR for single-channel data. We constructed an EmbeddedMatrix from the single-channel EEG signal and applied ASR to it. This approach offers a promising solution for artifact reduction on smartphones in naturalistic EEG experiments. To evaluate the proposed Embedded-ASR (E-ASR) framework, we analyzed its performance using metrics such as relative root mean square error, correlation coefficient, average power ratio, and reduction in blink count, measured before and after applying E-ASR. The framework was tested on both semi-simulated and real EEG datasets. A graphical overview of the proposed method is presented in Figure 3.1.

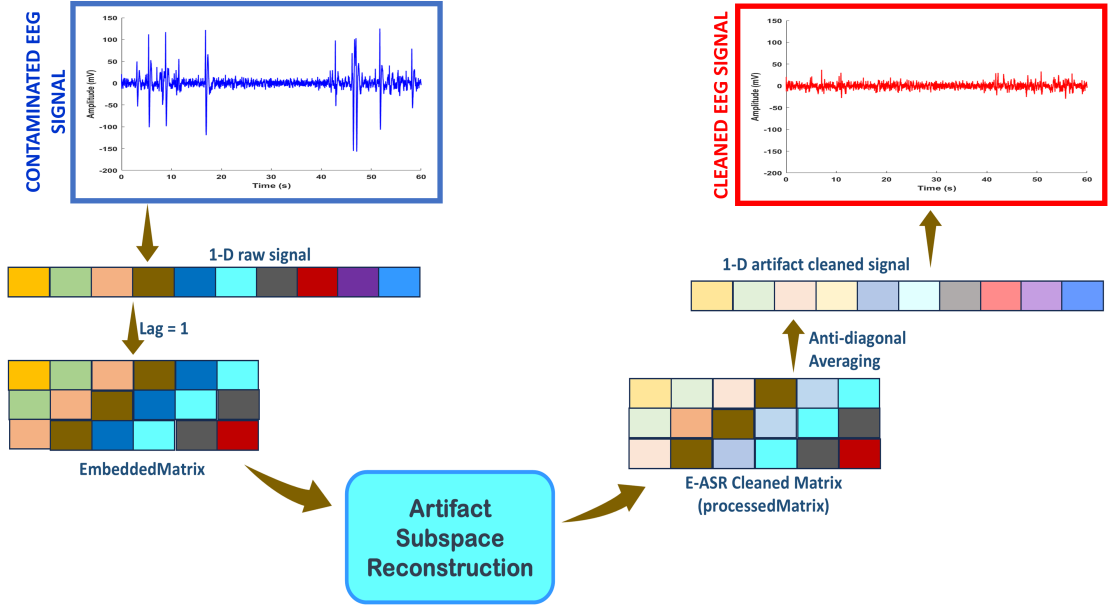


Figure 3.1: Graphical abstract for the proposed E-ASR framework on a single electroencephalogram channel. Each colored block represents a single time point.

3.2 Materials and Methods

3.2.1 Data Acquisition and Preprocessing

The experimental protocol described in this chapter was approved by the Human Ethics Committee of the Indian Institute of Technology Guwahati. All procedures adhered to the Declaration of Helsinki and complied with relevant local regulations. EEG recordings were obtained from four participants (two males and two females) with an average age of 28 years and a standard deviation of 4.33. Data was acquired using the CameraEEG Android application, which allows for simultaneous video and EEG recording [81]. The application supports Android smartphones running version 5.0 (Lollipop) or later. For the experiment, we used the CameraEEG app in combination with a 24-channel Easy-Cap headcap (<https://www.easycap.de/>) and the Smarting wireless EEG system from mBrainTrain (<https://mbraintrain.com/smarting-wireless-eeeg/>). Each participant was instructed to keep their eyes open for five minutes. The EEG and video recordings were saved on the phone in .bdf and .mp4 formats, respectively. A sampling rate of 500 Hz was used throughout the recording. Photographs of the experimental setup are provided in Figure 3.2.

For the analysis presented in this study, we used the 5-minute eyes-open EEG

3. Development of an Electroencephalogram Artifact Reduction Algorithm for Smartphone Applications using Single Channel



Figure 3.2: (a) The data recording setup for the resting-state eyes-open task, featuring (i) a OnePlus Nord CE 2 Lite 5G smartphone placed on a tripod in front of the subject, (ii) an EasyCap 24-channel EEG cap, and (iii) an mBrainTrain Smarting device mounted on the EEG cap. (b) The CameraEEG Android app running on the smartphone, recording synchronized EEG and video data.

recordings from all participants. From these recordings, the Fp1 and Fp2 channels, both located in the frontal region of the scalp, were selected and treated as single-channel EEG signals. These channels were chosen because they are highly sensitive to eye-blink and eye movement artifacts. The signals were normalized using zero-centered normalization [55]. Subsequently, a bandpass filter (0.5-100 Hz) was applied, followed by a notch filter at 50 Hz to remove electrical line noise [55] [140]. A visual inspection revealed no prominent linear trend in the signals; hence, detrending was not applied. This omission may represent a potential limitation of the current study. All data processing and analysis were performed using MATLAB version 2022b (MathWorks, Natick, MA, USA) on a system running an Intel® Core™ i7-8700 CPU @ 3.19 GHz with 16 GB RAM.

For additional validation of the proposed E-ASR framework, a publicly available EEG dataset from OpenNeuro (<https://openneuro.org/datasets/ds004148/versions/1.0.1>) was also utilized. Specifically, the test-retest resting-state and cognitive-state EEG dataset [141] was considered in this study. The dataset contains EEG recordings acquired during two resting conditions (eyes open and eyes closed) and three subject-driven cognitive tasks, namely memory, music, and subtraction. For the present analysis, only the eyes-open resting-state EEG recording from Subject 1 was utilized as a

representative proof-of-concept evaluation. Furthermore, only the Fp2 channel, located in the frontal region of the scalp and highly susceptible to ocular artifacts, was selected and treated as a single-channel EEG signal for the current work. The dataset was originally acquired using a 61-channel EEG system with a sampling frequency of 500 Hz and was provided in BrainVision format (.eeg, .vhdr, and .vmrk). Similar preprocessing steps were applied prior to analysis, including zero-centered normalization, bandpass filtering, and notch filtering.

3.2.2 Construction of Multichannel EEG Matrix Using Embedding Approach

The embedding matrix offers a means to represent the temporal dynamics of an EEG signal [139]. It is formed by generating a sequence of delayed vectors from single-channel EEG data. This matrix helps in capturing information related to the underlying EEG sources using only one channel [142] [143]. Suppose we have a single-channel EEG signal denoted as $X = [x(1), x(2), \dots, x(N)]$, where N is the total number of data points. The corresponding multidimensional representation can then be expressed as in Equation 3.1:

$$X = \begin{bmatrix} x(1) & x(2) & \cdots & x(K) \\ x(2) & x(3) & \cdots & x(K+1) \\ \vdots & \vdots & \ddots & \vdots \\ x(M) & x(M+1) & \cdots & x(N) \end{bmatrix} \quad (3.1)$$

Here, M denotes the embedding dimension, and $K = N - M + 1$ represents the number of delay vectors. If f_s is the sampling rate and f_L is the lowest frequency of interest, then the embedding dimension M [139] can be calculated using Equation 3.2, as suggested in [139]:

$$M \geq \frac{f_s}{f_L} \quad (3.2)$$

In our approach, the time lag is set to 1, which is supported by empirical evidence from [139]. We shall henceforth refer to Equation 3.1 as *EmbeddedMatrix*.

The embedding dimension (M) is a crucial parameter in decomposing time series data. It determines the number of lagged components of the time series. Selecting an appropriate embedding dimension M is essential because it influences the quality of the decomposition and the ability to extract meaningful information from the time series. If M is too small, important information may be lost, leading to incomplete decompo-

sition. On the other hand, if M is too large, it can lead to overcomplexity and noise in the decomposition, making it harder to extract meaningful components [139]. Choosing the optimal M often involves a balance between capturing important patterns and minimizing noise [139].

3.2.3 Artifact Subspace Reconstruction

In the first step of ASR (i.e., calibration phase), the EEG data (X) is input for the `asr_calibrate` function along with the sampling frequency in Hertz (Hz) to construct the calibration data and determine rejection thresholds from the calibration data [55]. To do so, the covariance matrix of X is calculated. Mixing matrix (M_C) is calculated as the square root of covariance matrix as in Equation 3.3.

$$M_C M_C^T = \text{Cov}(X) \quad (3.3)$$

The eigenvalue decomposition of M_C results in eigenvectors (V_C) and eigenvalues (D_C). The principal component space is calculated as Equation 3.4.

$$Y_C = X \cdot V_C \quad (3.4)$$

Component-wise root mean square (RMS) values with a non-overlapping sliding window of 1 second [55] are calculated and transformed into z-score. ASR selects the windows with z-score in range of $-3.5 < z < 5.5$ [55], defines them as clean (artifact-free) sections, and concatenates them to generate the calibration data. From the clean sections of each principal component, the mean (μ) and standard deviation (σ) of each component are calculated. The threshold of each component is calculated as Equation 3.5, where i refers to the principal component number and k is the cut-off parameter, whose value was 17 [55].

$$T_i = \mu_i + k\sigma_i \quad (3.5)$$

The threshold matrix T is the matrix product of diagonal matrix of threshold values T_i and the transpose of eigenvectors V_C . The threshold matrix T and the mixing matrix M_C are the outputs of this calibration phase, which are stored in a variable 'state' [55].

In the second step (i.e., process phase) of ASR, eigenvalue decomposition is performed on data within a sliding window (0.5 s) [55] to obtain the eigenvalues (D_T) and eigenvectors (V_T) of the data. Then `asr_process` function applies thresholds deter-

mined in the calibration phase to create X_T [55]. If an eigenvalue within that sliding window exceeds the threshold, its corresponding eigenvector is removed (zeroed). The left-over eigenvectors (V_{trunc}) are therefore retained, and the data are reconstructed within that window according to Equation 3.6 from [55].

$$(X_T)_{\text{clean}} = M_C ((V_T^T M_C)^+_{\text{trunc}}) V_T^T X_T \quad (3.6)$$

Due to the rank reduction from truncation, the Moore–Penrose pseudoinverse (+) ensures a reliable reconstruction by finding an optimal solution that minimizes reconstruction error. This approach allows for accurate data recovery, even when the matrix is singular or lacks full rank. The cleaned windows $((X_T)_{\text{clean}})$ are concatenated to form the clean artifact-free signal X_{Clean} . More details on the ASR algorithm can be found in [126] [140].

3.2.4 Proposed Method: Embedded Artifact Subspace Reconstruction

The EmbeddedMatrix was constructed by introducing time delays into the preprocessed single-channel EEG signal. The embedding dimension (M) was chosen to be sufficiently large to retain the essential information within the signal. For the EEG data used in this study, M was calculated using the equation provided in Equation 3.2. The one-dimensional EEG signal was then converted into the *EmbeddedMatrix* as outlined in Section 3.2.2, using a time lag of 1. We implemented ASR on the *EmbeddedMatrix* using MATLAB scripts from the open-source EEGLAB plug-in *clean_rawdata* [144]. This produced a *processedMatrix* of the same size. To recover the E-ASR denoised signal, antidiagonal averaging was applied to the *processedMatrix*, following the method described in [143].

3.2.5 Construction of Semi-Simulated Single Channel EEG and Eye-Blink Artifact

We created a semi-simulated dataset as given in [134] for testing the proposed method. The EEG signals were acquired using the Smarting device, sampled at 500 Hz with a resolution of 24 bits (<https://mbraintrain.com/smarting-wireless-eeeg/>). Two clean EEG segments about ten seconds long, without eye-blinks, are manually identified and extracted from Fp1 channel of subject 4. These two segments are then replicated and

concatenated to form a 1-minute long ground truth single-channel EEG signal. Further, two eye-blink artifacts are manually segmented and extracted from the same dataset, which is about 2 s long. To achieve a consistent signal length of 10 s, we extended the isolated eye-blink segments by adding zeros on both ends. Each clean segment is combined with one eye-blink segment using Equation 3.7:

$$z = s + \alpha m \quad (3.7)$$

where z is the semi-simulated contaminated EEG segment, s is the clean EEG segment, m is the eye-blink segment, and α is the mixing coefficient that controls the signal-to-noise ratio (SNR) of the constructed noisy signal [145] [146]. The mixing coefficient α can be calculated using Equation 3.8:

$$\text{SNR} = 10 \log \left(\frac{\text{RMS}(s)}{\text{RMS}(\alpha, m)} \right) \quad (3.8)$$

The SNR values were considered within the range -7 dB to 2 dB to calculate α [146].

The root mean square (RMS) is given by Equation 3.9:

$$\text{RMS}(s) = \sqrt{\frac{1}{n} \sum_{i=1}^n s_i^2} \quad (3.9)$$

where n is the total number of samples in the signal, and s_i represents the i^{th} sample. Four variations were created by combining these clean and eye-blink segments in different orders. Finally, these were concatenated to create a 1 min semi-simulated contaminated EEG signal. A similar procedure was also followed using the publicly available test-retest EEG dataset, where ground truth clean EEG and semi-simulated contaminated EEG signals were generated from the selected Fp2 channel of the eyes-open recording. Figure 3.3 shows the schematic representation of the steps involved in creating semi-simulated signal.

3.3 Performance Metrics

We evaluated the effectiveness of our method on both a semi-simulated single-channel EEG and real EEG signals using two well-known metrics: the relative root mean square error (RRMSE) and the correlation coefficient (CC). The RRMSE is a commonly used measure for assessing the performance of artifact removal techniques in semi-simulated

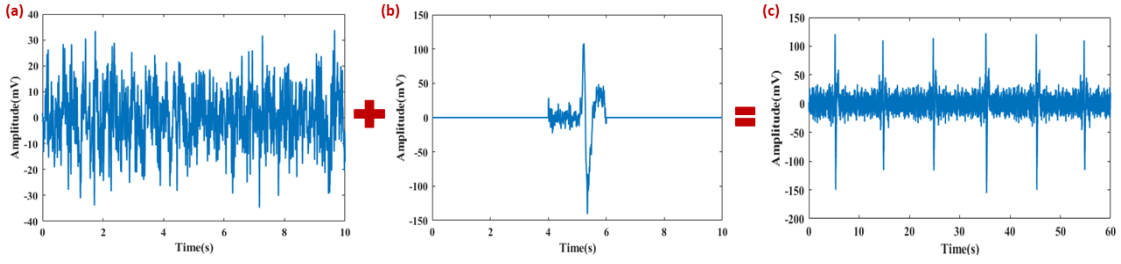


Figure 3.3: Framework for creating semi-simulated signal: (a) 10 s clean EEG segment from subject 4, (b) eye-blink, and (c) superposition of both clean EEG and eye-blink to create semi-simulated signal.

EEG data [145]. The CC, a statistical metric, reflects the relationship between two signals and is used to assess the effectiveness of the artifact removal process [145]. A higher CC value suggests a stronger linear relationship, implying better performance of the artifact removal method [145]. These metrics are calculated between the ground truth signal, which is free of eye-blink artifacts, and the artifact-cleaned signal [145] [146]. Additionally, we analyzed the average power ratio across different frequency bands and the reduction in eye-blinks [146]. This analysis involves dividing the average power of each frequency band by the overall average power of the entire signal to gauge the relative contribution of each frequency band to the total signal strength [146]. In addition to these parameters, we employed blink count estimation using an amplitude threshold technique, as detailed below.

3.3.1 Blink Count Estimation Using Amplitude Threshold

The eye-blinks in the signal are calculated using amplitude, which ensures that any large-amplitude artifacts arising from the single channel in prefrontal region can be attributed to eye-blinks or eye movements. Any signal amplitude value exceeding a threshold would be considered as an eye-blink [147]. We experimented by varying the constant parameter from 1 to 10 for Fp1 and Fp2 electrodes of three subjects. The ground truth eye-blink count from the CameraEEG [81] video data was used to validate the results obtained using the amplitude threshold method. We observed that the constant parameter of 6 matched with the ground truth eye-blink count. A minimum distance between peaks exceeding this blink amplitude threshold was used to differentiate one eye-blink from another and to avoid multiple detections of a single blink event [147]. The minimum peak distance and threshold values were varied until the expected separation and oc-

currence of eye-blinks was reached for the EEG signals used in this study. Therefore, the blink amplitude threshold used was determined as given in Equation 3.10 and the minimum distance between subsequent peaks was set at 250 ms [148].

$$\text{Blink Amplitude Threshold} = 6 \times \frac{\sum_{i=1}^n |x_i|}{n} \quad (3.10)$$

where x is the amplitude of the signal at sample number i with total sample points n .

The eye-blinks are counted in this manner for the single channel EEG data before and after application of E-ASR. The large amplitude artifacts were calculated for each subject (Fp1 and Fp2). The percentage reduction in artifacts was calculated as given in Equation 3.11.

$$\text{Percentage reduction} = \frac{\text{Before ASR} - \text{After ASR}}{\text{Before ASR}} \times 100 \quad (3.11)$$

3.4 Results

3.4.1 Results with Semi-Simulated Single Channel EEG Signal

Figure 3.4 presents the superimposed plots of the semi-simulated contaminated EEG, the E-ASR-cleaned signal, and the ground truth signal obtained using the proposed approach. As seen in Figure 3.4.b, the application of E-ASR significantly reduces eye-blink artifacts in the contaminated EEG. When E-ASR was applied to the semi-simulated signal, it achieved an RRMSE of 43.87% and a CC of 0.91. To compare our method with the state-of-the-art ASR algorithm, a separate semi-simulated dataset was created by forming a two-channel signal. The standard ASR was applied to this two-channel data, and its performance on the first channel yielded an RRMSE of 56.82% and a CC of 0.85. To evaluate the spectral performance of the method, we analyzed the average power distribution across standard EEG frequency bands after eyeblink artifact removal, as shown in Table 3.1. These bands included delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz), covering the entire 0.5–100 Hz range. In addition, eye-blink counts were estimated using Equation 3.10. The semi-simulated contaminated EEG contained six eye-blinks, all of which were successfully removed by E-ASR.

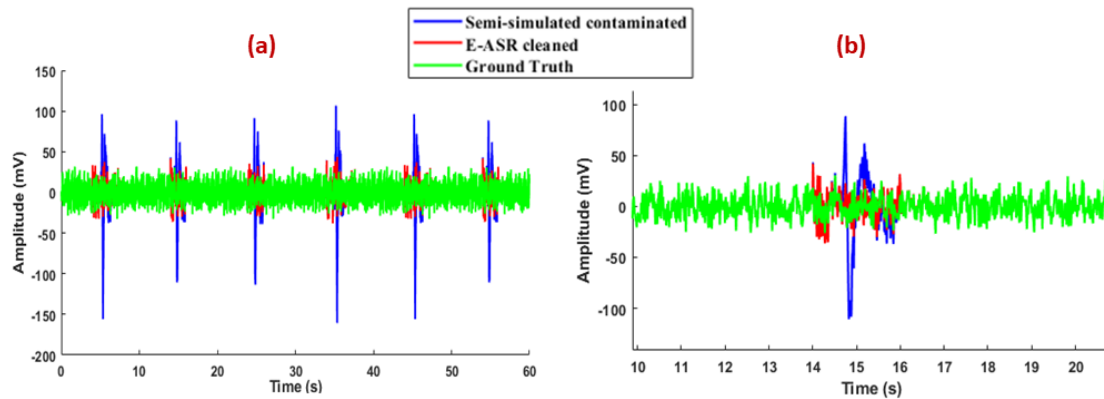


Figure 3.4: The superposition plots of semi-simulated contaminated EEG, E-ASR-cleaned, and ground truth signal using the proposed algorithm: (a) plot for 1 min time duration signal; (b) zoomed version of (a) showing one eye-blink.

Table 3.1: Average power distribution of EEG frequency bands for semi-simulated contaminated signal, ground truth, and E-ASR-cleaned signal.

Frequency Bands	Contaminated EEG	E-ASR-Cleaned EEG	Ground Truth EEG
Delta (0.5–4 Hz)	0.63	0.21	0.23
Theta (4–8 Hz)	0.14	0.14	0.15
Alpha (8–13 Hz)	0.04	0.10	0.10
Beta (13–30 Hz)	0.15	0.44	0.41
Gamma (30–100 Hz)	0.04	0.12	0.10

3.4.2 Results with Real EEG Signals

In contrast to simulated signals, where the original underlying signal is known, real EEG data does not provide an explicit ground truth. To evaluate the performance of our method in this context, we manually selected artifact-free portions from the 5-minute eyes-open recordings and concatenated them to form a 1-minute clean artifact-free signal. The effectiveness of the proposed E-ASR method was then assessed by computing the RRMSE and CC between this clean signal and its E-ASR-processed counterpart, as summarized in Table 3.2. The results indicate that the method reliably yields high correlation values (with CC close to 0.9) and maintains acceptable error margins (RRMSE) across all subjects and channels. Additionally, the average power ratio between the artifact-free and E-ASR-cleaned signals for each subject is presented in Figure 3.5.

The proposed E-ASR framework was also evaluated on the OpenNeuro test-retest dataset [141]. Semi-simulated contaminated EEG signals and corresponding ground truth clean EEG signals were generated from the Fp2 channel of the eyes-open record-

3. Development of an Electroencephalogram Artifact Reduction Algorithm for Smartphone Applications using Single Channel

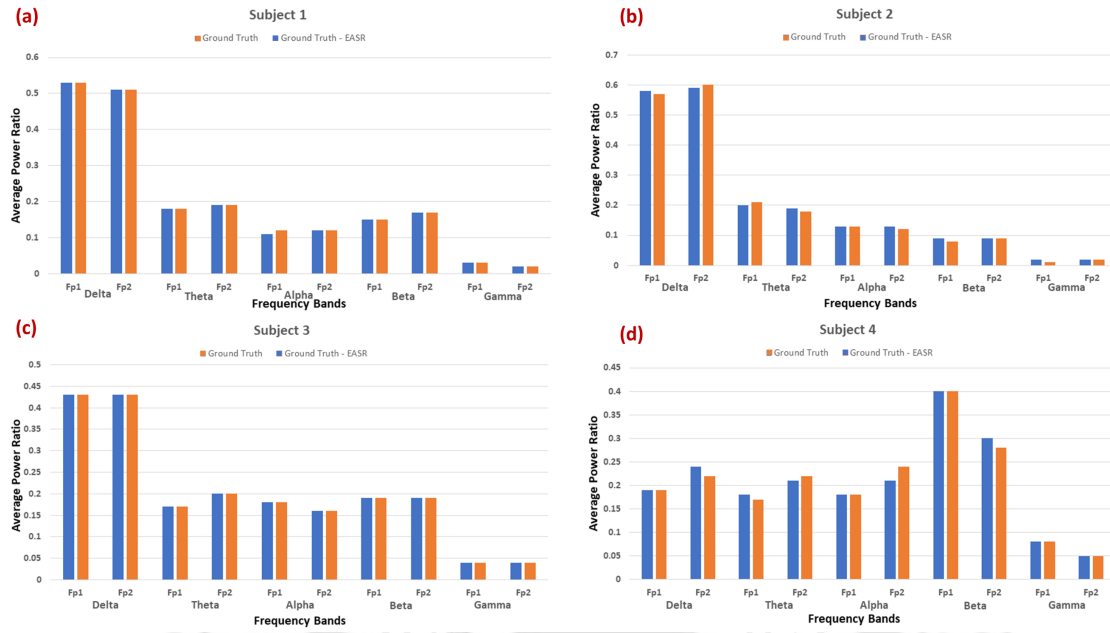


Figure 3.5: Comparison of average power ratio between the artifact-free signal and its E-ASR-cleaned version for all subjects. The E-ASR algorithm successfully restored the power distribution across the EEG spectrum for each subject.

ing of Subject 1 following the same procedure described previously. Figure 3.6 illustrates the comparison between the semi-simulated contaminated signal, the E-ASR-cleaned signal, and the ground truth signal. The proposed framework achieved a correlation coefficient (CC) of 0.84 and an RRMSE of 54.77%, demonstrating the effectiveness of E-ASR on an independent dataset.

We sought to evaluate the performance of the proposed EASR algorithm against the original ASR algorithm. The 24-channel data we originally collected was cleaned by the ASR algorithm. In contrast, for the application of E-ASR, a single channel was used

Table 3.2: RRMSE and CC between the artifact-free signal and its E-ASR-cleaned version.

Subject	Channel	RRMSE (%)	CC
1	Fp1	41.06	0.91
	Fp2	38.72	0.92
2	Fp1	47.37	0.88
	Fp2	52.07	0.86
3	Fp1	46.26	0.89
	Fp2	45.98	0.89
4	Fp1	43.53	0.90
	Fp2	40.45	0.91

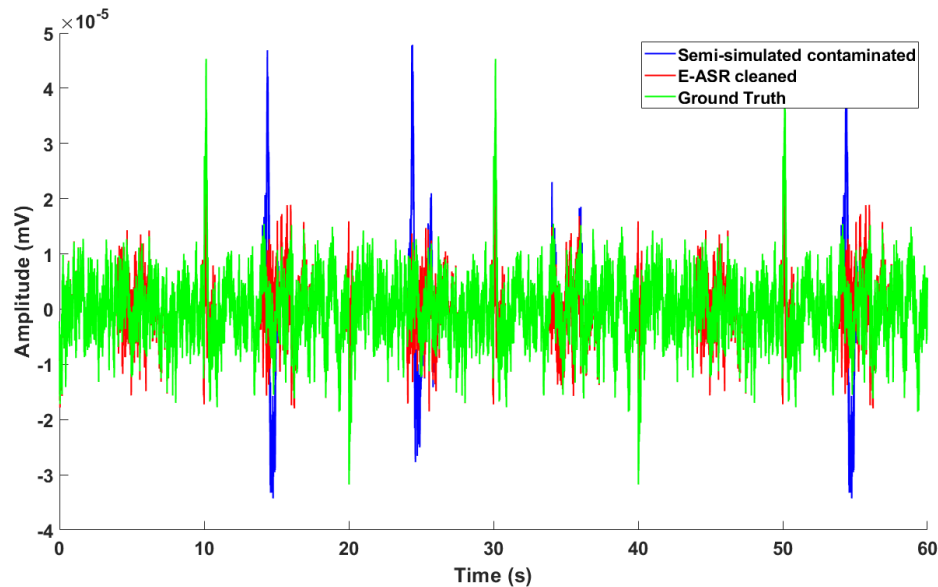


Figure 3.6: Comparison between the semi-simulated contaminated signal (blue), E-ASR-cleaned signal (red), and ground truth signal (green) for the test-retest dataset.

from the 24-channel montage. The ASR-cleaned Fp1 and Fp2 channels were considered for the time domain comparison with the proposed EASR algorithm in Figure 3.7. Eye-blinks exhibit a distinctive peak that becomes evident in time-domain EEG signals. Notably, the distinct peaks corresponding to eye-blinks in the signal are eradicated after the application of E-ASR. Table 3.3 presents the number of eye-blinks recorded before and after the application of E-ASR for each subject. All subjects demonstrated a complete elimination of eye-blinks following E-ASR. The computational time reflects the duration taken for processing, varying slightly among subjects. Also, the generality of the framework is shown by considering different sampling frequency and electrode locations (Appendix 1: Tables A.1 and A.2).

To illustrate the impact of applying E-ASR to a single channel, topographic plots were generated at a specific time point during which the subject exhibited an eye-blink. Figure 3.8A illustrates that in the absence of ASR application, distinct high-amplitude peaks (dark red regions) were observed in the prefrontal region from eye-blinks [149]. Upon applying single-channel E-ASR to Fp1, the resulting ASR-cleaned channel was used in the 24-channel EEG configuration for the purpose of generating topographic plots. The associated scalp map in Figure 3.8B demonstrates the successful removal of the blink artifact from Fp1. However, Fp2 continued to have blink-related activity. E-

3. Development of an Electroencephalogram Artifact Reduction Algorithm for Smartphone Applications using Single Channel

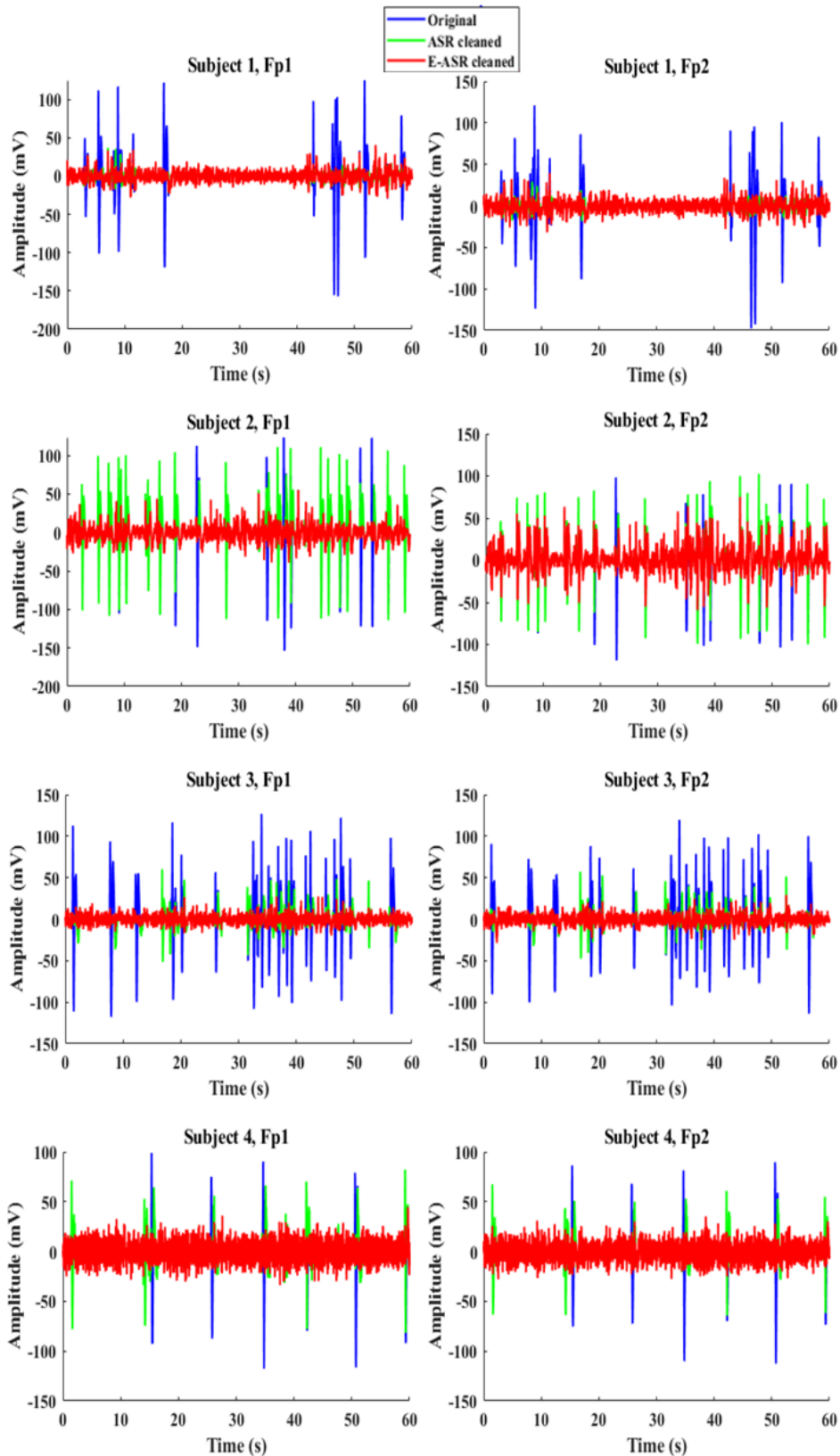


Figure 3.7: Time-domain comparison of original (blue), ASR-cleaned (green), and E-ASR-cleaned (red) on Fp1 and Fp2 channels across all subjects.

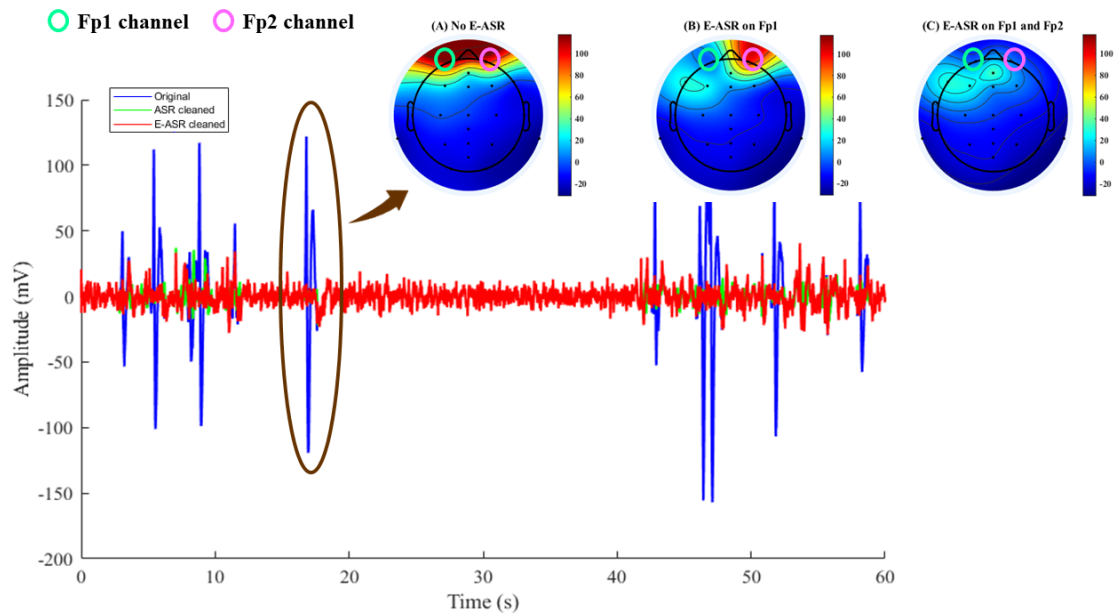


Figure 3.8: Spatial distribution of source activities at an eye-blink time point for (A) no E-ASR, (B) E-ASR only applied on Fp1, and (C) E-ASR applied on Fp1 and Fp2 channels of subject 1. Red indicates the presence of an eye-blink artifact whereas blue indicates the absence. The green circle indicates the location of Fp1 electrode and pink indicates the location of Fp2 electrode.

ASR was also independently applied on both Fp1 and Fp2 electrodes, and we observed effective elimination of the eye-blink activity, as depicted in Figure 3.8C. This suggests that the single-channel E-ASR framework is reasonably effective in removing artifact content.

To further evaluate the robustness of the proposed framework under motion conditions, the E-ASR algorithm was applied to walking EEG data containing motion-related

Table 3.3: Change in number of eye-blinks before and after E-ASR on 1 min single-channel real EEG data for all subjects. Their computational time is also reported.

Subject	Channel	Eye-Blinks Before	Eye-Blinks After	Percentage Reduction (%)	Time (s)
1	Fp1	9	0	100	5.2
	Fp2	9	0	100	4.9
2	Fp1	8	0	100	5.3
	Fp2	4	0	100	5.3
3	Fp1	14	0	100	5.6
	Fp2	16	0	100	5.4
4	Fp1	7	0	100	4.7
	Fp2	7	0	100	4.5

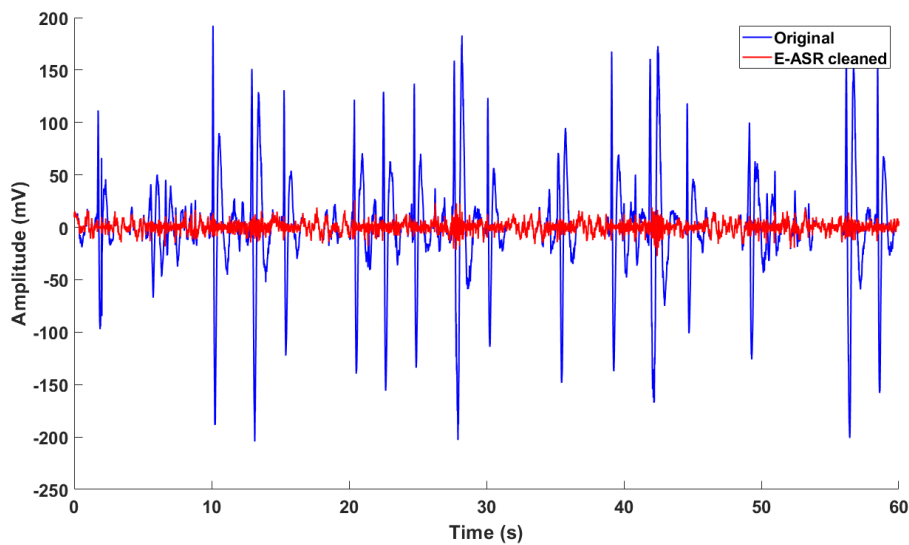


Figure 3.9: Time-domain comparison between the original walking EEG signal (blue) and the E-ASR-cleaned signal (red) during walking conditions.

artifacts. Figure 3.9 shows the comparison between the original walking EEG signal and the E-ASR-cleaned signal. The proposed framework was able to substantially reduce motion-related artifacts while preserving the underlying EEG activity.

3.5 Discussion

The proposed framework aims to evaluate the efficacy of a novel Embedded Artifact Subspace Reconstruction (E-ASR) for artifact removal in single-channel EEG data. This approach is based on the concept of dynamical embedding, originally introduced for single-channel ICA to separate ocular artifacts [142]. This idea was extended to create an embedding matrix from single-channel EEG data for implementing the artifact subspace reconstruction algorithm. Although ASR has been effectively utilized in multichannel EEG applications on Android smartphones, the current study focuses on extending its utility to single-channel EEG recordings. The framework's performance was examined using established evaluation criteria such as RRMSE, CC, average power ratio, and the percentage reduction of eye-blinks. For this implementation, an embedding dimension of 90 and a time lag of ($L = 1$) were used, following previous studies [139] [150].

The application of the E-ASR algorithm onto semi-simulated EEG data exhibited highly promising results (Figure 3.4). The algorithm achieved complete removal of

eye-blink artifacts, reflected by an RRMSE of 43.87% and a high CC of 0.91. These metrics indicate that the E-ASR method not only effectively eliminates artifacts but also preserves critical features of the underlying EEG signal, which is essential for ensuring signal fidelity. To compare its performance with the state-of-the-art ASR algorithm, a two-channel semi-simulated dataset was generated. ASR was applied to this dataset, and its performance was evaluated by calculating the RRMSE and CC for the first channel of the ASR-cleaned data. This resulted in a higher RRMSE of 56.82% and a lower CC of 0.85. These comparative results highlight the superior performance of E-ASR in achieving a better trade-off between artifact elimination and signal preservation. Direct comparison of RRMSE values with previously reported studies is challenging because EEG datasets, artifact characteristics, preprocessing pipelines, and evaluation methodologies often differ substantially across studies.

Minor discontinuities can be observed near the reconstructed blink boundaries in Figure 3.4. These effects may arise both from the E-ASR reconstruction process and from the construction of the semi-simulated dataset itself. Specifically, the isolated eye-blink artifacts were extended using zero-padding and combined with replicated clean EEG segments, which may introduce abrupt transitions near segment boundaries. In addition, the anti-diagonal averaging reconstruction employed in the proposed method does not explicitly enforce continuity constraints, which may further contribute to slight boundary mismatches between the reconstructed and ground-truth signals. In continuous EEG applications, such discontinuities could potentially introduce abrupt transitions if not appropriately smoothed. Therefore, the absence of continuity-preserving reconstruction and smoothing mechanisms remains a limitation of the present framework, which may affect signal smoothness near reconstructed artifact boundaries.

Eye-blink artifacts primarily affect the lower-frequency EEG components (0-12 Hz) [134] [148], typically resulting in an increased power concentration within the delta band and a subsequent reduction in power across other frequency ranges. This pattern was observed upon introducing eye-blink artifacts into the semi-simulated EEG signal. Nonetheless, the E-ASR algorithm successfully reestablished the original power distribution across the EEG spectrum, as detailed in Table 3.1. Notably, the cleaned signal's power across delta, theta, alpha, beta, and gamma bands showed close correspondence with the ground truth, demonstrating that E-ASR effectively counteracts

the spectral distortion introduced by eye-blinks while preserving the native frequency structure of the EEG data.

Evaluating artifact removal techniques on real EEG data is inherently difficult due to the absence of a clearly defined ground truth. To overcome this limitation, we manually compiled a one-minute clean signal by selecting artifact-free portions from the EEG recordings. A semi-simulated dataset was constructed using artifact-free real EEG segments and manually extracted eye-blink artifacts to enable quantitative evaluation with a known ground truth. This manually constructed signal was then compared with its E-ASR-processed counterpart to assess performance. We used RRMSE and CC to quantify the performance of our method. The results, with a mean RRMSE of 44.43% and a CC of 0.89 (from Table 3.2), demonstrate that the proposed E-ASR algorithm performs consistently well in preserving the underlying signal characteristics while effectively reducing artifacts. Publicly available eye-blink EEG datasets can further facilitate benchmarking and comparison across studies. Accordingly, the proposed framework was also evaluated on a publicly available test-retest EEG dataset using the same semi-simulated signal generation procedure. The results obtained on the test-retest dataset demonstrated a CC of 0.84 and an RRMSE of 54.77%, indicating that the proposed E-ASR framework maintains effective artifact suppression capability even when applied to an independent dataset acquired using a different EEG configuration.

The proposed E-ASR framework also inherits an important limitation of the original ASR algorithm, namely the requirement for relatively clean or minimally contaminated EEG reference segments for calibration. Previous ASR studies similarly recommended recording an artifact-free EEG segment prior to the experimental session for reliable calibration. In highly naturalistic or high-motion recording environments, however, obtaining sufficiently clean reference data may not always be feasible, which could influence artifact detection and reconstruction performance. To further evaluate robustness under naturalistic conditions, the proposed E-ASR framework was additionally tested during walking conditions containing motion-related artifacts (Figure 3.9), where the algorithm demonstrated the capability to reduce motion contamination in the EEG recordings. For calibration, a relatively clean 1-minute standing EEG recording was acquired prior to the walking experiment and used as the reference segment for E-ASR processing. These findings suggest that the embedding-based ASR framework remains reasonably robust

under moderate movement conditions. However, the proposed E-ASR framework still inherits an important limitation of the original ASR algorithm, namely the requirement for relatively clean or minimally contaminated EEG reference segments for calibration. In highly dynamic environments with severe motion artifacts or continuously contaminated EEG recordings, obtaining sufficiently clean calibration data may not always be feasible, which could affect artifact detection and reconstruction performance. Moreover, the robustness of the proposed framework under such highly challenging recording conditions remains a limitation of the present study.

In real EEG recordings, eye-blink artifacts exhibit greater variability and complexity, making their removal more difficult. Nevertheless, the E-ASR algorithm showed strong performance on real EEG data (Figure 3.7), effectively eliminating the distinct peaks associated with eye-blinks. This indicates that E-ASR is well-suited to manage the dynamic nature of eye-blink artifacts in practical settings, reinforcing its real-world applicability. The algorithm's effectiveness is further validated by the complete removal of eye-blink artifacts, with a 100% reduction observed across all subjects (Table 3.3). Eye-blinks are particularly problematic in EEG analysis, as they can obscure the brain activity of interest. Our results not only confirm the robustness of E-ASR in mitigating such artifacts but also highlight its potential utility in improving the quality of EEG data for subsequent analyses, such as event-related potential studies and assessments of brain connectivity.

Applying the E-ASR algorithm to 1-minute segments of real EEG data resulted in a complete elimination (100%) of eye-blink artifacts, as shown in Table 3.3. Although we have not yet conducted a real-time implementation, we have reported the algorithm's average computational time on a desktop system, which was approximately 5.14 seconds for each 1-minute EEG segment. While the original ASR algorithm processes similar data slightly faster at the same sampling frequency, it is not suitable for single-channel EEG, unlike E-ASR. The additional computation time in E-ASR is mainly due to the embedding and reconstruction stages. Despite this, the algorithm offers a favorable trade-off between artifact removal performance and processing time, making it a practical tool for improving EEG signal quality without major loss of meaningful information.

Furthermore, comparing the performance of E-ASR with the conventional ASR algorithm offered important insights into the strengths of our approach. While ASR demon-

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strated some effectiveness in cleaning the EEG data, the persistence of eye-blink activity in Figure 3.7 after its application highlights the limitations of conventional methods. In contrast, the E-ASR algorithm's ability to fully eliminate eye-blinks from both Fp1 and Fp2 channels illustrates its superior capacity for artifact removal. This is further supported by the topographic maps in Figure 3.8, which show a noticeable reduction in high-amplitude activity in the prefrontal region following E-ASR application. These results not only confirm the efficacy of our method but also underscore its potential utility in both clinical diagnostics and neuroscience research. By preserving meaningful brain signals during blink events, E-ASR may enhance the interpretability of EEG recordings and contribute to more reliable cognitive and clinical evaluations.



4

Designing a Pipeline for Implementing Machine Learning Classifier on an Android Smartphone Application

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4.1 Introduction

With the increasing demand for cognitive state monitoring in naturalistic settings, mobile EEG systems have evolved from laboratory extensions into smartphone-integrated EEG classification platforms. This chapter explores the growing trend toward smartphone-based EEG classification, with a particular focus on approaches that eliminate cloud dependency by executing machine learning algorithms directly on the smartphone.

The monitoring of brain activity beyond controlled laboratory settings has attracted increasing interest in recent years due to the rising need for portable, user-friendly, and privacy-conscious neurotechnology solutions. Smartphones combined with wireless electroencephalogram (EEG) systems have become promising tools for evaluating cognitive states because of their widespread availability, computational capabilities, and ability to function without external computing resources. Mobile EEG platforms, including systems such as the Smartphone Brain Scanner, have demonstrated that advanced neural imaging tasks, including three-dimensional source reconstruction, can be performed on commonly available handheld devices, thereby enabling applications in neurofeedback and real-world neuroscience research [42]. In addition, portable EEG technologies have facilitated the assessment of attention and engagement in educational settings [151], as well as vigilance monitoring in transportation environments, contributing to safer and more adaptive real-world interventions [152]. Furthermore, performing EEG analysis directly on the device instead of transmitting data to cloud-based systems minimizes latency, enhances data privacy, and ensures continuous operation even in the absence of internet connectivity [153].

One of the most basic and extensively investigated EEG-based applications is the classification of eye states, specifically eyes open (EO) and eyes closed (EC). These two conditions exhibit characteristic neural activity patterns and are commonly employed as baseline states in neurophysiological research studies [154] [155]. Accurate real-time detection of EO and EC states has important practical applications, including identifying driver fatigue or drowsiness [156] [157], enabling adaptive learning approaches in educational environments [158] [159], and supporting neurofeedback-based training systems [160]. Implementing such classification directly on a mobile device provides several advantages, including improved portability, the ability to acquire data in real-world

settings, reduced dependence on cloud-based infrastructure, and enhanced protection of user privacy, which is particularly important when handling sensitive physiological information.

The integration of smartphones with wireless EEG headsets has facilitated the expansion of cognitive research beyond traditional laboratory settings [15] [161]. More recently, smartphone-based EEG applications have attracted considerable attention for their capability to perform real-time monitoring and analysis of brain activity [42] [67]. Such systems create opportunities for assessing cognitive conditions, including attention and engagement, within real-world and naturalistic environments. Nevertheless, a large number of these approaches still rely on cloud-based computation or offline data analysis, leading to increased latency, dependence on uninterrupted internet connectivity, and potential concerns regarding user privacy and data security [162].

Building upon these advancements, several researchers have proposed mobile EEG systems employing diverse processing frameworks. Many of these approaches utilize cloud-based computation to handle computationally intensive operations. For example, Lasefr et al. developed a smartphone application for epileptic seizure detection that performs EEG classification through cloud processing and delivers real-time outputs using wireless internet connectivity [163]. Likewise, a study published in 2020 presented a wearable sensing system for the early detection of epileptic activity, where EEG data are transmitted to a smartphone and analyzed using machine learning algorithms hosted on a cloud platform. When preictal conditions are identified, the system automatically issues an emergency SMS alert to facilitate prompt medical assistance [164].

Several other studies have aimed to minimize reliance on external computing resources and expert intervention. Tran et al. proposed a framework for human activity recognition in which smartphones collected sensor data that were subsequently transmitted to a computer for Support Vector Machine (SVM) model training, while the classification results were returned to the smartphone, thereby demonstrating a hybrid mobile–remote processing architecture [165]. Koushik et al. developed a smartphone-integrated single-channel EEG system capable of performing real-time sleep stage classification using deep learning techniques, providing a more accessible substitute for conventional polysomnography (PSG) [67]. In another study, Ma et al. introduced a smartphone-assisted sleep apnea diagnosis framework utilizing pulse oximetry and

SVM-based analysis, although the approach continued to depend on cloud computing resources [166]. To overcome these limitations, Adi et al. designed an on-device deep learning framework for human activity recognition (HAR), employing Long Short-Term Memory (LSTM) networks to classify sensor data directly on smartphones without requiring cloud-based processing [167].

More recently, research has shifted toward fully embedded on-device EEG solutions. Mai et al. proposed an emotion recognition framework based on ear-EEG signals and machine learning techniques, where EEG data are processed locally on an embedded TinyML device while a companion smartphone application presents the results and notifies users about negative emotional conditions [168]. In another development, Blum et al. introduced the SCALA application, which enables EEG signal acquisition directly on Android smartphones [46]. Similarly, applications such as AFEx and Record-a work alongside the Smarting app to facilitate EEG data collection [28]. Furthermore, Bateson et al. developed the io:bio system for recording event-related potentials (ERPs) during both seated and walking activities, demonstrating the adaptability of mobile EEG technologies across varying conditions [48]. The CameraEEG Android application additionally enables integrated multimodal experimentation through synchronized acquisition of EEG signals and video recordings (refer to chapter 2).

Most currently available smartphone-based EEG systems depend on cloud-based computation, which can reduce system autonomy, introduce processing delays, and create concerns regarding data privacy. In contrast, the proposed work performs EEG classification entirely on the mobile device by integrating Support Vector Machine (SVM) models implemented using TensorFlow Lite, thereby enabling complete on-device operation. This approach advances mobile autonomy and presents a novel implementation framework for deploying classical machine learning models directly on smartphones.

The TensorFlow Lite pipeline has mainly been utilized for deploying deep learning models in applications such as voice activity detection [71], diabetic retinopathy screening [72], and skin disease classification [169]. Nevertheless, its use with traditional machine learning methods has remained relatively limited. To address this gap, we propose a novel workflow that combines a Support Vector Machine (SVM) model with TensorFlow Lite for efficient on-device EEG classification. Since EEG signals capture underlying brain activity and provide meaningful information about cognitive states, this framework

has potential applications in areas such as human–computer interaction, driver monitoring and safety, and educational technologies. By supporting efficient EEG processing directly on mobile devices using a minimal number of electrodes, the proposed approach enables practical real-time monitoring in diverse real-world environments while maintaining user privacy and convenience.

4.2 Methodology

4.2.1 Data Description

Prior to EEG data acquisition from human participants, ethical clearance for the study was granted by the Institute Ethics Committee. The experiment included ten healthy right-handed volunteers, of whom three were female. Only right-handed participants were recruited to maintain sample consistency and reduce inter-subject variability associated with hemispheric asymmetry [170]. Although visual processing in occipital regions is typically bilateral and only minimally affected by handedness, restricting participation to right-handed individuals is a commonly adopted practice in EEG research to improve reproducibility. Despite the relatively small cohort size ($n = 10$), this pilot investigation establishes the feasibility of the proposed methodology and serves as a basis for future large-scale studies. The participants had a mean age of 25.9 ± 3.36 years, ranging from 20 to 31 years, and none reported any visual or auditory impairments.

During the experimental sessions, participants remained seated in a relaxed resting position inside an empty classroom environment. EEG recordings were collected under two conditions: a 4-minute eyes-closed (EC) session followed by a 4-minute eyes-open (EO) session. The choice of these experimental paradigms was motivated by established neurophysiological findings demonstrating increased alpha-band oscillatory activity within occipital and visual cortical regions during the eyes-closed state [171] [172]. This clear neurophysiological distinction provides a reliable basis for developing and evaluating the proposed classification framework.

EEG signals were recorded using the EasyCap RBE-24 cap together with the Smarting amplifier developed by mBrainTrain, operated through the CameraEEG Android application (refer to chapter 2). The EasyCap RBE-24 cap contains 24 electrodes positioned according to the international 10-20 electrode placement system, enabling re-

4. Designing a Pipeline for Implementing Machine Learning Classifier on an Android Smartphone Application

liable EEG acquisition for both clinical and research purposes. The Smarting amplifier is a research-grade EEG acquisition system featuring 24-bit resolution, high input impedance, and low intrinsic noise characteristics. Owing to its compact design and portability, the device is suitable for both laboratory-based experiments and real-world field studies. EEG signals were sampled at a frequency of 500 Hz.

4.2.2 Data Preprocessing

For the purpose of single-channel EEG classification, the occipital electrode O2 was chosen for analysis. The complete workflow of the proposed approach is illustrated in Figure 4.1. To enhance signal quality and enable the extraction of meaningful discriminative features, the raw EEG recordings were preprocessed using the Embedded Artifact Subspace Reconstruction (E-ASR) technique (Refer to chapter 3). The E-ASR method suppresses artifacts in single-channel EEG signals by forming an embedded matrix through delay-coordinate vectors, thereby making it possible to apply the Artifact Subspace Reconstruction (ASR) framework [55], which is traditionally designed for multichannel EEG recordings. This preprocessing stage is important to ensure that the subsequent machine learning model is trained using artifact-reduced neural signals. All preprocessing operations were carried out in MATLAB R2021a (<https://www.mathworks.com/products/matlab.html>), as illustrated in Figure 4.1.

From five minutes of E-ASR-processed eyes-open and eyes-closed EEG record-

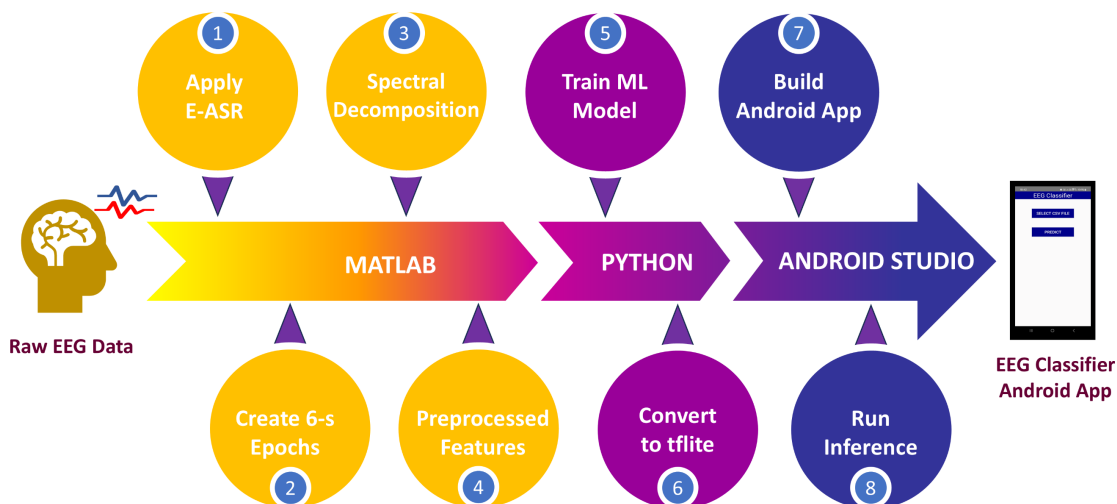


Figure 4.1: Schematic of the proposed pipeline for incorporating a machine learning model into an Android app with TensorFlow Lite.

ings, six-second epochs were segmented following the procedure described by Hohaia et al. [104], who examined alpha-band activity under EO and EC conditions. The power spectral density (PSD) of each epoch was then estimated using the MATLAB 'pwelch' function to analyze the distribution of signal power across frequency bands. This spectral representation enables effective differentiation between EO and EC conditions, particularly within the alpha frequency range, which demonstrates significant modulation between the two states.

The dataset was balanced and consisted of 40 EO trials and 40 EC trials per participant, ensuring equal representation of both classes. Each trial contained 513 PSD-based features corresponding to different EEG frequency bins. These features captured the spectral properties of neural activity and reflected variations associated with cognitive and eye states. To maintain data consistency and reliability, artifacts and noise were reduced during the E-ASR preprocessing stage. For classification, PSD features extracted from the eyes-open condition were assigned the label 0, whereas features from the eyes-closed condition were assigned the label 1.

4.2.3 Support Vector Machine for EEG Signal Classification

SVMs, proposed by Boser et al. [173] in 1992, stand out as a powerful supervised learning algorithm. Their versatility allows them to excel in both classification tasks, where data points are categorized, and regression tasks, where continuous values are predicted. SVMs achieve this by meticulously identifying an optimal separation boundary, known as a hyperplane, that divides data points belonging to distinct classes [174]. This hyperplane isn't merely a random line; SVMs are specifically designed to find the one that maximizes the margin between the closest data points from each class. The focus on maximizing the margin imbues SVMs with robustness against outliers and exceptional capability in handling high-dimensional data, making them effective even in complex scenarios. By employing SVMs, we can transform seemingly unstructured datasets into well-organized clusters, facilitating clearer analysis and accurate predictions.

The equation of a plane is given by the following Equation 4.1 [175]:

$$f(x) = wx + b \quad (4.1)$$

where, w is the weight and b is the bias.

4. Designing a Pipeline for Implementing Machine Learning Classifier on an Android Smartphone Application

Let's assume x_i represents the input features and y_i represents the class labels where $y_i \in \{-1, +1\}$. Hence the equations for hyperplanes H_1 and H_2 are given by Equations 4.2 and 4.3:

$$H_1 : w^T x + b = 1 \quad (4.2)$$

$$H_2 : w^T x + b = -1 \quad (4.3)$$

We define a hyperplane such that

$$w^T x + b \geq +1 \quad \text{when } y_i = +1 \quad (4.4)$$

$$w^T x + b \leq -1 \quad \text{when } y_i = -1 \quad (4.5)$$

Equations 4.4 and 4.5 can be combined into a single constraint as shown in Equation 4.6, where $g_i(x)$ represents the functional margin of the classifier for the i -th training instance.

$$g_i(x) = y_i(w^T x_i + b) \geq 1 \quad (4.6)$$

To find the optimal H_0 plane, we optimize the distance between H_1 and H_2 [175]. Subtracting both the planes, i.e., Equation 4.4 and 4.5, we get the distance between the two as given in Equation 4.7:

$$d = \frac{2}{\|w\|^2} \quad (4.7)$$

Hence, the optimization problem associated can be expressed as Equation 4.8:

$$f(x) = \min \frac{1}{2} \|w\|^2 \quad (4.8)$$

Also, we need to give a condition under which the optimization function should minimize i.e., given by Equation 4.6.

Hence, using Lagrangian norms, we get Equation 4.9 as

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_i^l \alpha_i g_i(x) \quad (4.9)$$

where α is the Lagrange multiplier. To find w , we have to apply

$$\frac{\partial L}{\partial w} = 0, \quad \frac{\partial L}{\partial \alpha} = 0, \quad \frac{\partial L}{\partial b} = 0 \quad (4.10)$$

By using Equation 4.10, we get

$$w = \sum_i \alpha_i y_i x_i \quad (4.11)$$

Now, putting Equation 4.11 in 4.1 we get the hyperplane Equation 4.12 as below

$$H_0 = y(x) = \sum_i \alpha_i y_i x^T x_i + b \quad (4.12)$$

where, $y(x) > 0 \Rightarrow 1$, $y(x) < 0 \Rightarrow -1$.

4.2.4 Soft Partitioning as Hyperparameter Tuning

Soft partitioning in SVM is a technique used to handle noisy datasets effectively. Unlike hard partitioning, where data points are strictly classified into one of the classes, soft partitioning allows for some degree of misclassification, known as the “soft margin” [176]. This soft margin helps to accommodate outliers or noise in the dataset, leading to a more flexible and robust classification model [177].

In SVMs, soft partitioning is implemented through the use of a penalty parameter, often denoted as C . This parameter controls the trade-off between maximizing the margin and minimizing the classification error. A larger value of C results in a smaller soft margin, meaning fewer misclassifications are allowed, while a smaller value of C results in a larger soft margin, allowing more misclassifications [178].

The objective function for soft partitioning SVM can be expressed as Equation 4.13:

$$\min_{w,b,\alpha} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l \alpha_i \quad (4.13)$$

subject to the constraints:

$$\begin{aligned} y_i(w \cdot x_i + b) &\geq 1 - \alpha_i, \quad i = 1, 2, \dots, n \\ \alpha_i &\geq 0, \quad i = 1, 2, \dots, n \end{aligned}$$

where, C is the regularization parameter. In this work, we tune the SVM classifier using different values of C to identify the optimal trade-off between margin maximization and classification accuracy, thereby improving the model's generalization performance on unseen EEG data.

4.2.5 Performance Metrics

To evaluate the model's predictive performance, we employed precision, sensitivity (recall), specificity, F1 score, and Matthews Correlation Coefficient (MCC) as key metrics [179] [180] [181]. MCC is included alongside F1 score as it provides a more bal-

anced evaluation by considering true and false positives and negatives, offering a robust measure of overall model performance [182]. Before defining these metrics, it is essential to understand the following terms: True Positives (TP) refer to the instances correctly predicted as positive by the model, False Positives (FP) are the instances incorrectly predicted as positive when they are actually negative, and False Negatives (FN) are the instances incorrectly predicted as negative when they are actually positive. These metrics are calculated as follows:

- **Precision:** It measures the accuracy of positive predictions, calculated as Equation 4.14 below:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4.14)$$

Precision reflects the proportion of correctly identified positive instances out of all instances predicted as positive.

- **Sensitivity (Recall):** It assesses the model's ability to identify all relevant instances and is calculated as Equation 4.15:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (4.15)$$

Sensitivity indicates the proportion of actual positive instances that the model successfully identifies.

- **Specificity:** It assesses the model's ability to correctly identify negative instances and is calculated as Equation 4.16:

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (4.16)$$

Specificity indicates the proportion of negative instances that the model successfully identifies.

- **F1 Score:** The harmonic mean of precision and sensitivity, used to balance these two aspects, especially when there is an uneven class distribution. It is defined as Equation 4.17:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (4.17)$$

The F1 score provides a single measure of model accuracy that considers both

false positives and false negatives.

- **Matthews Correlation Coefficient (MCC):** A balanced metric that considers all four confusion matrix components, providing a more comprehensive assessment of classification performance [182]:

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (4.18)$$

MCC (Equation 4.18) produces a value between -1 and +1, where +1 indicates perfect classification, 0 indicates no better classification than random choice, and -1 represents total disagreement between prediction and actual labels [182] [180].

4.3 Android Implementation

4.3.1 Software Description

Creating the application primarily consisted of two parts. First is training the model in Python TensorFlow, and the second is integrating the trained model within the Android application using Android Studio (Figure 4.1). The application was built using Python (Version 3.9) and Android Studio. Python TensorFlow Lite is a lightweight version of the TensorFlow framework, designed specifically for smartphone and embedded devices. It is optimized for efficient execution on these platforms, with a small binary size and low latency. TensorFlow Lite allows developers to train and deploy machine learning models on Android, iOS devices, microcontrollers and other embedded systems (<https://ai.google.dev/edge/litert>). On the other hand, Android Studio is the official integrated development environment (IDE) for Android application development, created by Google. It provides a comprehensive set of tools for developing, testing, and deploying Android apps, including a code editor, debugger, emulator, and visual layout editor (<https://developer.android.com/>). The implementation procedure consisted of two primary phases. The first phase involved training the model using Python and TensorFlow, while the second phase focused on incorporating the trained model into the Android application through Android Studio, as illustrated in Figure 4.1.

4.3.2 Integration of trained model into the Android App

In the present study, EEG recordings were obtained from ten participants. To achieve a robust evaluation across subjects, a Leave-One-Out Cross-Validation (LOO-CV) strategy was adopted, in which data from one participant were reserved for testing while the classifier was trained using data from the remaining nine participants. This process was iteratively repeated for every subject, allowing subject-specific performance analysis as well as assessment of the model's generalization capability. Within each validation fold, the classifier was trained to distinguish between eyes-open and eyes-closed conditions. After completing the validation process, the trained model was integrated into the Android application to enable on-device inference.

The Support Vector Machine (SVM) model trained in Python was later converted into a TensorFlow Lite format (.tflite) for deployment within the Android application. TensorFlow Lite models can embed metadata that includes both human-readable descriptions and machine-interpretable details, which helps in automatically generating appropriate pre-processing and post-processing workflows during on-device execution.

The integration of a .tflite model into an Android application follows several steps, as shown in Figure 4.1. Initially, an Android project is created in Android Studio, and the TensorFlow Lite dependency is added in the 'build.gradle' file. The .tflite file is then placed in the assets directory so that it is packaged within the application without compression. If required, necessary permissions such as external storage access are declared in the 'AndroidManifest.xml' file. The model is loaded using the 'Interpreter' class, which accesses the .tflite file from the 'assets' folder. Input data are then reshaped to match the model's expected input dimensions, and inference is carried out through the Interpreter instance, with the outputs subsequently processed according to application-specific requirements. Finally, the application is tested across different devices and optimized using hardware acceleration to enhance execution efficiency.

4.3.3 Android Application for Brain State Prediction

The developed Android application offers a simple and user-friendly interface for classifying eye states (eyes open or eyes closed) from preprocessed EEG signals. It enables users to load EEG recordings, execute on-device prediction using the embedded Sup-

port Vector Machine (SVM) model converted with TensorFlow Lite, and view the predicted class along with the corresponding inference time. The graphical user interface (GUI) of the EEG Classifier application is shown in Figure 4.2. The design prioritizes ease of use for experiments conducted in natural environments, allowing EEG-based inference and result interpretation directly on the device without relying on external computing resources. A detailed description of the implementation and interface workflow is included in the accompanying Help File.

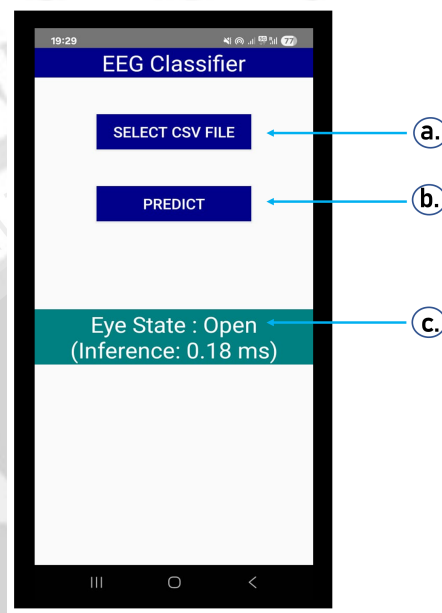


Figure 4.2: Graphical user interface of the EEG Classifier app; (a) button for selecting CSV file, (b) predict button, and (c) display area showing the predicted eye state along with the inference time.

4.4 Results

4.4.1 Classification Results

Hyperparameter tuning was performed to investigate how changes in the regularization parameter (C) affect the performance of the single-channel SVM classifier, as shown in Figure 4.3. This evaluation systematically explores multiple values of (C) to determine the setting that yields the highest classification accuracy. The regularization parameter plays an important role in controlling model complexity, reducing the risk of overfitting, and improving generalization to unseen data. The results show that increasing C from 10^{-6} to 10^{-3} improves accuracy from 60% to 90%, indicating that very low regularization restricts performance, while moderate regularization enhances it. However, further in-

4. Designing a Pipeline for Implementing Machine Learning Classifier on an Android Smartphone Application

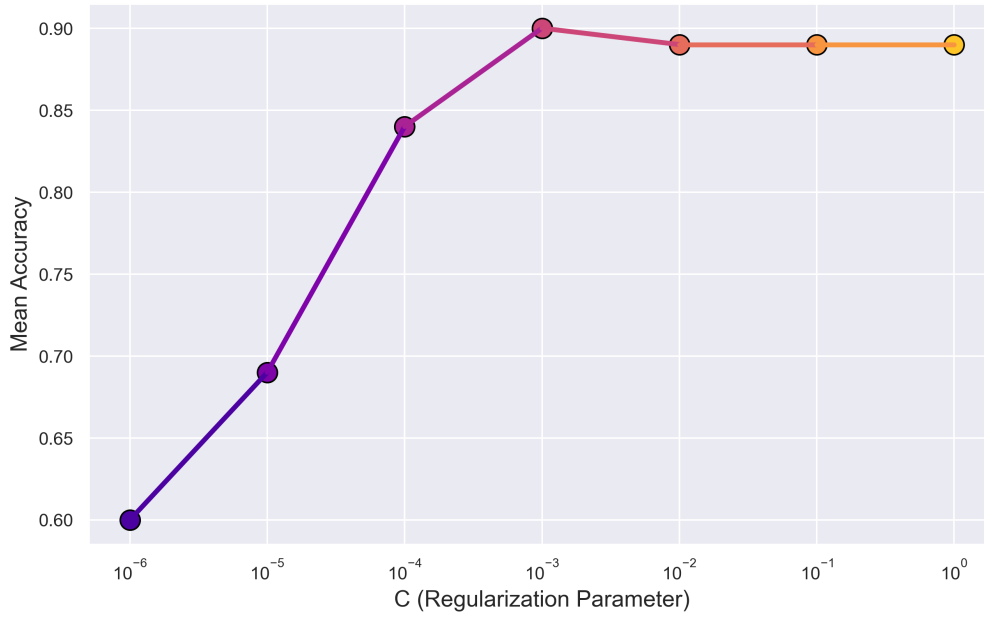


Figure 4.3: Mean accuracy of the single-channel SVM classifier as a function of the regularization parameter C . Accuracy rises up to 0.90 for $C = 10^{-3}$ and remains stable thereafter.

creasing (C) beyond 10^{-3} does not lead to additional gains, suggesting that (C) = 10^{-3} is the most suitable value for this classification problem.

To assess the classifier's performance at the individual subject level, Figure 4.4 presents subject-wise confusion matrices for the model with (C) = 10^{-3} using Leave-One-Out Cross-Validation (LOO-CV). Each matrix illustrates the relationship between the actual and predicted labels for eyes-open (EO) and eyes-closed (EC) conditions across all participants. Overall, the classifier performs strongly for most subjects, with several achieving perfect classification (no misclassifications), including Subjects 3, 5, 6, 7, 8, and 9, where all 40 EO and 40 EC samples were correctly identified

However, a few subjects exhibit misclassifications. For Subject 1, 26 EC samples are incorrectly classified as EO, along with 5 EO samples misclassified as EC, indicating a notable reduction in performance for this participant. Similarly, Subject 2 shows 37 EC trials misclassified as EO, reflecting difficulty in accurately identifying the EC condition. Subjects 4 and 10 also present a small number of classification errors. Despite these isolated errors, the overall results remain strong, confirming the robustness of the classifier in distinguishing EO and EC states across individuals. These variations in performance are likely due to inter-subject differences in EEG signal characteristics.

To further examine this variability, the signal-to-noise ratio (SNR) was calculated

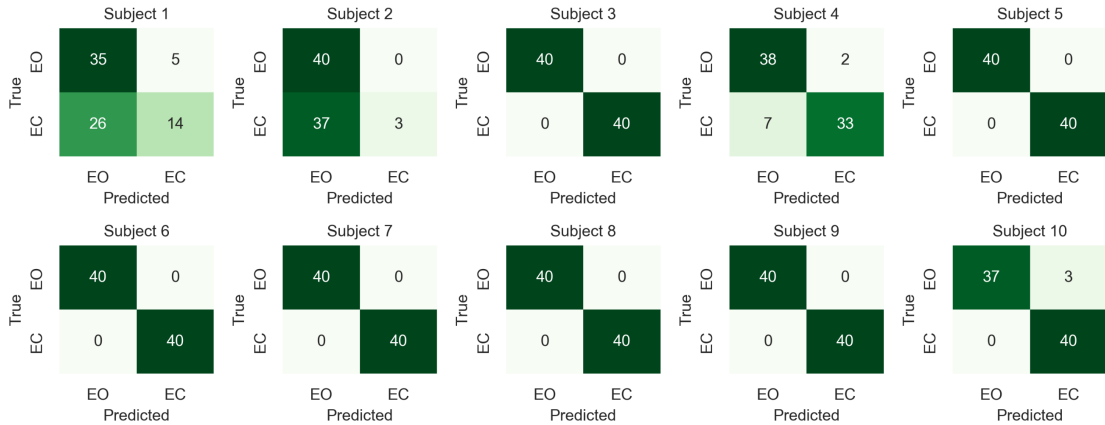


Figure 4.4: Using LOO-CV, confusion matrices were generated for each subject to show the predicted versus true labels of the eyes open (EO), and eyes closed (EC) classes for the single-channel EEG classifier. Notably, Subjects 1 and 2 exhibit relatively lower classification accuracy due to higher EC misclassifications, whereas the remaining subjects show near-perfect separation between the two classes.

for all ten subjects after E-ASR preprocessing (Table 4.1). Subjects 1 and 2 showed relatively low SNR values (22.62 dB and 18.40 dB, respectively), which is consistent with their reduced classification performance. Interestingly, some subjects with similarly low SNR values, such as Subjects 6 and 10, still achieved high accuracy, suggesting that model performance is influenced not only by overall signal quality but also by subject-specific EEG patterns and artifact structures.

Figure 4.5 illustrates the subject-wise performance of the single-channel EEG classification model evaluated using multiple statistical measures. The classifier attains perfect scores (100% accuracy, precision, sensitivity, specificity, F1-score, and MCC) for Subjects 3, 5, 6, 7, 8, and 9, indicating highly separable EEG patterns for these individuals. In contrast, noticeable performance differences are observed for Subjects 1, 2, 4, and 10. Subject 2 shows the weakest results, with an accuracy of 0.54, sensitivity of 0.07, and MCC of 0.20, reflecting a high rate of misclassification of eyes-closed (EC) samples. Subject 1 also exhibits reduced performance, with an accuracy of 0.61, sensitivity of 0.35, and MCC of 0.20, indicating difficulty in correctly identifying the EC con-

Table 4.1: Signal to noise ratio after artifact removal from raw EEG signal using EASR

Subject	1	2	3	4	5	6	7	8	9	10
SNR (dB)	-22.62	-18.40	-11.04	-18.32	-14.95	-21.83	-17.19	-16.24	-15.76	-20.44

4. Designing a Pipeline for Implementing Machine Learning Classifier on an Android Smartphone Application

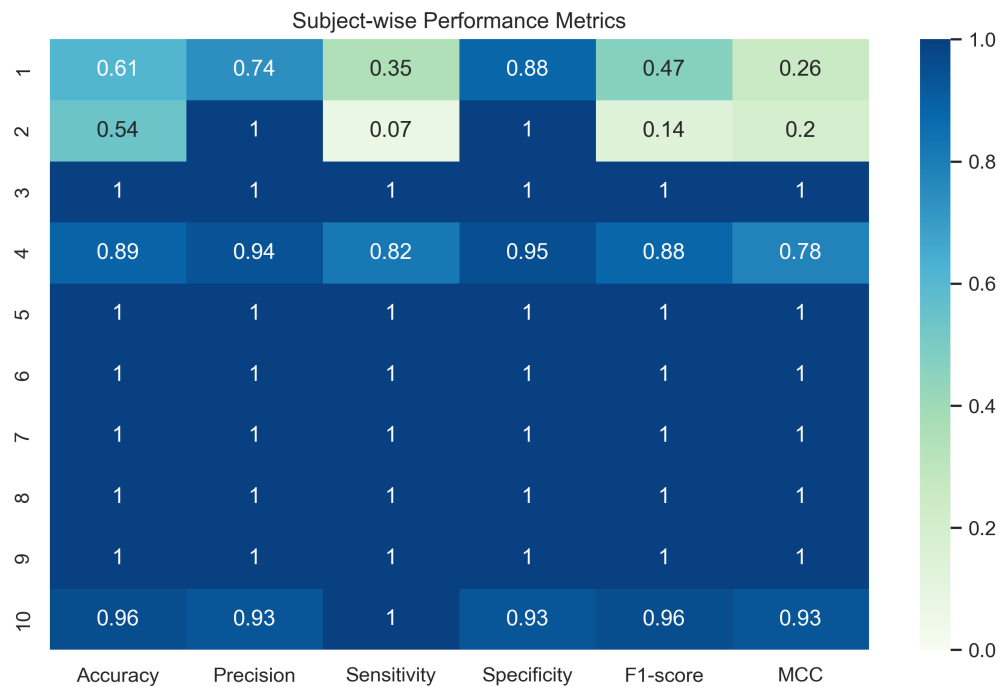


Figure 4.5: Performance metrics of the single-channel EEG classification model for each subject were assessed LOO-CV. Subjects 1 and 2 show lower metric values, indicating classification difficulties due to higher variability in EEG signals, while the remaining subjects demonstrate near-perfect performance across all metrics.

dition. Subject 4 performs comparatively better, achieving 0.89 accuracy, though slight reductions in precision (0.94) and F1-score (0.88) occur due to a small number of eyes-open (EO) samples being incorrectly labeled as EC. Subject 10 demonstrates strong overall results, with 0.96 accuracy and 0.96 F1-score, but shows marginally lower specificity (0.93) and MCC (0.93) due to minor EO misclassifications. Overall, these results confirm the strong robustness of the proposed model across most participants and support its applicability for on-device deployment in resource-constrained mobile environments. The variability observed between subjects is likely due to individual differences in EEG signal characteristics, particularly during the eyes-closed state, suggesting that incorporating subject-specific calibration or adaptation could further improve generalization performance.

To further justify the selection of the SVM classifier, a comparative evaluation was performed across multiple classical machine learning models within the proposed framework. Table 4.2 summarizes the overall classification accuracy of each method along with its deployment feasibility in the Android integration pipeline. Among all tested models, SVM delivered the best deployable performance (90%), highlighting its effectiveness

Table 4.2: Evaluation of machine learning models for suitability in smartphone-based EEG classification, highlighting the trade-off between accuracy and deployment.

Model	Accuracy (%)	Deployable (Y/N)
Linear Discriminant Analysis (LDA)	76.25	Y
Logistic Regression	84	Y
Linear Regression	68.49	Y
Support Vector Machine (SVM)	90	Y
Random Forest	75.75	N
K-Nearest Neighbors (KNN)	100	N
XGBoost	84.37	N

for real-time on-device EEG classification. Although KNN and XGBoost achieved high accuracies (100% and 84.37%, respectively), they were not suitable for deployment due to limitations in model conversion and the inability to extract required parameters such as weights and bias terms within the TensorFlow Lite conversion workflow. On the other hand, models like Logistic Regression, LDA, and Linear Regression were successfully deployable but demonstrated comparatively lower accuracy than SVM. Overall, these findings confirm that SVM provides the best trade-off between classification performance and practical deployability on Android smartphones.

4.4.2 Integration of the trained model and system properties of the Android application

The single-channel SVM classifier was first developed and trained in Jupyter Notebook using Python 3.9 and E-ASR-preprocessed EEG recordings, achieving strong classification performance. After training, the model was converted into a TensorFlow Lite (.tflite) format and integrated into the Android application to enable fully offline classification. The developed application can classify eyes-open and eyes-closed EEG signals locally on the device using the extracted EEG features without requiring internet connectivity. The conversion of the SVM model into a tflite file and its integration within an Android app were carried out as part of B.Tech. project by Mr. Sanjay Chhaba in 2024.

During experimental evaluation, the EEG Classifier application operated reliably without crashes or stability issues. The application supports Android devices running version 5.0 or later and does not require additional external dependencies, provided that the EEG data intended for classification are stored in the device memory. Performance

testing was conducted on multiple smartphones, including high-end devices such as the Google Pixel 7 Pro and Samsung Galaxy S22, as well as a mid-range Realme 7 Pro device. Consistent and reliable operation was observed across all tested platforms, with no noticeable lag or slowdown even on the mid-range smartphone. These findings indicate that the proposed framework is suitable for deployment on both premium and mid-range Android devices, improving its practicality for real-world applications.

To further assess performance, inference time measurements were obtained on different smartphones. The average inference time was approximately 0.12 ms on the Samsung S22, 0.21 ms on the Realme 7 Pro, and 0.27 ms on the Google Pixel 7 Pro. These results demonstrate that the proposed model performs offline EEG classification with near-instantaneous prediction capability from preprocessed EEG inputs.

4.5 Discussion

Several approaches are available for incorporating a trained classification model into an Android Studio application. Model training can be performed using tools such as MATLAB Coder, Simulink, or alternatively through Python-based frameworks. However, direct integration of applications developed using MATLAB Simulink into Android Studio remains difficult because of compatibility and version-related limitations, which complicate model deployment. Consequently, machine learning and deep learning frameworks such as TensorFlow, PyTorch, and Scikit-learn are generally more suitable for Android-based applications. Considering these integration constraints, Python and TensorFlow were selected in this work due to their flexibility and better compatibility with Android deployment pipelines. For on-device inference, TensorFlow Lite was employed because it supports efficient execution on smartphones while also enabling the deployment of classical machine learning models such as SVM. This facilitates resource-efficient inference without requiring large-scale training data or cloud-based computation. Comparative analysis further revealed that deployability is equally as important as classification accuracy when designing on-device EEG systems. Although models such as KNN, Random Forest, and XGBoost achieved strong offline classification performance, they could not be successfully converted into TensorFlow Lite format because of architectural and conversion limitations. In contrast, the SVM model provided high classification accuracy

while remaining fully deployable on Android devices, thereby demonstrating its suitability for real-time mobile EEG classification. These findings emphasize the importance of considering deployment feasibility alongside predictive performance when developing smartphone-based neurotechnology systems. To evaluate on-device efficiency, inference time was measured on multiple Android smartphones. Average inference times were 0.12 ms on Samsung S22, 0.21 ms on Realme 7 Pro, and 0.27 ms on Google Pixel 7 Pro. These results demonstrate that the TensorFlow Lite-based classifier performs offline EEG classification with very low latency, enabling near-instantaneous prediction on mobile devices. Although detailed CPU, memory, and battery utilization profiling was not systematically performed in the present study, the observed inference performance indicates that the proposed framework is computationally lightweight and suitable for practical smartphone deployment.

The proposed framework enables the conversion of machine learning models into TensorFlow Lite (.tflite) format for deployment within Android applications. This strategy supports efficient on-device inference while reducing dependence on very large training datasets. Unlike deep learning approaches, which typically require substantial amounts of data to achieve strong performance, the proposed machine learning-based framework minimizes this requirement, making it particularly suitable for resource-constrained devices such as smartphones. Beyond model deployment, preprocessing plays an essential role in achieving reliable EEG classification. In the current implementation, preprocessing is carried out in MATLAB using the E-ASR technique. However, alternative signal filtering and preprocessing approaches can also be implemented directly in Java within Android Studio. This adaptability provides flexibility for customizing the preprocessing pipeline according to different mobile platforms and application-specific performance requirements. At present, preprocessing is performed offline because the E-ASR algorithm is only available in MATLAB. Nevertheless, incorporating preprocessing directly on the smartphone would further enhance the development of a fully integrated mobile EEG framework. Therefore, future work will focus on translating the E-ASR algorithm into Python or Java to enable real-time preprocessing within the Android application itself. Such an advancement would remove the need for external desktop-based processing and support complete end-to-end on-device EEG analysis.

Earlier studies on eyes-open/eyes-closed (EO/EC) classification have largely de-

pendent on multichannel EEG recordings analyzed offline under controlled laboratory conditions [154] [183]. In contrast, the proposed work introduces a smartphone-integrated framework for on-device single-channel EEG classification. The EO/EC paradigm was selected as a physiologically well-established benchmark task because alpha-band modulation between these two states provides a reliable and interpretable neural signature for validating lightweight on-device EEG classification models. In addition to serving as a proof-of-concept for mobile EEG inference, EO/EC detection also has practical relevance in applications involving vigilance monitoring [155], fatigue assessment [157], adaptive learning environments, and attention-state evaluation [158] in naturalistic settings. To the best of our knowledge, previous research has not demonstrated EO/EC classification performed entirely on-device. Therefore, this study represents an important initial step toward real-time EEG-based state prediction using portable and cost-effective systems. In addition to the technical contributions, the proposed approach also carries broader practical significance. By enabling EEG classification directly on smartphones, the framework improves user privacy by eliminating dependence on cloud-based computation, ensuring that sensitive neural data remain stored and processed locally on the device. Furthermore, deploying lightweight machine learning models on commonly available smartphones reduces the cost and accessibility barriers associated with EEG-based technologies. This supports the development of affordable neurotechnology solutions for both research and clinical applications. The portability and low-cost nature of the proposed system also create opportunities for applications such as mental health monitoring, classroom-based cognitive evaluation, and day-to-day brain-computer interaction in naturalistic environments. In addition, smartphone-based EEG systems may support longitudinal monitoring applications for conditions such as stress, depression, anxiety, fatigue, and addiction-related behavioral assessment. Collectively, these advantages demonstrate the potential of the proposed framework to contribute not only to advances in mobile EEG technology but also to improved accessibility and broader real-world societal impact.

Motivated by the findings reported by Hohaia et al. [104], an occipital electrode was chosen for the proposed single-channel EEG classification framework because this brain region is closely linked to alpha-band activity during eyes-open and eyes-closed conditions. Their work showed that alpha power markedly increases in the occipital cor-

tex when the eyes are closed and decreases during the eyes-open state, indicating that this region provides strong discriminative information for differentiating between these two conditions. By utilizing this well-established neurophysiological characteristic, the proposed model relies on a physiologically meaningful signal source, thereby improving classification capability while preserving a minimal-electrode configuration suitable for practical EEG applications in natural environments.

To optimize the proposed classification framework, hyperparameter tuning was performed to investigate the effect of varying the regularization parameter C on model performance. The analysis revealed that increasing C from 10^{-6} to 10^{-3} substantially improved classification accuracy, with the highest accuracy of 90% achieved at $C = 10^{-3}$. These findings suggest that an appropriate level of regularization improves the model's generalization capability while reducing the risk of overfitting. However, no further improvement in performance was observed for values of C greater than 10^{-3} , indicating that $C = 10^{-3}$ provides the most suitable balance for this classification task.

Subject-wise analysis using Leave-One-Out Cross-Validation (LOO-CV) further demonstrated the robustness of the proposed model. High classification accuracy was achieved for most participants, with several subjects showing perfect classification performance. Nevertheless, inter-subject differences in EEG signal characteristics resulted in some classification errors, particularly for the eyes-closed (EC) condition. In particular, Subjects 1 and 2 exhibited noticeable misclassification, where a proportion of EC trials were incorrectly identified as eyes-open (EO). Despite these subject-specific variations, the classifier maintained strong overall performance in differentiating EO and EC states, highlighting its suitability for mobile EEG-based cognitive monitoring applications. Although E-ASR preprocessing improved EEG signal quality across participants, residual artifacts in recordings with low signal-to-noise ratio (SNR), especially for Subjects 1 and 2, likely contributed to the observed misclassifications between EO and EC conditions. Subjects 1 and 2 exhibited relatively lower SNR values (22.62 dB and 18.40 dB, respectively), which corresponded with their reduced classification accuracies. This suggests that poorer signal quality, potentially associated with variability in electrode attachment during the earlier recording sessions, may have contributed to the observed performance differences. However, some later subjects also demonstrated comparatively lower SNR values while still achieving higher classification performance, suggesting that

subject-specific EEG variability and differences in artifact composition additionally influenced the classification outcomes. These findings indicate that both signal quality and inter-subject EEG variability influence classification performance. Future research may incorporate adaptive calibration methods or subject-specific normalization approaches to better address these differences and further enhance model robustness. Variability between subjects can arise from differences in EEG signal patterns, electrode positioning, and individual neural response characteristics, all of which may affect classification outcomes. In the present study, the SVM classifier was trained using pooled data from all participants, which may not entirely capture these personalized variations. Therefore, future work will focus on developing adaptive calibration strategies to personalize the model for individual users, thereby improving both accuracy and generalization capability. To further investigate whether the reduced performance observed for Subjects 1 and 2 was related to the choice of classifier, an additional evaluation was performed using a Convolutional Neural Network (CNN) model. The CNN achieved an overall classification accuracy of 87.5%; however, the accuracies for Subjects 1 and 2 remained relatively low (66.25% and 50%, respectively), comparable to the SVM results (61% and 54%). These observations suggest that the lower performance is primarily associated with subject-specific EEG characteristics and residual artifacts rather than limitations of a particular classification architecture. In addition, the present classification framework was evaluated on a relatively limited participant cohort, which may restrict the statistical robustness and generalizability of the reported findings. The current study was primarily intended as a proof-of-concept investigation to demonstrate the feasibility of smartphone-based single-channel EEG classification using lightweight on-device machine learning models. Although the proposed framework achieved promising classification performance across the analyzed participants, larger-scale studies involving more diverse subject populations, multiple recording sessions, and varied real-world conditions will be necessary to further validate the robustness, reproducibility, and broader applicability of the proposed approach.

Figure 4.5 presents the overall classification results aggregated across all participants. The proposed model achieved an average accuracy of 90%, demonstrating effective discrimination between the two classes. The classifier also attained a high mean precision of 96%, indicating a low occurrence of false positive predictions. Furthermore,

the average sensitivity was 82%, reflecting the model's capability to correctly detect positive instances, whereas the mean specificity reached 97%, highlighting its strong ability to correctly identify negative cases. The average F1-score of 85% indicates a balanced trade-off between precision and recall. In addition, the mean Matthews Correlation Coefficient (MCC) of 0.82 demonstrates a strong agreement between predicted and true labels, further supporting the robustness of the proposed framework. Although the classifier exhibited strong overall performance, future improvements may focus on enhancing sensitivity through advanced feature engineering methods, adaptive threshold selection, and data augmentation techniques to further minimize classification errors. Taken together, these findings highlight not only the feasibility of deploying efficient eye-state classifiers on smartphones but also the broader versatility of the proposed pipeline for cognitive workload monitoring [184].



5

Conclusions

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5.1 Summary

This thesis presents a comprehensive framework for smartphone-based electroencephalography (EEG) acquisition and analysis, targeting real-time EEG signal acquisition, artifact reduction, and cognitive state classification in unconstrained, natural environments. Traditional EEG experiments, often restricted to highly controlled laboratory settings, limit the ecological validity of cognitive and behavioral neuroscience studies. In contrast, naturalistic EEG paradigms, supported by mobile platforms, open up new possibilities for studying brain function in real-world conditions. The work presented in this thesis aligns with recent developments emphasizing the integration of experimental paradigms, compatible EEG hardware, real-time preprocessing pipelines, lightweight machine learning classifiers, and Android-based applications. It directly addresses several key challenges, including limited computational power, the presence of motion and physiological artifacts, and the need for accurate real-time EEG classification on resource-constrained mobile devices. While the implementation of artifact removal algorithms on Android platforms remains relatively underexplored, this thesis presents and validates practical and working solutions on a computer desktop. These solutions may be adapted for implementation on smartphones in the future. Despite these promising contributions, several limitations should be acknowledged. The validation studies presented in this thesis were conducted on relatively limited participant cohorts and device configurations, primarily as proof-of-concept investigations intended to establish the feasibility of smartphone-based EEG acquisition, preprocessing, and on-device classification. Consequently, the statistical robustness and broader generalizability of the findings remain limited. We acknowledge that the absence of larger and more diverse participant populations, multiple recording sessions, and wider cross-device validation represents a limitation of the present work, which may affect the reproducibility, scalability, and real-world applicability of the proposed approaches.

Chapter 1 reviewed recent developments in EEG research, particularly focusing on the emergence of smartphone-based EEG systems for use in natural environment applications. It highlighted limitations of traditional lab-based experiments and emphasized the growing demand for ecologically valid paradigms enabled by portable EEG technologies. The chapter examined existing systems and identified three essential components

for real-time EEG analysis on smartphones: acquisition hardware, artifact removal algorithms, and lightweight classifiers. Artifact reduction techniques such as ASR and rASR were discussed in other studies for their efficacy. Meanwhile, studies have not only proposed models like CNN and MobileBERT as promising on-device classifiers but also demonstrated their effectiveness through practical implementation. In conclusion, the chapter outlined key challenges, including limited processing power, and emphasized the need for optimized, low-latency pipelines.

Chapter 2 validated the CameraEEG Android application, which supports synchronized EEG and video recording on a single platform. Using eyes-closed and eyes-open protocols, the system captured alpha band activity during eye closure and its suppression upon eye opening, consistent with established EEG findings. These results confirm the application's ability to accurately record meaningful brain signals using mBrainTrain's Smarting device, which sampled data at 500 Hz. The acquired EEG data samples were consistently matched with the duration of corresponding video recordings across all sessions. The app also performed reliably on mid-range smartphones released after 2020, with minimal thermal strain and efficient resource use at 480p video resolution. By integrating data acquisition and video recording into a single interface, CameraEEG reduces dependency on multiple tools, making it highly adaptable for diverse applications.

Chapter 3 introduced a novel method for implementing ASR on single-channel EEG recordings. This was achieved by generating a multichannel dataset through time-lagged embedding of prefrontal single-channel EEG signals, a process known as dynamical embedding. The Embedded-ASR (E-ASR) method effectively removed eye-blink artifacts from this EmbeddedMatrix, achieving an average reduction of 100% in detected blinks in real EEG datasets. This result underscores the critical impact of artifacts on neural analysis and the importance of their removal for reliable interpretation. Furthermore, the algorithm preserved the integrity of underlying brain signals, as reflected by consistent CC and RRMSE. An embedding dimension of 90 and an ASR cut-off parameter of 17 were used, ensuring optimal spectral decomposition and brain signal preservation. Future research may explore the effects of varying the embedding dimension on performance and processing speed. Owing to its computational efficiency and minimal electrode requirements, the E-ASR framework may be well-suited for integration into smartphone applications in the future, offering a compelling approach for

real-world EEG studies.

Chapter 4 demonstrated the feasibility and effectiveness of an offline Android-based EEG classifier for cognitive state monitoring, specifically for eye state detection. By integrating an autonomous EEG classification framework directly onto Android smartphones, this work addressed the privacy concerns and functional limitations associated with cloud-dependent approaches. The implementation of SVM models within the EEG Classifier application enabled accurate eye state classification in both single-channel and multi-channel configurations. In particular, the single-channel setup provides a convenient, portable, and minimally invasive solution, improving the accessibility of EEG monitoring for real-world applications such as epilepsy and seizure detection, cognitive workload assessment, and mental health monitoring. The single-channel classification model achieved an accuracy of 90% using a regularization parameter (C) of 0.001 (10^{-3}). These findings highlight the effectiveness of the preprocessing pipeline, especially the E-ASR technique, in improving EEG signal quality and enhancing classification performance. The successful deployment of the single-channel model within the Android application demonstrates the practicality of on-device EEG classification for smartphone-based cognitive monitoring. This work contributes significantly to smartphone EEG research and further reinforces the potential of on-device machine learning for portable, privacy-preserving cognitive monitoring systems. Future work will focus on extending the framework to additional cognitive states and implementing fully on-device real-time EEG processing.

5.2 Future Directions

While this thesis demonstrates the feasibility of smartphone-based EEG acquisition, preprocessing, and classification in natural environment experiments, looking ahead, several research directions can further enhance the utility, scalability, and real-world applicability of the proposed system:

- **Implementation of E-ASR on Android:** The integration of the E-ASR algorithm into an Android application for real-time EEG artifact reduction represents an important future milestone. This would allow on-device preprocessing of a single-channel EEG signal, improving data quality before classification. Achieving this

will require optimization of the algorithm for mobile environments, particularly in terms of memory usage and computational efficiency.

- **Development of a Low-Cost In-House Amplifier for the CameraEEG App:** At present, the application utilizes a commercial EEG amplifier (Smarting), which, while offering high-quality signal acquisition, is expensive and limits the app's scalability and accessibility. Future work could involve the development and integration of a cost-effective, in-house amplifier. This would make the system more affordable and suitable for large-scale deployment in resource-constrained or field-based settings.
- **Integration of Additional Cognitive and Clinical State Classifiers:** The current work focuses on eye state classification using a machine learning pipeline. Future research may extend this framework to detect a broader range of cognitive and affective states, such as drowsiness, stress, attention, workload, anxiety, depression-related neural patterns, and addiction-associated behavioral states. Such extensions could support longitudinal monitoring and assistive neurotechnology applications in clinical and public health settings.
- **End-to-End Integration within CameraEEG:** A promising direction is the seamless integration of both the E-ASR artifact removal algorithm and the classification model within the CameraEEG Android application. This would transform CameraEEG from a standalone data acquisition tool into a fully autonomous mobile neuroimaging system capable of real-time artifact reduction and cognitive state prediction. Such integration would enhance usability, portability, and real-time feedback for a wide range of natural environment EEG [185].
- **Extension to Multi-Channel EEG Systems:** Although the present work primarily focuses on single-channel EEG processing and classification to support lightweight smartphone deployment, future studies may investigate the integration of multi-channel EEG configurations. Multi-channel systems could provide improved spatial information, enhanced artifact separation capability, and support for more advanced neurophysiological and clinical analyses, including functional connectivity and cognitive network assessment [186] [187] [188].

- **Making CameraEEG Compatible with Other EEG Amplifiers:** At present, the CameraEEG application is compatible with mBrainTrain devices. Expanding support to include other consumer-grade and open-source EEG hardware (e.g., Open-BCI, NeuroSky) could democratize EEG data acquisition further and allow wider adoption in resource-constrained settings.
- **Energy-Efficient Architecture Design:** Prolonged EEG recording sessions may lead to thermal issues and battery drain on smartphones. Future work could explore adaptive sampling strategies, efficient data compression, and energy-aware scheduling of tasks to improve long-term usability in real-world scenarios.
- **Cloud-Optional Hybrid Architecture:** While this thesis emphasizes privacy through offline processing, a hybrid architecture that enables secure optional cloud integration for model updates, longitudinal data analysis, or telehealth monitoring could expand the application's capabilities.
- **User-Centric Design and Usability Testing:** To transition from research to real-world deployment, the usability of the system must be evaluated across diverse populations, including patients, clinicians, and educators. Incorporating user feedback into design iterations will ensure that the technology is both intuitive and effective in practical applications.
- **Validation in Clinical and Educational Settings:** Pilot studies in real-world environments such as classrooms, outpatient clinics, rehabilitation centers, and home-based monitoring systems will be essential to assess the system's robustness, scalability, and long-term usability [187] [40] [189] [190]. Future studies should also evaluate the framework under realistic deployment conditions involving motion artifacts, environmental noise, prolonged recording sessions, and heterogeneous smartphone hardware. In clinical contexts, mobile and wearable EEG systems have shown growing potential for applications such as neurological monitoring, cognitive assessment, neurorehabilitation, epilepsy monitoring, and mental health evaluation [191] [192] [193]. Such investigations will be important for establishing the reliability and translational applicability of the proposed framework in practical clinical and public health scenarios [189].

A

Appendix

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A.1 Appendix 1

Table A.1: Eye-blinks and computational time corresponding to occipital, temporal, parietal, and midline cen-tral electrodes for all subjects.

Subject	Channel	Eye-Blinks Before	Eye-Blinks After	Time (s)
1	O2	0	0	4.88
	T8	0	0	4.82
	P7	0	0	4.98
	Cz	1	1	4.90
2	O2	2	2	4.67
	T8	0	0	4.65
	P7	1	1	4.69
	Cz	0	0	4.73
3	O2	0	0	4.80
	T8	0	0	4.65
	P7	0	0	4.67
	Cz	0	0	4.84
4	O2	0	0	4.64
	T8	0	0	4.62
	P7	0	0	4.72
	Cz	0	0	4.67

Table A.2: E-ASR results of 250 Hz sampling frequency for all subjects.

Subject	Channel	Eye-Blinks Before	Eye-Blinks After	Time (s)
1	Fp1	6	0	1.44
	Fp2	9	0	1.45
2	Fp1	8	0	1.29
	Fp2	5	2	1.50
3	Fp1	15	0	1.42
	Fp2	16	0	1.32
4	Fp1	7	0	1.35
	Fp2	7	0	1.23

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ADDENDUM

During the tenure of my PhD, several additional works were undertaken beyond the core research objectives. Some of these efforts received recognition through national and international competitions, as detailed below.

(i) **Auditory EEG Challenge: ICASSP 2023**

The *Auditory EEG Challenge* at ICASSP 2023 focused on developing models that relate brain responses to natural speech using EEG data. EEG is widely used for auditory research and clinical diagnostics due to its high temporal resolution and non-invasive nature. Decoding auditory attention from EEG signals holds promise for next-generation assistive technologies, such as smart hearing aids.

The challenge provided a large EEG dataset consisting of recordings from 85 young, normal-hearing, Dutch-speaking participants, collected in a soundproof, electromagnetically shielded booth using a 64-channel Biosemi ActiveTwo system with a sampling rate of 8192 Hz. Each subject listened to 8-10 randomized trials of single-speaker Flemish audio, totaling approximately 157 hours of data. The dataset was divided into:

- Training Set: EEG data from 71 subjects (508 trials), using 57 distinct stimuli, amounting to approximately 120 hours. All subjects listened to at least one common reference story.
- Test Set:
 - *Test Set 1 (Held-out Stories)*: New stories for the 71 training subjects, totaling around 944 minutes.
 - *Test Set 2 (Held-out Subjects)*: EEG recordings from 14 unseen subjects, totaling 1260 minutes.

Two tasks were defined in the challenge:

- Task 1: Match-Mismatch Classification

This classification task required the model to identify which of two audio segments (one matched and one mismatched) corresponded to a given 3-second EEG segment. Each trial included:

- A segment of EEG,
- A temporally aligned speech stimulus (match),
- An imposter stimulus (mismatch).

Classification accuracy (%) was used as the evaluation metric. Strategies such as segment re-use and windowing were employed to enhance generalization and avoid overfitting.

- Task 2: Stimulus Reconstruction (Regression)

This task involved reconstructing the speech envelope from EEG recordings. The similarity between the reconstructed and original envelopes was measured using the *Pearson correlation coefficient*. The envelope was defined using the provided preprocessing code, although participants could employ custom models and processing pipelines.

We actively participated in Task 1 of the challenge and submitted our model to the official competition leaderboard. Our submission achieved the 11th position out of 22 participating teams. The official leaderboard is available at:

<https://expor1.github.io/auditory-eeg-challenge-2023/task1/leaderboard/>

(ii) Seizure Detection Challenge: ICASSP 2023

Epilepsy is a common neurological disorder that affects approximately 1% of the global population. A significant proportion of individuals with epilepsy, around 30%, do not achieve seizure control despite taking anti-seizure medications (ASM). Accurate monitoring of seizure activity is therefore essential to guide clinical decisions and optimize treatment plans. However, conventional self-reporting methods, such as seizure diaries, are often unreliable, with many patients failing to report more than half of their episodes.

To address this limitation, EEG-based seizure detection systems offer an objective approach for tracking seizures, particularly during long-term video EEG (vEEG) monitoring. Nevertheless, these systems typically require full-scalp EEG recordings, which are impractical for daily or at-home use. Consequently, the development of wearable EEG devices that can continuously and discreetly monitor seizures has gained growing interest.

The Seizure Detection Challenge at ICASSP 2023 aimed to promote research in this direction by providing participants with wearable EEG data recorded at UZ Leuven and inviting them to design machine learning (ML) models capable of accurately detecting seizure events. The competition was structured into two main tasks:

- **Seizure Detection Task:** Develop an ML model that maximizes seizure detection performance using the provided behind-the-ear EEG (bhe-EEG) dataset.
- **Data-Centric Task:** Improve the performance of a fixed neural network architecture (ChronoNet) through data preprocessing and augmentation strategies.

Our approach proposed a data-minimal training framework designed to address the severe class imbalance inherent in seizure detection datasets. We introduced a novel projection layer comprising a fully connected recurrent neural network (RNN) based on Long Short-Term Memory (LSTM) units. This layer transforms low-dimensional inputs into a higher-dimensional latent space, effectively capturing more informative representations for the target domain.

We further analyzed the learned latent features to investigate whether domain adaptation facilitated cross-domain generalization. In the source domain, the projection-RNN approach achieved a sensitivity of 89.37% with 94 false alarms per hour. In the target domain, it achieved a sensitivity of 42% with 19 false alarms per hour, demonstrating the model's adaptability.

In addition, we applied data-centric optimization to the ChronoNet model using our proposed data-minimal strategy. This enhancement yielded a perfect sensitivity of 100% with only 3 false alarms per hour, showcasing the effectiveness of systematic data engineering in improving baseline models.

These solutions were among the top-performing submissions in the challenge. Our team secured the second position out of 12 participating teams [194].

- (iii) **Synchronous Brain and Camera Signal Acquisition using Smartphones for Human Drowsiness Detection**

This project was done with Ms. Shivani Mittal as part of her M.Tech thesis requirement at IIT Guwahati. It was showcased at the PanIIT World of Technology Conference 2025 TechExpo in the Research Pavilion, where our team was recognized as one of the winning teams.

The study presents a mobile-based framework for real-time drowsiness detection using facial landmarks, implemented on Android devices. Using MediaPipe's Face Landmark Detection, the application continuously tracks facial features to calculate the Eye Aspect Ratio (EAR), a key metric for identifying eyelid closure and potential drowsiness. When the EAR remains below a predefined threshold for a sustained duration, the system triggers an alert to notify the user. The application offers complete customization of the detection logic and thresholds, making it adaptable to a range of application-specific requirements. The use of an open-source library like MediaPipe ensures transparency and scalability, particularly valuable for industrial use.

To extend the system's capability to neurocognitive monitoring, the drowsiness detection module was integrated into the CameraEEG Android application [81]. This integration allows for synchronous recording of EEG signals and facial video data, enabling the correlation of visual signs of drowsiness with corresponding brain activity. The resulting system provides a robust platform for exploring behavioral and neurological markers of alertness and fatigue, particularly in safety-critical domains such as driver monitoring, sleep research, and human-computer interaction. Preliminary results confirm the viability of using this system as a low-cost and accessible tool for real-time drowsiness detection. This work was presented at the 3rd IEEE Guwahati Subsection Conference in June 2026.

LIST OF PUBLICATIONS

Publications:

- **D. Hazarika**, S. Chanda, and C. N. Gupta. "Smartphone-Based Natural Environment Electroencephalogram Experimentation-Opportunities and Challenges," *IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, pp. 370–375, 2022.
- **D. Hazarika**, S. Madhavan, and C. N. Gupta. "CameraEEG: Synchronous Recording of Electroencephalogram and Video Data for Neuroergonomics Applications," *Engineering Proceedings*, vol. 55, p. 46, 2023.
- **D. Hazarika**, K.N. Vishnu, R. Ransing, and C.N. Gupta. "Dynamical Embedding of Single-Channel Electroencephalogram for Artifact Subspace Reconstruction," *Sensors*, vol. 24, no. 20, p. 6734, 2024.
- **D. Hazarika**, S. Chhaba, R. Ransing, and C.N. Gupta. "On-device Single Channel EEG Classification on Android Smartphones using Lightweight Machine Learning Models," *Biomedical Physics Engineering Express*, vol. 12, no. 1, p. 015071, 2026.
- K. N. Vishnu, N. Singh, **D. Hazarika**, and C. N. Gupta. "Low to High Dimensional Projection of Seizure Electroencephalography Using Recurrent Neural Network," *IEEE 20th India Council International Conference (INDICON)*, pp. 186-191, 2023.
- S. Mittal, **D. Hazarika**, K.N. Vishnu, and C.N. Gupta. "Enhancing the CameraEEG Application for Realtime Drowsiness Detection using Video Data," *3rd IEEE-Guwahati Subsection Conference (GCON)*, June 2026 [Accepted].

Achievements:

- One of the five winners in the Idea Challenge Competition at the BRICS Youth Council Entrepreneurship Pre-Consultations on 7th February 2025, participating as a team with Vishnu K. N. and Shivani Mittal.

List of Publications

- One of the four winners in the Research Pavilion at the PanIIT World of Technology Conference 2025 TechExpo on 21st January 2025, as part of a team with Shivani Mittal and Vishnu K. N.
- A project proposal was submitted as a team with Vishnu K. N. to the NEWGEN IEDC, DST, Govt. of India at IIT Guwahati and was selected for funding in the financial year 2023–24.
- Participated as a team with Dasari Shivakumar, Vishnu K. N., and Nanaki Singh in the Auditory EEG Challenge at ICASSP 2023 (placed 11th among 22 teams). <https://expor1.github.io/auditory-eeeg-challenge-2023/task1/leaderboard/>
- Participated as a team with Vishnu K. N. and Nanaki Singh in the Epilepsy Challenge (placed 2nd among 12 teams) at ICASSP 2023. https://biomedepi.github.io/seizure_detection_challenge/
- Participated as a team with Vishnu K. N. in the Emprendimiento Challenge, RIC 2023 and secured 4th position.

Workshop attended:

- Participated in the summer school “Computational Approaches to Memory and Plasticity” held at the Indian Institute of Science Education and Research (IISER) Pune, Maharashtra, India, from 1st to 17th July, 2024.
- Participated in the iBrain Lecture Series: Diverse Approaches in Brain and Cognitive Sciences Session 2, under the Integrated Track in Brain and Cognitive Sciences initiative, organized at IIT Guwahati on 20th and 22nd September, 2023.
- Attended a high-end workshop on “Fundamentals of Deep Learning” (under the Karyashala Scheme - A SERB initiative) organized by IIT Guwahati from 12th to 18th September, 2022.
- Attended the India EMBO Lecture Course on ‘Noninvasive Brain Stimulation: Advances in Research and Clinical Practice’ jointly organized by EMBO and IIT Gandhinagar from 12th to 17th December, 2022.

- Participated online in the TwinBrain Summer School 1.0 “Neuroscience of Movement: Exploring the Dynamics of the Human Brain in Motion” from 6th to 10th July, 2021.



