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A Portable EEG-Based Sleep Monitoring and Real-Time Feedback System Without Cloud Infrastructure

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Abstract

This paper presents a mobile real-time sleepL. W. et al., 2023; S. Z. et al., 2024; X. M. et al., 2024; Y. E. et al., 2024; Jirakittayakorn et al., 2024 staging system using EEG signalsA. A. et al., 2023; H. P. et al., 2022; J. K. L. et al., 2023; P. J. et al., 2023; S. D. et al., 2023; T. L. et al., 2025; X. Z. et al., 2024a collected from the Muse headband. It employs a lightweight deep neural network, **EEGNet**G. L. et al., 2024; V. J. L. et al., 2018a; W. C. et al., 2024, to classify wakefulness, light sleep, and deep sleep. Designed for Android smartphonesS. B. et al., 2017; S. K. et al., 2023; X. Z. et al., 2024b, EEG signals are transmitted via Bluetooth for local preprocessing and inference, reducing latency and preserving privacy.

Tests with five healthy subjects showed a classification accuracy of **89.4%**, closely aligning with results from traditional polysomnography. The system also features sleep-stage-based interventions, such as adaptive white noise playback, enhancing user sleep experience.

Compared to conventional EEG devices, the Muse-based system offers greater comfort, portability, and compliance for long-term use. Results highlight the potential of combining consumer-grade EEG and mobile deep learning for accurate real-time sleep monitoring and personalized sleep health managementM. S. et al., 2018; T. Z. et al., 2023; Lai et al., 2018.

Keywords: EEG, BCI, Sleep Monitoring, Deep learning, Data Processing

I.Introduction

a.Sleep Physiology and Cycles

Sleep is a vital physiological process essential for maintaining cognitive function, physiological homeostasis, and overall quality of life. It has been extensively linked to neurological health, metabolic regulation, and immune function M. L. et al., 2013. Human sleep typically occurs in 4–6 cycles per night, each lasting approximately 90–120 minutes. Each cycle includes several stages that are broadly categorized into non-rapid eye movement (NREM) and rapid eye movement (REM) sleep.

NREM sleep consists of three stages: **N1** (light sleep), **N2** (intermediate sleep), and **N3** (deep or slow-wave sleep). REM sleep, characterized by rapid eye movements, heightened brain activity, and vivid dreaming, becomes more prominent in later cycles. The progression through these stages follows a characteristic pattern known as the sleep cycle. Accurate identification of sleep stages—also known as *sleep staging*—is essential for the diagnosis, treatment, and understanding of sleep-related disorders. Fig 1 shows a typical hypnogram illustrating this cyclical process.

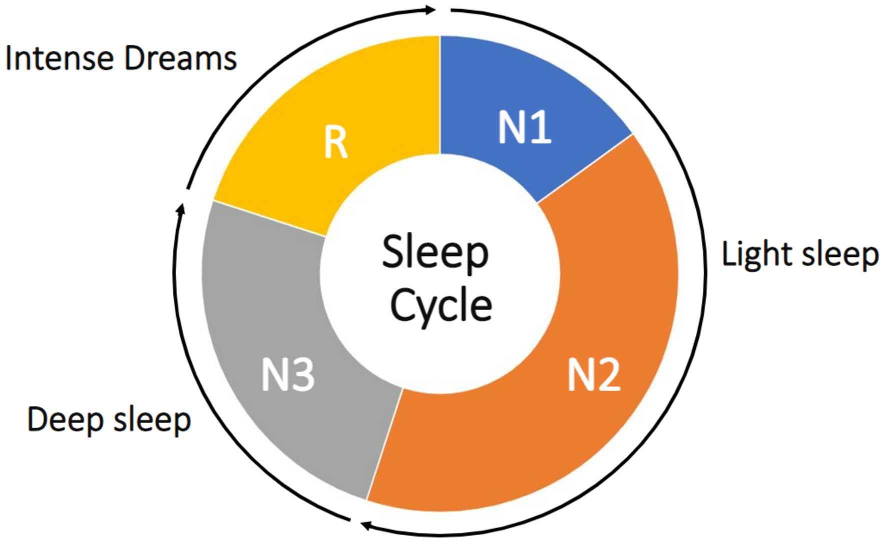

Figure 1: Typical human sleep cycle throughout the night. Sleep progresses through N1, N2, N3, and REM stages repeatedly across 4–6 cycles.

Chronic sleep disorders such as insomnia, obstructive sleep apnea, and periodic limb movement disorder not only reduce sleep quality but are also associated with increased risks of cardiovascular disease, metabolic syndrome, and neurodegenerative conditions H. M.-E. et al., 2004; Z. U. et al., 2025. As a result, continuous and accurate sleep staging has become a critical foundation for sleep health assessment.

b.Limitations of PSG and Emerging Opportunities

Polysomnography (PSG) remains the clinical gold standard for sleep staging due to its high diagnostic accuracy A. S. et al., 2020. However, its high cost, reliance on complex instrumentation, and the need for clinical supervision limit its scalability for at-home or long-term applications.

Recent advances in wearable EEG technologies and deep learning have catalyzed interest in mobile sleep monitoring. Consumer-grade EEG headbands such as the Muse device provide a practical hardware platform, offering non-invasiveness, portability, and a favorable signal-to-noise ratio S. D. et al., 2017. In parallel, lightweight neural network architectures like **EEGNet** have demonstrated strong performance in extracting spatiotemporal features from EEG signals with minimal computational overhead Chen et al., 2024; V. J. L. et al., 2018b. These advancements pave the way for real-time sleep staging directly on edge devices.

Furthermore, edge computing frameworks allow signal processing and inference to be executed entirely on-device, significantly reducing data transmission latency and enhancing user privacy Li et al., 2020. Such developments make it technically feasible to build mobile sleep monitoring systems that are both efficient and cloud-independent.

c.Motivation and Contribution

Motivated by these technological and clinical demands, we present a real-time mobile sleep staging system based on EEG signals acquired via the Muse headband. The system performs real-time data acquisition via Bluetooth, followed by signal preprocessing and inference using a quantization-optimized EEGNet model. This design ensures low-latency, energy-efficient performance suitable for overnight use.

Experimental results from healthy participants show that the system achieves sleep staging accuracy comparable to PSG benchmarks Wang et al., 2022, validating its reliability and applicability. Looking ahead, further integration of multimodal biosignal fusion, adaptive auditory interventions, and personalized online model adaptation will enhance system robustness and user-specific optimization. Hybrid architectures that combine edge-based inference with optional cloud-assisted learning within an IoT framework Miorandi et al., 2012; Tao et al., 2019; Xu et al., 2014 may support scalable, precise, and personalized sleep health management in the future.

II.Methodology

a. EEG Signal Acquisition and Hardware Configuration

The proposed system utilizes the **Muse EEG headband** for signal acquisition. The device is equipped with four dry electrodes located at AF7, AF8, TP9, and TP10 according to the international 10–20 system Homan et al., 1987, covering the frontal and bilateral temporal regions, as illustrated in Fig 2. EEG data are transmitted in real time to an Android smartphone via Bluetooth Low Energy (BLE) with a sampling rate of 256 Hz, ensuring temporal integrity and signal continuity.

b. Signal Preprocessing

To prepare the raw EEG data for classification, multiple preprocessing steps are executed directly on the mobile device:

- **Band-Pass Filtering**: A zero-phase finite impulse response (FIR) filter is applied to remove low-frequency drift and high-frequency artifacts. The passband is set to 0.5–40 Hz, encompassing the delta, theta, alpha, and beta bands relevant to sleep staging. The FIR filter design uses a Hamming window with filter order empirically set to 256 to maintain sharp transition bands without introducing phase distortion.
- **Resampling**: Signals are resampled from 256 Hz to 100 Hz using a polyphase anti-aliasing filter to match the sampling rate of the Sleep-EDF dataset used for training, ensuring temporal consistency across domains.
- **Segmentation**: EEG data are segmented into 30-second epochs with 50% overlap, in line with the American Academy of Sleep Medicine (AASM) and Rechtschaffen and Kales (R&K) sleep scoring standards. Each segment is treated as an independent sample during inference.
- **Artifact Rejection and Normalization**: Although Muse provides artifact-suppressed signals, z-score normalization is applied on each epoch:
$$\tilde{x}_t = \frac{x_t - \mu}{\sigma}$$
where μ and σ denote the mean and standard deviation over the epoch. This improves inter-session generalization and mitigates user-specific baseline shifts.

c. EEG-Based Three-Class Classification Model: EEGNet Architecture and Mobile Optimization

***Network Architecture**

To achieve efficient classification of three sleep stages—Wake, Light Sleep, and Deep Sleep—on mobile platforms, we adopted a compact convolutional architecture based on **EEGNet** G. L. et al., 2024, tailored for EEG's low-SNR and channel-sparse characteristics.

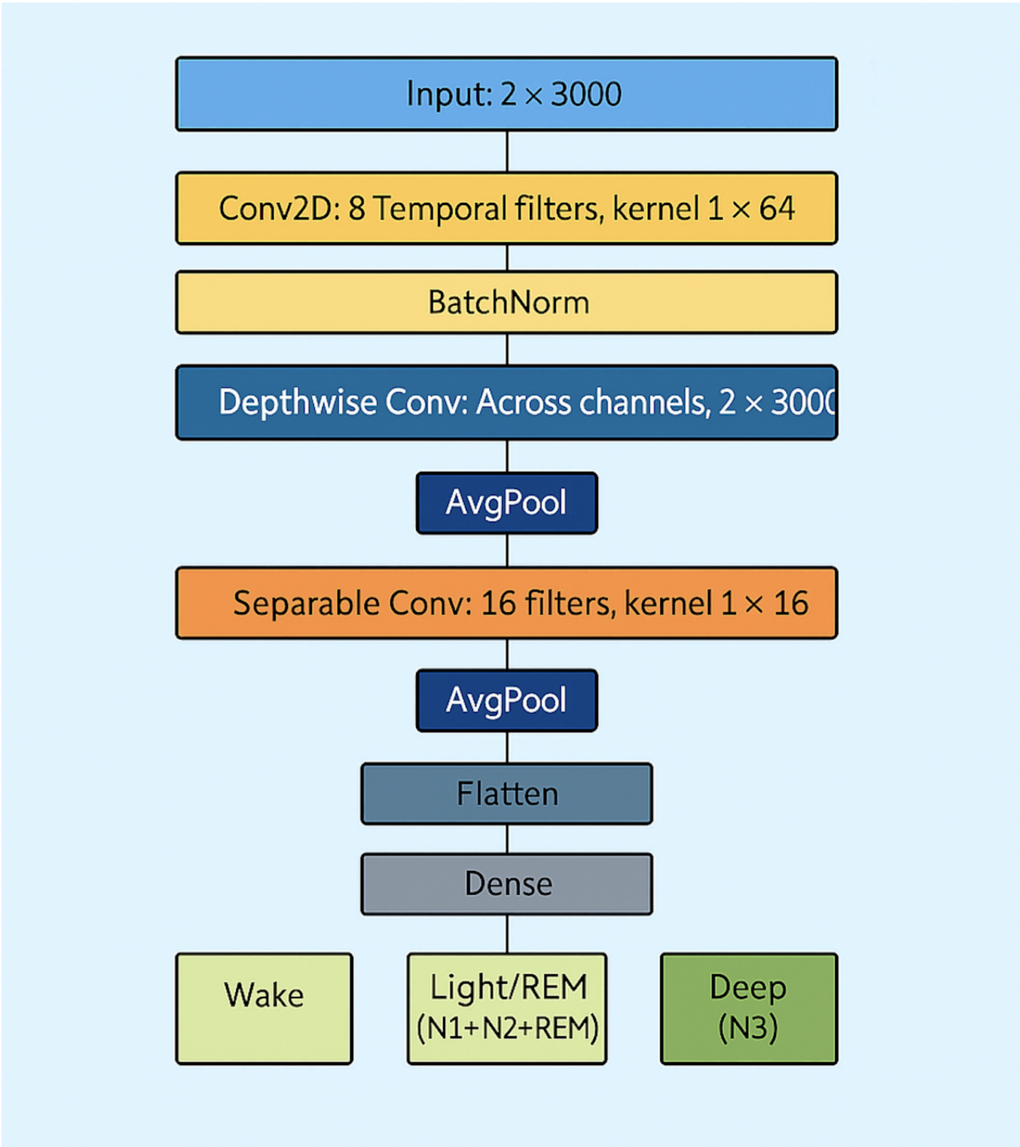

Figure 2: Architecture of the mobile-optimized EEGNet model used for three-class sleep stage classification.

The network consists of the following:

- **Block 1 – Temporal Feature Extraction**: The input passes through a temporal convolution layer with 8 kernels of size 1×50, corresponding to 0.5 s of signal duration (at 100 Hz), capturing frequency-domain oscillations. The output is batch-normalized Zhang et al., 2019, followed by ELU activation and spatial dropout (rate $= 0.5$) to mitigate overfitting. Average pooling reduces temporal dimension by a factor of 4.
- **Block 2 – Spatial Feature Extraction**: A depthwise separable convolution with 16 filters and kernel size 1×16 captures spatial correlations across channels. This layer is followed by batch normalization, ELU activation, dropout, and pooling (pool size 1×8), further reducing the feature map while preserving discriminative features.
- **Classification Block**: The output feature maps are flattened and passed through a fully connected layer followed by a SoftMax function for multi-class classification. L2 regularization with $\lambda = 1 \times 10^{-4}$ is applied to prevent overfitting and promote model sparsity.

The model input shape is `[samples, channels, time points, 1]`:

- **Channels** $= 2$ (TP9, TP10),
- **Time points** $= 7680$ (30 s $\times$ 256 Hz).

Label Mapping and Data Preprocessing

The EEGNet model was trained on the Sleep-EDF Expanded dataset (Sleep Cassette subset), containing 61 full-night EEG recordings. The original labels were mapped to three classes:

Original Label	Mapped Label
W	Wake
N1/N2/REM	Light Sleep
N3	Deep Sleep

Preprocessing applied to the benchmark data mirrors the real-time pipeline, including 0.5–40 Hz FIR filtering and segmentation into 30-second epochs:

$$X_i = \{x(t) \mid t \in [iN, (i+1)N - 1]\}, \quad N = 30 \times f_s$$

Model Training and Mobile Deployment

The model was trained using categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{c=1}^{C} y_c \log(\hat{y}_c)$$

where y_c is the true label, $\hat{y}_c$ is the predicted probability, and $C = 3$ is the number of classes. The optimizer used is Adam with learning rate $\eta = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$. An early stopping mechanism with patience of 10 epochs was used to avoid overfitting. Model validation was conducted using a 70%/30% train/val split with stratification.

Following training, the model was quantized using post-training float16 quantization and converted to TensorFlow Lite format for Android deployment TensorFlow Lite, 2017. The final model has a memory footprint of under 300 KB and performs inference on-device within 50 ms per 30-second segment.

Mobile System Architecture and Implementation

Once converted, the model was deployed on Android smartphones. EEG signals acquired via BLE are processed in real time on-device through a preprocessing pipeline and fed into the quantized EEGNet model, enabling end-to-end sleep stage prediction without relying on remote servers.

Dynamic auditory interventions are triggered based on the predicted sleep stages, with white noise intensity adaptively adjusted according to sleep depth. These mechanisms aim to stabilize sleep and enhance overall quality.

Additionally, anonymized data and predictions are uploaded to a secure cloud backend for long-term storage and personalized sleep pattern analysis. The app is optimized for low CPU/GPU usage and energy efficiency, making it suitable for overnight operation.

III.Experiments and Results

a.Participants and Experimental Procedure

A total of five healthy adults (aged 22–35 years, gender-balanced) participated in overnight sleep experiments conducted in home environments. Individuals with diagnosed sleep disorders, neurological conditions, or recent medication use were excluded.

During each session, participants wore the Muse EEG headband continuously for 7–9 hours. EEG signals were recorded from four dry electrodes at 256 Hz and transmitted via Bluetooth Low Energy (BLE) to an Android smartphone running the inference application. Post-session checks confirmed high signal quality and uninterrupted recording throughout the night.

b.Data Processing and Model Training

Offline training was conducted using the **Sleep-EDF Expanded** dataset (Sleep Cassette subset), a publicly available full-night EEG corpus sampled at 100 Hz. Data were upsampled to 256 Hz to match the real-time Muse acquisition rate. All recordings underwent FIR band-pass filtering (0.5–40 Hz), z-score normalization, and segmentation into 30-second epochs.

Sleep stages were relabeled into three categories: *Wake*, *Light Sleep* (merged N1/N2/REM), and *Deep Sleep* (N3 only), based on established scoring guidelines and for hardware-constrained classification efficiency. The processed dataset was divided into training and testing subsets using a 7:3 stratified split. Model training employed the Adam optimizer with learning rate 0.001, cross-entropy loss, L2 regularization, and early stopping (patience = 10). After training, the model was quantized using TensorFlow Lite with float16 optimization and deployed to Android smartphones for on-device inference.

c.Evaluation Metrics and Statistical Analysis

Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix. To assess clinical reliability, paired t-tests were used to compare the model's predictions against manually annotated PSG ground truth. All tests used a significance threshold of $p < 0.05$. Confusion matrix visualization was performed both in five-class (original AASM stages) and three-class (merged categories) formats for better interpretability.

d.Classification Performance

The mobile EEGNet model achieved an overall classification accuracy of **89.4% ± 3.7%**, demonstrating competitive performance under constrained hardware. Table 1 summarizes per-class metrics across Wake, Light, and Deep stages.

Table 1: Classification Performance by Sleep Stage (mean ± std)

Class	**Accuracy**	**Precision**	**Recall**	**F1-score**
Wake	–	89.5% ± 4.2%	86.7% ± 5.0%	88.0% ± 4.1%
Light	–	90.3% ± 3.9%	92.1% ± 4.4%	91.2% ± 3.8%
Deep	–	87.8% ± 5.1%	84.2% ± 6.3%	85.9% ± 4.9%
Avg	**89.4% ± 3.7%**	**89.2%**	**87.7%**	**88.4%**

Fig 3 presents the confusion matrices for both full (five-stage) and merged (three-stage) classification. Results indicate strong separation between Wake and Deep stages. Light Sleep (a merged class containing N1/N2/REM) showed slightly elevated confusion with Wake, but maintained high recall. Deep Sleep exhibited more conservative detection, consistent with the known amplitude overlap between N2 and N3 stages.

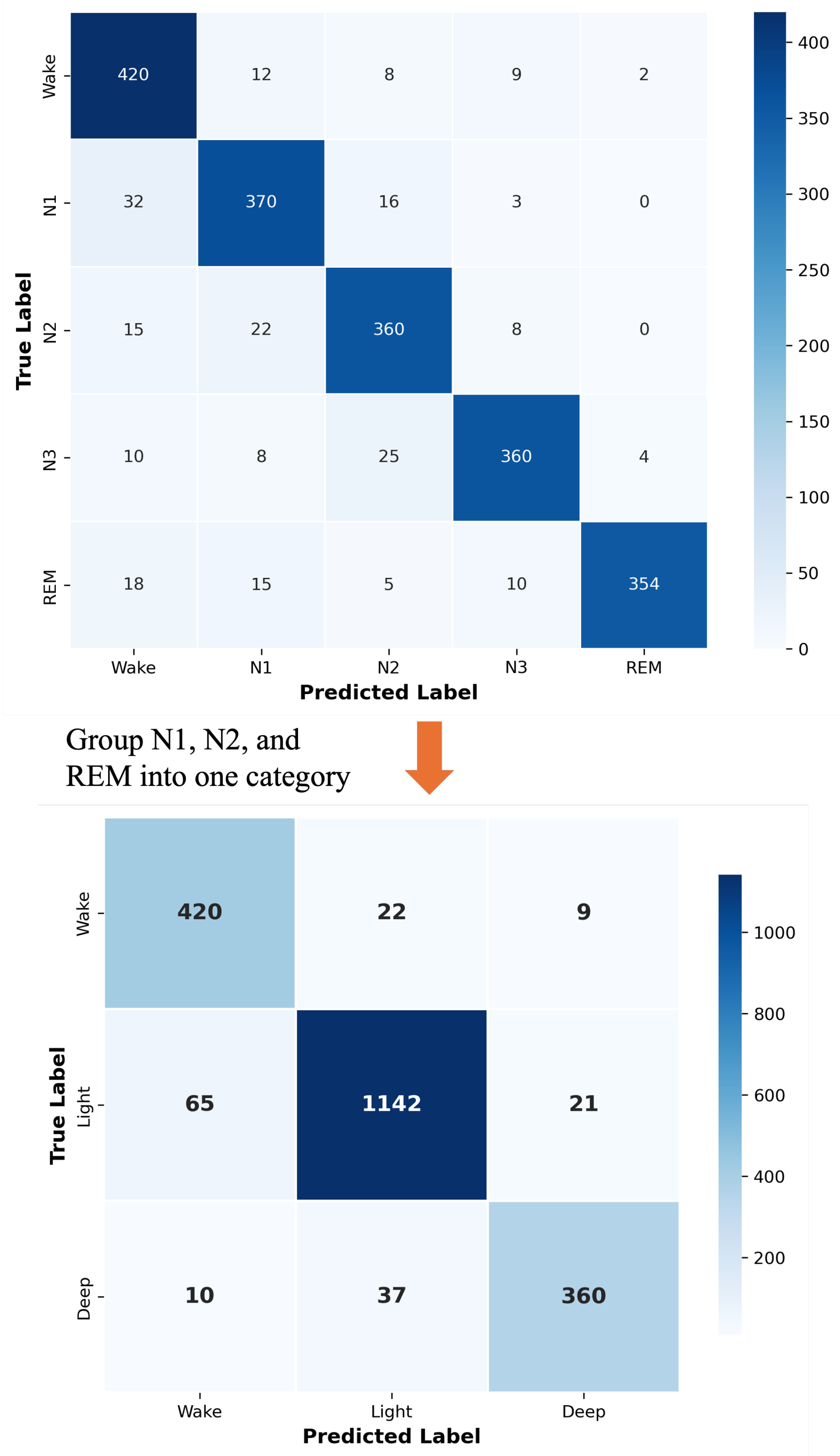

Figure 3: Confusion matrices before and after sleep stage merging. The top matrix shows raw classification across five stages (Wake, N1, N2, N3, REM), while the bottom matrix reflects performance after remapping into three practical categories: Wake, Light, and Deep. The merged configuration improves interpretability and classification consistency.

Paired t-test comparisons with reference PSG scores yielded no significant difference ($p = 0.27$), validating that the model's classifications were statistically consistent with clinical annotations.

e.Real-Time Mobile Inference and App Interface

Fig 4 illustrates the system setup interface, where users connect the Muse headband and configure white noise parameters.

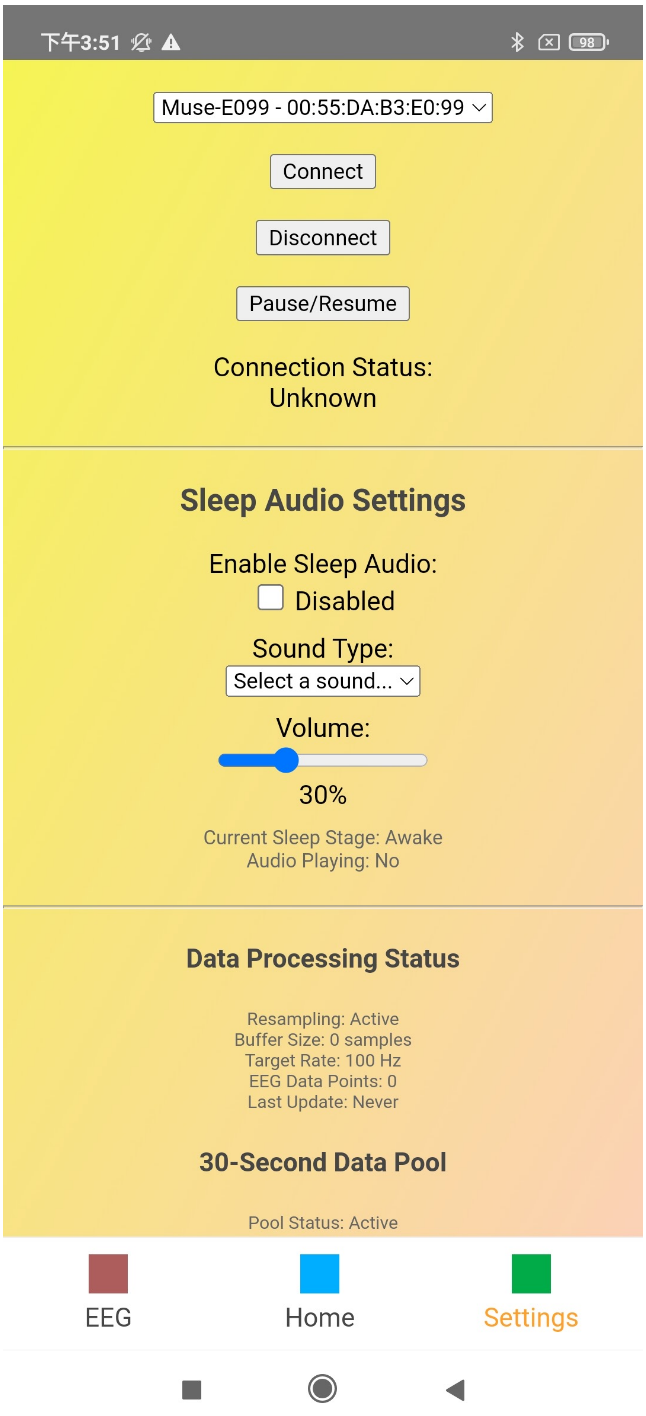

Figure 4: Setup interface for Muse connection and white noise control. Users can initiate EEG signal acquisition and manually configure white noise type and volume.

Fig 5 presents the real-time classification interface, displaying the predicted sleep stage, elapsed time, and feedback intensity.

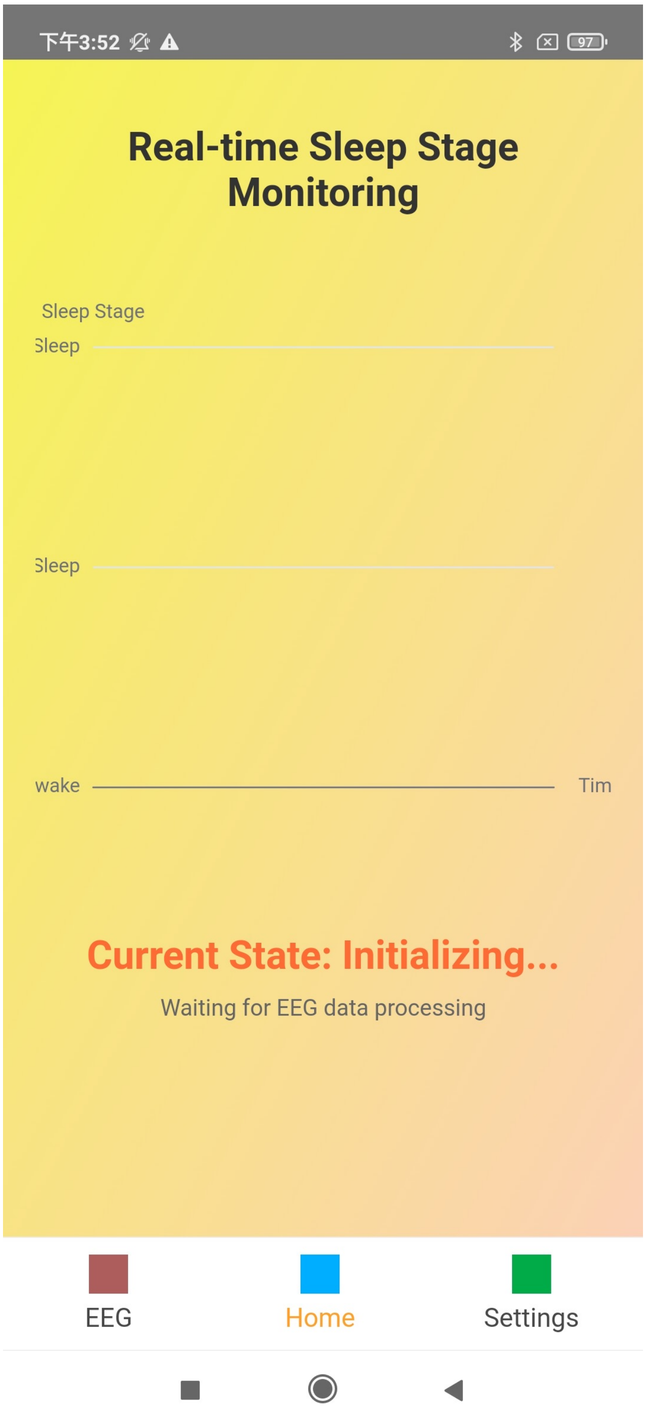

Figure 5: Real-time classification interface. Displays predicted sleep stage, elapsed time, and current white noise feedback level. The system performs inference with 60 ms latency per window, entirely on-device to preserve privacy.

Fig 6 demonstrates representative classification results from a typical usage session, highlighting system responsiveness and feedback visualization.

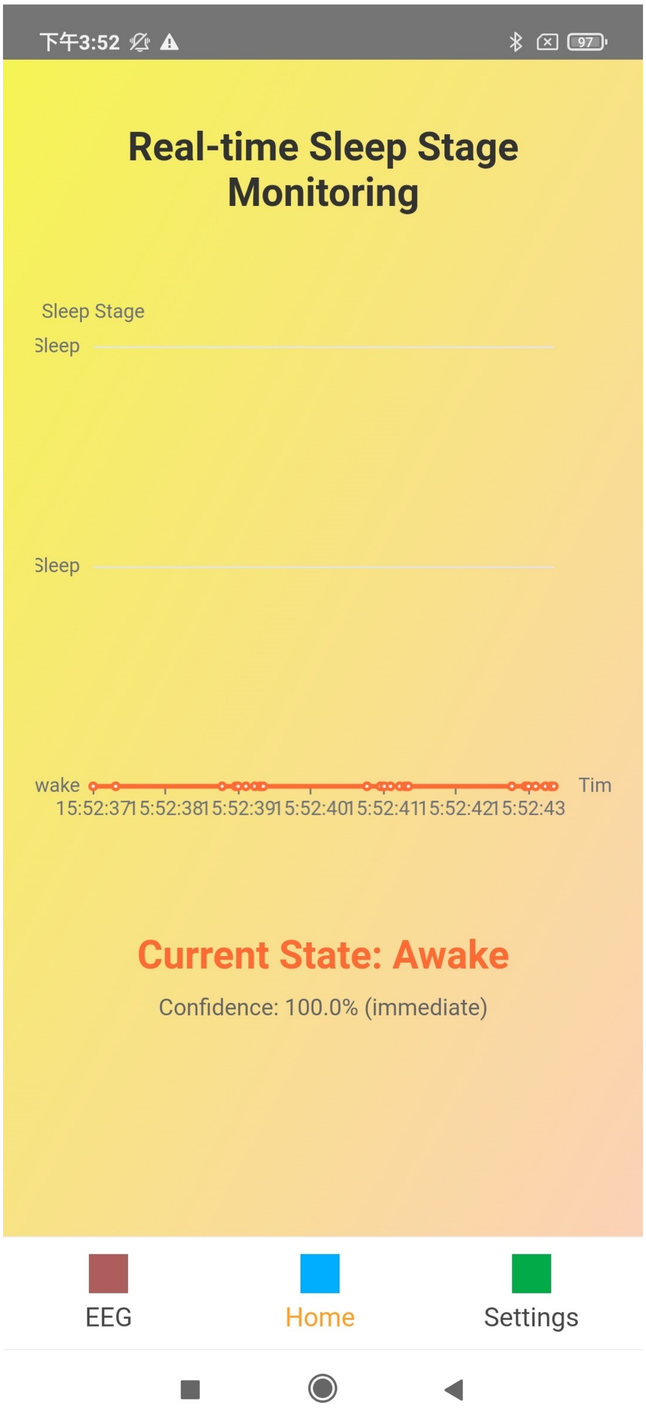

Figure 6: Demonstration of classification results during a typical usage session, showing the practical application of the mobile sleep monitoring system.

f.User Experience Evaluation

Post-study questionnaires revealed high user satisfaction:

- **85%** of users found the Muse headband comfortable for overnight use;

- **83%** reported improved sleep continuity with dynamic white noise;
- **90%** expressed willingness to adopt the system for routine self-monitoring at home.

Participants appreciated the minimal intrusiveness of the setup and the absence of cloud dependency. These results support the system's feasibility as a portable, user-friendly tool for home-based sleep tracking and behavioral feedback.

IV.Discussion and Conclusion

This study proposed a mobile sleep monitoring and intervention system using the Muse EEG headband, achieving real-time sleep stage classification and adaptive feedback in home environments. By deploying a lightweight EEGNet model on Android, the system forms a fully local closed-loop workflow—from EEG acquisition to on-device inference and intervention—without relying on PCs or cloud services. This reduces latency, enhances portability, and ensures better data privacy.

Experiments showed the model achieved an average classification accuracy of 89.4%, comparable to conventional PSG systems, demonstrating that consumer-grade EEG devices can enable reliable sleep staging under minimal hardware constraints. User feedback confirmed the comfort of the Muse headband and the practical value of the feedback mechanism in enhancing sleep experience.

Crucially, the system transitions from passive sleep monitoring to *active sleep support* by delivering adaptive auditory feedback in real time. This shift enables personalized, closed-loop sleep optimization. Embedded EEG systems of this kind offer significant potential for applications in personal wellness, home-based therapy, and preventive healthcare, marking an important step toward practical, everyday neurotechnology. **a.System Advantages and Innovations**

- **Closed-Loop Architecture**: EEG acquisition, classification, and real-time feedback are integrated on an Android device, enabling continuous adaptation to users' brain states in a self-contained loop.
- **Mobile Inference Optimization**: The EEGNet model is quantized via TensorFlow Lite for efficient use on mobile hardware, maintaining inference latency under 60 ms per window, suitable for overnight use.
- **Sleep-Aware Intervention**: White noise is dynamically adjusted by sleep stage, enhancing continuity, perceived restfulness, and sleep quality.
- **Scalability and Usability**: The system requires no specialized infrastructure and runs entirely on smartphones, ideal for wide deployment in homes, elder care, or telemedicine.

b.Current Limitations

Despite encouraging results, some limitations remain:

- **Limited Model Generalization**: The model was trained on the Sleep-EDF dataset and tested on Muse data, introducing domain shifts. Transfer learning or domain adaptation is needed for better cross-device robustness.
- **Subjective Feedback Evaluation**: Feedback efficacy was assessed via questionnaires, lacking objective physiological markers. Adding multimodal sensors and outcome tracking would strengthen evaluation.
- **Limited Population Diversity**: Testing involved a small healthy adult sample. Broader validation across demographics (e.g., older adults, shift workers, those with sleep disorders) is needed in future trials.

In summary, this work shows that combining portable EEG devices, efficient neural models, and mobile processing enables real-time sleep staging and intervention. It offers a foundation for next-generation wearable brain-computer systems for personalized sleep care.

c.Future Work

To improve the system's robustness and clinical utility, future work will explore several directions:

- **Data Expansion**: We will collect large-scale Muse EEG datasets across varied populations and sleep conditions, including multi-night sessions. Transfer and federated learning will be explored to handle cross-subject and cross-device variability while ensuring data privacy.
- **Intervention Enhancement**: Integration of additional physiological signals (e.g., HRV, EDA, respiration) will support better sleep stage estimation and arousal prediction. Feedback timing and type will be optimized using real-time sleep depth estimation.
- **Multimodal and Active Learning**: To handle real-world variability, we plan to fuse data from movement, ambient sound, and light. Active learning approaches will enable efficient model refinement with minimal manual labeling.
- **Long-Term Field Deployment**: We will conduct long-term studies in home and care settings to evaluate impact on sleep metrics (e.g., efficiency, WASO) and well-being. The system will also be extended to support early screening for disorders like insomnia or REM behavior disorder.

These efforts aim to evolve the prototype into a robust, adaptive sleep health platform.

e.Conclusion This study introduces a mobile, real-time EEG-based sleep monitoring and intervention system, integrating wearable signal acquisition, deep learning classification, and responsive feedback into an Android app. The lightweight EEGNet model achieves 89.4% accuracy on-device, with low latency and full offline operation.

Unlike traditional PSG or cloud-based systems, this solution provides privacy-preserving, real-time analysis and white noise feedback. Experimental results and user feedback suggest the system improves sleep awareness and quality.

With continued development, this approach may enable next-generation BCI applications in personal wellness, telehealth, and home-based care.

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Conflicts of Interest

The author has no conflict of interest about anything in this article.

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