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EquiliMind: An EEG-IMU Multimodal Fusion System for Early Warning of Meniere's Disease Episodes

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Abstract. Meniere's disease is a chronic inner-ear disorder associated with recurrent vertigo and balance impairment; sudden vertigo can result in falls and threaten patients' daily safety. To address the limited capability of conventional symptom assessment for continuous risk monitoring, this paper presents EquiliMind, a multimodal early-warning system. The system integrates electroencephalography (EEG) and an inertial measurement unit (IMU) to synchronously obtain neural activity and body-posture information through a wearable EEG device and motion sensors, and employs EEGNet for balance and motion-state recognition. The experimental protocol included four states: normal standing, single-leg standing, straight walking, and protected simulated falling. Each state was recorded 10 to 15 times for 5 s per trial, yielding 40 to 60 valid task trials and 200 to 300 s of state recordings. EEG data were processed by band-pass filtering, artifact removal, and average referencing, while IMU data were used to extract resultant acceleration, angular-velocity magnitude, and posture-angle change features. Experimental results show that the developed model can distinguish different balance and motion states and detect simulated fall events within 500ms. Channel analysis indicates relatively high relevance scores for T7 and T8, suggesting that temporal channels play an important role in vertigo and balance-risk recognition. The system establishes a complete technical route from multimodal state perception to real-time risk warning, providing a new method for wearable safety monitoring of patients with Meniere's disease.

Keywords: Meniere's disease; electroencephalography; inertial measurement unit; EEGNet; early warning.

1. Introduction

Meniere's disease (MD) is a chronic inner-ear disorder affecting auditory and vestibular functions. Common manifestations include sudden vertigo, tinnitus, aural fullness, fluctuating hearing, nausea, and vomiting. The U.S. National Library of Medicine reports that the timing of attacks is difficult to predict and that approximately 615,000 people in the United States are affected; persistent unsteadiness can interfere with daily life [1]. According to the international diagnostic criteria, definite MD is commonly characterized by recurrent spontaneous vertigo, low- to medium-frequency sensorineural hearing loss, and fluctuating aural symptoms such as tinnitus or fullness [2]. Therefore, the management of MD requires not only diagnosis and treatment in clinical settings but also attention to immediate safety during daily activities.

Clinical practice guidelines indicate that MD is identified mainly through a history of episodic vertigo, audiological evidence, and assessment of aural symptoms [3]. However, clinical evaluation alone cannot continuously capture changes in movement state when an attack arises suddenly: drop attacks may manifest as sudden imbalance or falling with preserved consciousness [4], and posturographic research has identified abnormal sway under several balance conditions in patients with MD [5]. These findings demonstrate a clear application need for continuous perception and rapid warning during walking, standing, and sudden loss-of-balance scenarios beyond clinical diagnosis and treatment.

Electroencephalography (EEG) non-invasively records brain electrical activity through scalp electrodes [6]. Neuroimaging research related to balance control indicates that static and dynamic postural control involves neural processes that can be represented by brain-function signals [7]. In

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parallel, an inertial measurement unit (IMU) continuously acquires acceleration and angular velocity and is commonly used in wearable fall-risk assessment and fall detection [8]. Recent studies integrating EEG and motion-sensor data further show that neural signals combined with body-movement information can be used for real-time detection of postural disturbances [9]. Combining the neural-activity sensing capability of EEG with the direct motion-risk representation of an IMU therefore provides a multimodal technical basis for exploring warnings of vertigo-related hazardous states. As shown in Fig. 1, disease manifestations and risk-monitoring requirements jointly motivate the system design presented in this work.

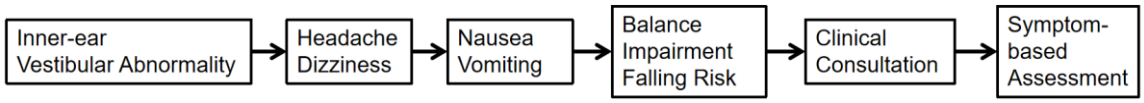


Fig. 1 Symptoms of Meniere's disease and the need for risk monitoring [6,10].

Based on these requirements, we designed and implemented EquiliMind, a wearable multimodal warning system. It integrates EEG acquisition, IMU motion monitoring, lightweight EEGNet-based state classification, and acoustic, visual, and vibrotactile feedback modules, forming an end-to-end process from data acquisition and signal processing to risk recognition and real-time notification. The main contributions of this work are a wearable EEG-IMU fusion architecture; a state-acquisition procedure covering normal standing, single-leg standing, straight walking, and protected simulated falling; multi-state balance and motion recognition using EEGNet; and a prototype pathway connecting risk classification results to real-time alarm output for daily safety assistance.

2. Overall System Design

2.1. System Architecture

As shown in Fig. 2, EquiliMind consists of sensing, processing, and feedback layers. The sensing layer employs an EEG module and a 10-axis IMU to acquire EEG signals and motion/posture data, respectively. The processing layer performs preprocessing, feature extraction, and state classification using a local computing unit. The feedback layer is controlled by an ESP32 and uses a buzzer, an LED, and a vibration module to notify the user after a hazardous state is detected. This architecture combines neural-activity analysis with physical-motion detection for real-time wearable processing and feedback. The main components and their corresponding functions are listed in Table 1.



Fig. 2 Hardware layout of the EquiliMind wearable multimodal monitoring and warning system.

Table 1. Main components of the EquiliMind prototype system.

Component	Function
EEG cap / dry-electrode module	Continuously acquires EEG signals related to balance state
10-axis IMU	Records acceleration, angular velocity, and posture changes
NUC computing unit	Performs real-time data processing and model inference
ESP32 microcontroller	Receives recognition results and controls alarm modules
Buzzer, LED, and vibration motor	Provides acoustic, visual, and tactile risk notifications
Battery and DC-DC converter module	Powered by a 24 V lithium battery and converted to 12 V through the DC-DC module

2.2. Workflow

During system operation, EEG and IMU data are synchronously acquired and transmitted to the local computing unit. The EEG signals are then filtered, artifact-corrected, and re-referenced, while IMU signals are converted into temporal features describing movement amplitude and postural change. The processed inputs enter the EEGNet model for state recognition. When the output corresponds to a high-risk motion state, the system activates the alarm module for immediate notification. The processing operations and outputs at each stage are summarized in Table 2.

Table 2. System processing workflow.

Step	Processing operation	Output
Data acquisition	Synchronous recording of EEG and IMU signals	Raw multimodal time-series data
Signal processing	Filtering, artifact removal, re-referencing, and motion-feature calculation	Standardized feature input
Intelligent recognition	Analysis of motion and balance states using EEGNet	State classification result
Real-time warning	Activates acoustic, visual, and vibration modules according to risk classification	Immediate user notification

3. Experimental Methods

3.1. Experimental Validation Objective and Procedure

We performed closed-loop technical validation of signal processing, state recognition, and alarm output by synchronously acquiring EEG and IMU signals under different balance and motion states. The four tasks cover baseline balance, dynamic activity, and sudden risk states; the protected simulated fall was used to verify the linkage between real-time detection and acoustic, visual, and vibrotactile alerts.

3.2. Experimental Equipment and State Design

As shown in Fig. 3, the experiment was conducted in a protected indoor environment. The participant wore a device integrating an 11-channel dry-electrode EEG module and a 10-axis IMU and performed four tasks: normal standing, single-leg standing, straight walking, and protected simulated falling. Each state was repeated 10 to 15 times for 5 s per trial, with movement onset and offset synchronized by manual annotations. According to the protocol, 40 to 60 valid trials and 200 to 300 s of valid state data were recorded in total. The four state settings are presented in Table 3.

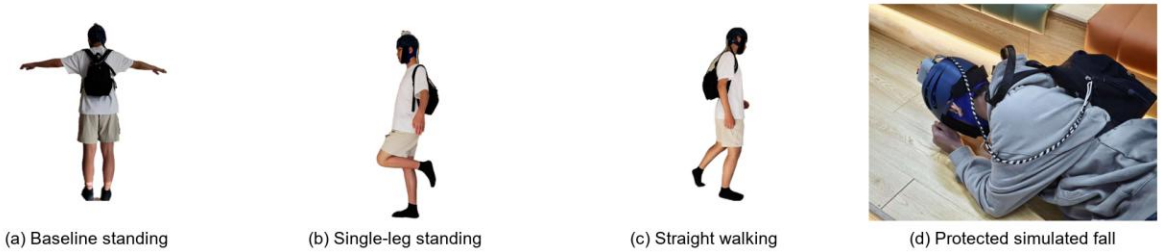


Fig. 3 Four balance and motion states during experimental data acquisition.

Table 3. Experimental state settings.

State category	Action description	Recognition objective
Normal standing	Stable standing on both feet	Establish baseline state
Single-leg standing	Maintain balance on one leg	Simulate a balance challenge
Straight walking	Perform normal dynamic movement	Represent daily activity
Protected simulated fall	Simulate sudden imbalance under protection	Represent a sudden-risk event

Table 4. Experimental acquisition and processing protocol.

Item	Experimental setting
Experimental environment	Protected indoor environment; participant performs movements under monitoring
Synchronous sensing signals	EEG signals and 10-axis IMU motion/rotation signals
Wearable task configuration	Integrated device with an 11-channel dry-electrode EEG module and a 10-axis IMU
States and repetitions	Four states; 10 to 15 repetitions per state; 5 s per trial
Valid task data volume	40 to 60 trials in total; 200 to 300 s of valid state recordings
Event synchronization method	Manual annotation synchronizes the onset and offset of each movement
EEG analysis chain	32-channel OpenBCI acquisition system; EEGLAB (MATLAB) preprocessing and analysis

Table 5. Scale of synchronized paired EEG-IMU data.

State category	Number of paired temporal segments	Duration per segment	Valid state duration
Normal standing	10 to 15 segments	5 s	50 to 75 s
Single-leg standing	10 to 15 segments	5 s	50 to 75 s
Straight walking	10 to 15 segments	5 s	50 to 75 s
Protected simulated fall	10 to 15 segments	5 s	50 to 75 s
Total	40 to 60 segments	—	200 to 300 s

As shown in Table 4, the protocol specifies synchronous acquisition and manual annotation; as shown in Table 5, the EEG and IMU signals in each valid trial share the same onset and offset and form one-to-one temporal segments under identical state labels for subsequent joint analysis of EEG state representations and IMU motion features.

3.3. EEG Data Processing

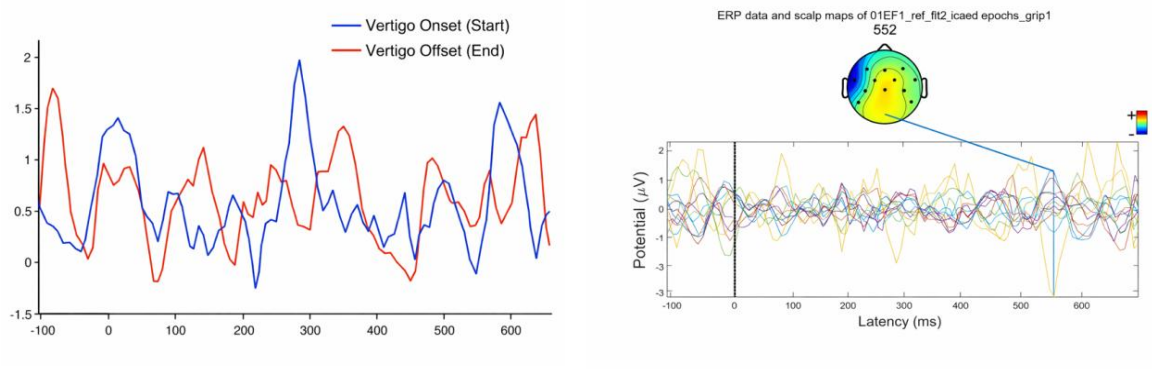
The EEG acquisition and processing chain used a 32-channel OpenBCI system to obtain raw signals, which were imported into EEGLAB (MATLAB) for processing. In the wearable state tasks, an 11-channel dry-electrode EEG module provided the recognition input. EEGLAB supports signal import, filtering, channel management, and independent component analysis (ICA) [11]. We first selected channels and configured channel locations, and then applied average referencing to reduce common-mode noise. A 0.5-45 Hz band-pass filter was subsequently applied to reduce physiological and power-supply noise. During artifact processing, frontal-channel artifact identification was combined with ICA to remove interference related to eye movements and muscle activity. The use of ICA for ocular-artifact separation is supported by established methods [12]. The processed signals were manually inspected before subsequent state analysis.

Let C denote the number of EEG input channels retained for recognition. The average-referenced signal of channel c and its band-pass processed result can be expressed as follows:

$$x'_c(t) = x_c(t) - \frac{1}{C}\sum_{j=1}^{C} x_j(t) \tag{1}$$

$$x_{c,bp}(t) = B_{0.5-45\,Hz}\{x'_c(t)\} \tag{2}$$

where $x_c(t)$ is the original EEG-channel signal, $x'_c(t)$ is the average-referenced result, $B_{0.5-45\,Hz}\{.\}$ denotes the 0.5-45 Hz band-pass processing operator, and $x_{c,bp}(t)$ is the signal entering artifact inspection and state analysis.



(a) EEG signals at vertigo onset and offset

(b) Scalp-map and event-related activity view

Fig. 4 EEG signal processing and visualization of vertigo-related activity.

As shown in Fig. 4, the visualized EEG state-analysis results include signal changes at the onset and offset of vertigo-related states, as well as event-related activity and scalp distribution. These results support observation of EEG variations across different state phases and, together with subsequent channel-contribution analysis, support the EEG state-recognition process.

3.4. IMU Feature Extraction

IMU data reflect postural and dynamic changes of the body under different movement states. We extracted resultant acceleration, resultant angular velocity, and posture-angle change to describe motion intensity, rotation magnitude, and short-term posture alteration. These three features are expressed as follows:

$$a_r(t) = \sqrt{a_x(t)^2 + a_y(t)^2 + a_z(t)^2} \tag{3}$$

$$\omega_r(t) = \sqrt{\omega_x(t)^2 + \omega_y(t)^2 + \omega_z(t)^2} \tag{4}$$

$$\Delta\theta_r(t) = \theta_r(t) - \theta_r(t-1) \tag{5}$$

where $a_r(t)$ is the resultant acceleration at sampling time t, $\omega_r(t)$ is the resultant angular velocity, and $\Delta\theta_r(t)$ is the posture-angle change between adjacent time instants. According to the data organization in Table 5, the IMU feature sequence forms 40 to 60 temporal input segments paired one-to-one with EEG, with each segment covering 5 s. Together with EEG signals, these features constitute the multimodal input to the recognition model and provide the data basis for balance-state and fall-risk analysis.

3.5. Multimodal State Recognition and Risk Triggering

The multimodal recognition procedure uses cleaned EEG signals and temporal IMU motion features as a joint description of the current state. EEGNet serves as the intelligent analysis core for identifying balance and movement states, while IMU features characterize rapid motion, rotation, and abrupt postural changes. At the output stage, normal standing, single-leg standing, and straight walking correspond to daily or balance-challenging states of different degrees, whereas protected simulated falling corresponds to a sudden-risk state requiring alarm activation. Thus, data processing, state determination, and alarm feedback form a continuous closed loop.

Let $h_{EEG}(t)$ denote the spatiotemporal EEG representation extracted by EEGNet. The system-level multimodal state vector can then be expressed as:

$$z(t) = [h_{EEG}(t), a_r(t), \omega_r(t), \Delta\theta_r(t)]^T \tag{6}$$

The classification output corresponds to four states: normal standing, single-leg standing, straight walking, and protected simulated falling. For state class k, the probability output can be written as:

$$p_k(t) = \frac{exp(s_k(t))}{\sum_{j=1}^{4} exp(s_j(t))}, \ k \in \{1,2,3,4\} \tag{7}$$

When the classification result identifies the risk state corresponding to protected simulated falling, the system outputs an alarm-trigger signal, which can be formalized as:

$$A(t) = 1\{\hat{y}(t) = y_{fall}\} \tag{8}$$

where $s_k(t)$ is the classification-layer output score for state class k, $p_k(t)$ is the probability of the corresponding state, $\hat{y}(t)$ is the predicted class, and A(t)=1 indicates that a trigger signal is sent to the ESP32 alarm module.

4. State Recognition Model and Software Implementation

4.1. EEGNet Model

We adopted EEGNet as the core recognition model. EEGNet is a compact convolutional neural network proposed for EEG classification tasks that reduces model complexity through depthwise and separable convolutions [13]. The model input in this study is 11-channel EEG time-series data. Temporal convolution first extracts time-domain features, depthwise convolution then extracts spatial information among channels, and separable convolution subsequently forms a joint spatiotemporal representation before the final output of movement-state classifications. As shown in Fig. 5, the model architecture and training-process curves jointly illustrate the implementation and training behavior of this recognition procedure. The implementation also referred to the structure of open-source EEGNet code [14], enabling the model-training and online-recognition interfaces to connect to the same processing pipeline.

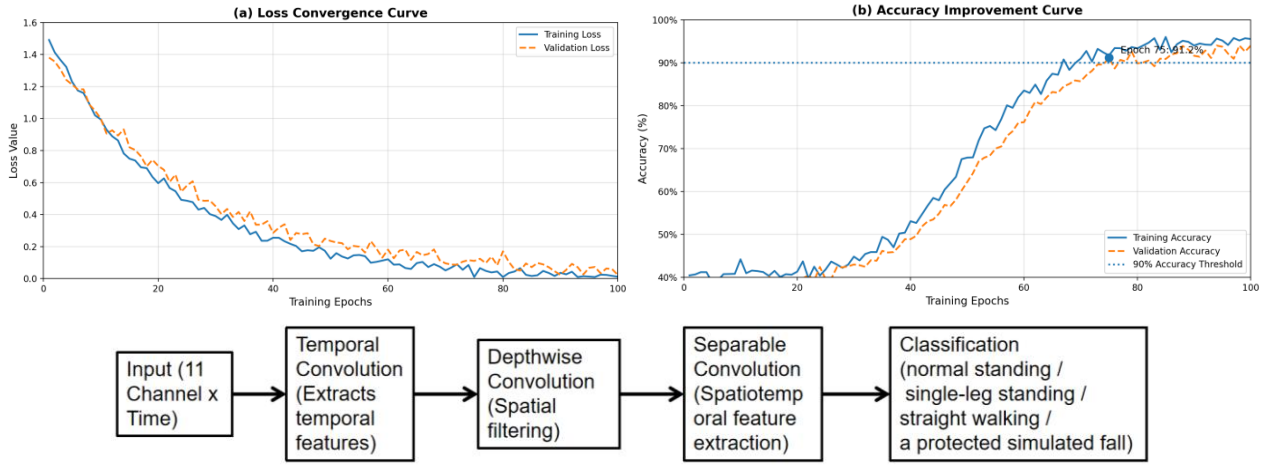


Fig. 5 EEGNet architecture and training-process curves.

4.2. Software Workflow and Online Detection

To enable closed-loop system operation, we developed interfaces for data acquisition, model training, and real-time detection. As shown in Fig. 6, the data-acquisition interface displays EEG waveforms for each channel and supports signal recording; the model-training interface presents accuracy and loss changes; and the real-time detection interface shows device connection status, the current recognized state, and real-time signal trends. When the system recognizes a fall-risk state, the ESP32 controls the alarm module to output notification signals.



(a) EEG data acquisition (b) Model training interface (c) Real-time detection interface

Fig. 6 Software interfaces for data acquisition, model training, and real-time detection.

5. Experimental Results and Analysis

5.1. Model Recognition and Training Process

Experimental results show that, for a single-participant multimodal recording containing four balance and movement tasks and a total of 40 to 60 valid trials, the EEGNet model can distinguish different balance and movement states. This result indicates that the technical pathway comprising synchronized acquisition, preprocessing, model training, and online recognition can support the state-perception task defined in this study. The technical validation results are summarized in Table 6.

Table 6. Summary of technical validation results.

Validation item	Displayed experimental result	System significance
Training-process behavior	Loss curve decreases while the accuracy curve increases and approaches stability	Indicates an effective training response in the recognition pipeline
Four-state recognition	Distinguishes normal standing, single-leg standing, straight walking, and simulated falling	Covers baseline, challenge, dynamic, and risk states
Binary risk recognition	Risk-recognition demonstration presents high accuracy performance	Supports normal/risk state determination
Simulated-fall response	Protected simulated-fall detection time less than 500ms	Supports immediate alarm triggering
EEG state visualization	Displays signal changes and scalp activity at the onset and end of vertigo-related states	Supports state-phase analysis
Channel-contribution analysis	T7=1.00, T8=0.98, FZ=0.95	Identifies EEG channels with higher contribution
Closed-loop operation validation	Completes the chain from acquisition, training, and detection to acoustic, visual, and vibrotactile warning	Supports real-time prototype operation

As shown by the training-process results in Fig. 5, the model loss curve decreases overall during training, while the accuracy curve gradually increases and approaches stability at later stages, indicating that the recognition model can form stable classification responses from the acquired task segments. In the binary risk-recognition demonstration, the system presents high recognition performance; for protected simulated-fall events, the detection response time is less than 500 ms, enabling prompt transmission of the risk determination to the alarm module.

5.2. Four-State and Multimodal Response Analysis

As shown in Fig. 3 and Table 3, normal standing provides a relatively stable baseline state, single-leg standing presents signal changes under a balance challenge, straight walking describes normal dynamic activity, and protected simulated falling represents a sudden risk requiring timely warning. These four tasks establish an analytical progression from baseline and balance challenge to dynamic movement and risk events, allowing the recognition output to reflect risk escalation in practical use.

Together with the comparison of EEG signals at the beginning and end stages and the scalp-activity visualization shown in Fig. 4, the EEG data provide a visual analytical basis for state-stage changes.

Meanwhile, resultant acceleration, angular-velocity magnitude, and posture-angle change from the IMU characterize movement magnitude and abrupt changes. Therefore, in the simulated-fall scenario, EEG state representations and IMU motion-risk features can be jointly used for risk recognition within identically time-annotated segments.

5.3. EEG Channel Analysis

As shown in Fig. 7, the relevance scores for all channels are T7=1.00, T8=0.98, FZ=0.95, P3=0.88, CZ=0.85, PZ=0.82, FC5=0.80, FC6=0.78, F3=0.75, F4=0.70, and O1=0.65. T7 and T8 obtain the highest scores, indicating that temporal-region channels merit particular attention in wearable electrode-layout and real-time signal-processing design. This result is consistent with an interpretation in which the temporal region participates in the integration of vestibular and spatial-perception information, and it can inform subsequent electrode-layout optimization and real-time feature selection.

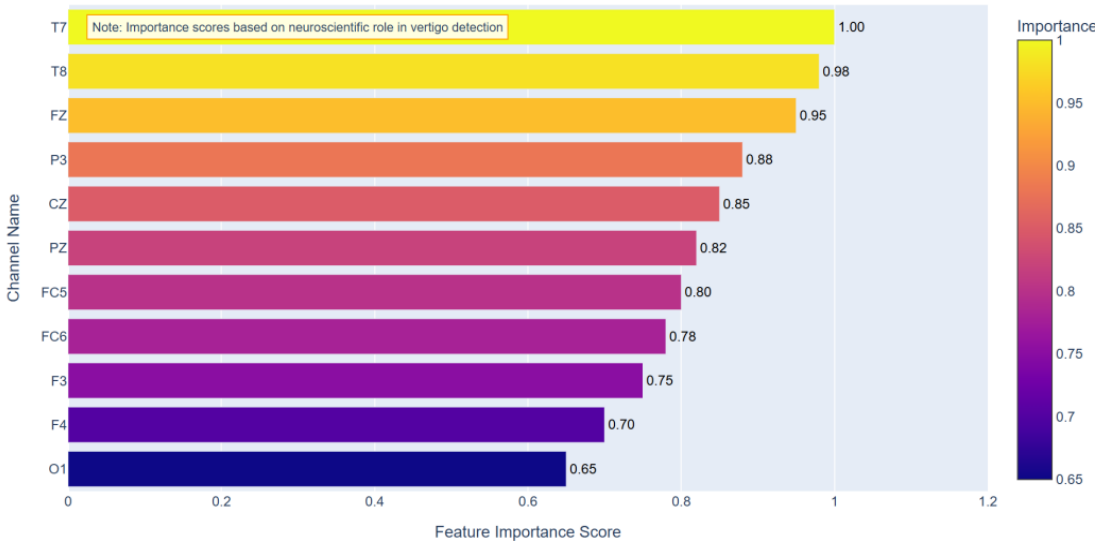


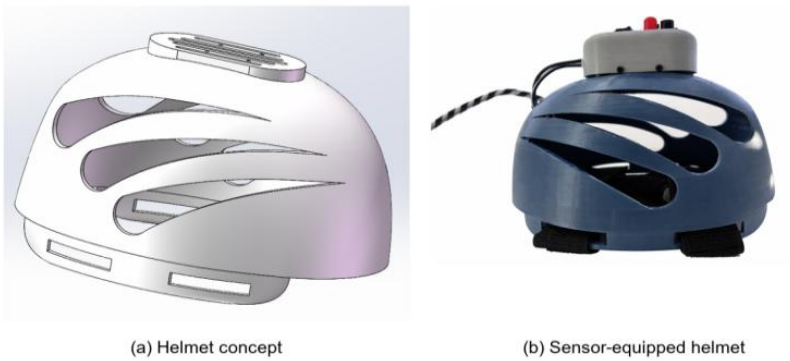
Fig. 7 Results of EEG channel relevance analysis.

5.4. Real-Time Warning and Closed-Loop Validation

As shown in Fig. 7, the data-acquisition interface records EEG waveforms, the model-training interface displays changes in accuracy and loss, and the real-time detection interface presents device connection status and the current recognized state; these interfaces correspond to acquisition, modeling, and deployment-validation stages, respectively. The system combines EEG state features with IMU motion-risk features, with online processing and state determination performed by a local NUC. When a high-risk state associated with simulated falling is recognized, the ESP32 activates the LED, buzzer, and vibration motor for notification. Together with this hardware feedback pathway, the simulated-fall detection response of less than 500 ms indicates that the prototype achieves closed-loop technical validation from state perception to risk warning. Existing research on wearable IMU fall detection and EEG-motion data fusion provides a basis for the real-time warning pathway in this work [8,9].

6. Application Prospects

As shown in Fig. 8, the wearable form of EquiliMind helps extend monitoring from experimental environments to daily activity scenarios. A helmet-type device can integrate EEG, IMU, and alarm units and work with a portable computing module to achieve continuous state perception. Further optimization may address device weight, wearing comfort, and power consumption and integrate the device into healthcare-service workflows to provide more continuous and convenient safety support for patients.



(a) Helmet concept (b) Sensor-equipped helmet

Fig. 8 Wearable-device form design

7. Conclusion

This paper presents EquiliMind, an EEG-IMU multimodal fusion system for early warning of Meniere's disease episodes. By synchronously acquiring EEG and motion data and combining EEG processing, IMU features, and EEGNet recognition, the system performs four-state analysis and acoustic, visual, and vibrotactile feedback. The experiment demonstrates that simulated falls can be detected within 500 ms and that T7 and T8 make relatively high contributions to state recognition, providing a technical solution for intelligent wearable monitoring of vertigo and fall risk.

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