Honeycomb-Inspired Concussion Protection Helmet with Intelligent EEG Feedback System

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***Abstract*—We present an intelligent helmet that combines a honeycomb inspired design with an internal 16-channel EEG subsystem capable of on-device real-time inference. The honeycomb structure provides impact distribution and breathability, while windowed EEG signals are decoded by *EEGConvTrans*, a lightweight 1D-CNN+Transformer model. Honeycomb-structured test samples are able to absorb more energy under vertical loading than solid or circular patterned ones, and finite-element analysis indicates more evenly distributed stress with localized reinforcement needs. Using a 12-label taxonomy, the system achieves high multi-class accuracy. Our design demonstrates a unified solution for physical protection and concussion monitoring in consumer applications.**

***Index Terms*—EEG, wearable helmet, honeycomb structure, deep learning, concussion monitoring**

I. Introduction

Concussions, a subtype of mild traumatic brain injury (TBI), are a global public health issue, mainly among adolescent athletes in contact sports. These injuries arise from blows to the skull or sudden motion within the cavity, causing side effects such as headache, dizziness, and memory loss, in addition to potential long-term cognitive impairment [5]. Although most concussions are recoverable, repeated or violent blows can lead to chronic traumatic encephalopathy (CTE) or other irreversible neurological issues [6]. Recent studies [8] suggest sports- and recreation-associated head injuries continue to increase, and teens aged 10–19 remain the group most often admitted to emergency departments. This trend highlights the need for better protective gear and real-time neurological monitoring.

Recreational helmets use expanded polystyrene (EPS) foam to dissipate impact; however, such design are limited in how they can reduce both linear and rotational forces while remaining comfortable and lightweight. Recent research suggests that honeycomb-inspired structures could yield better energy dissipation, reduced weight, and better mechanical strength. At the same time, wearable electroencephalogram (EEG) technology has transformed EEG from a clinical device to transportable systems capable of tracking brain activity in real time. Coupled with modern deep learning architectures like SPDTransNet [10], these systems have become highly successful at deciphering complex EEG signals towards a range of applications such as emotion recognition, sleep stage classification, and cognitive assessment.

In spite of advances in protective helmet design and wearable neural monitoring, no consumer device currently integrates both capabilities into a single sports-ready system. This matters because it enables continuous, in-play sensing in the same form factor athletes already wear while providing objective signals to support sideline decision-making. To address this gap, we introduce HiveGuard [2], an intelligent EEG-integrated helmet that combines a honeycomb-structured shell for impact absorption with an embedded multi-channel EEG subsystem and real-time hybrid deep learning inference. In this paper, we evaluate protection using mechanical impact testing and evaluate neural monitoring using EEG classification benchmarks, as a first step toward future coupled field validation in athletes wearing the full system.

II. Related Work

Research on protective helmets has focused on mechanical energy dissipation. Mills and Gilchrist [7] and Rowson et al. [9] analyzed thickened EPS foam liners in helmet design. Although such liners are capable of reducing linear acceleration, they are unable to control rotational acceleration and oblique hits, both of which play critical roles in brain damage. Kholoosi and Galehdar [3] introduced a graded honeycomb structure to replace traditional EPS foam, exhibiting higher energy dissipation over a larger duration. However, this design resulted in higher force transmission whenever it was accompanied by higher head acceleration, thus raising concerns about reliability when put into practice. These findings highlight the advantages and limitations of modern helmets' designs, primarily in controlling rotational acceleration, and distributing energy.

Simultaneously, wearable EEG systems have expanded beyond clinical settings to portable applications. Advances in electrode technology, including module-based acquisition boards running ADS1298 chip technology [13], wireless dry-electrode headsets [15], and

soft flexible devices running needle-shaped electrodes [4], now enable monitoring neural activity during movement. However, signal distortion and motion effects remain challenges. Wavelet decompositions combined with autoregressive model features [12] have improved cognitive testing and underscored the importance of maintaining signal integrity in active settings such as sports. At the same time, deep learning has transformed EEG analysis: optimized feature selection accompanied by Bi-LSTM architectures has achieved near-perfect emotion estimation [1], while Transformer-based networks such as SPDTransNet [10] and EEGformer [14] have set new standards in sleep staging, emotion recognition, and motor imagery by preserving long-range temporal and spatial structure. Overall, these advances highlight opportunities and challenges for helmet-based EEG monitoring.

III. HiveGuard Overview

HiveGuard is characterized by three design features: a honeycomb-structured shell, an embedded multi-channel EEG subsystem, and a low-latency real-time inference pipeline. The helmet is designed to accommodate the EEG cap and protect the signal chain while maintaining comfort, enabling continuous sensing and on-device or edge deployment in a single wearable platform.

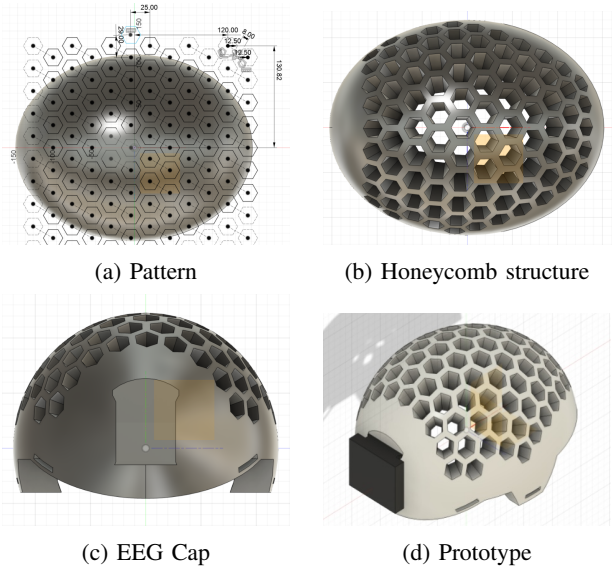
A. Helmet Structure

The helmet design follows the EN960 standard [11]. The helmet geometry is egg-shaped with a flat front and an inclining back to balance protection and comfort. Clearance is incorporated in the inner oval to fit an EEG cap. The outer shell thickness remains 30–40 mm, and the contour is offset to match natural head tilt for improved ergonomic fit. Ear and strap openings provide secure fixation and ventilation.

As shown in Fig. 1(a)–(b), a honeycomb structure is incorporated in the outer shell to enhance impact absorption and reduce weight. The surface is covered by hexagonal cells, with tighter patterns in high-risk areas (crown/lateral) to improve energy absorption and airflow. The pattern is integrated onto the curved surface, with junctions positioned to avoid weakening structural points. A protective compartment houses the EEG electronics, shielding the circuit boards, routing wires, and ensuring secure but accessible mounting (Fig. 1(c)). The final optimized prototype with reinforced casing is shown in Fig. 1(d). The honeycomb structure optimizes the trade-off between higher energy absorption capacity, decreased weight, and higher ventilation without compromising the seamless integration of EEG systems.

B. EEG System

The EEG system integrated in the helmet is for motion environments with microvolt-level signals with an emphasis on (i) high resolution, (ii) real-time data acquisition and on-board processing, (iii) compliance with safety features, and (iv) robust wired/wireless data transfer. Figure 2 shows the EEG system design.



(a) Pattern (b) Honeycomb structure

(c) EEG Cap (d) Prototype

Fig. 1: Helmet design overview.

The overall signal chain begins with an electrode lead set that includes electrostatic discharge (ESD) and electromagnetic interference (EMI) protection. The raw signals are then sent to an analog pre-conditioning stage for filtering, amplifying, and baseline adjustment. Next, a multi-channel Δ–Σ analog-to-digital converter (ADC) is used for high resolution digitization, and, finally, are managed by an embedded controller which handles buffering, communication, and local data storage.

ESD Isolation and Pre-filtering. Low-capacitance ESD arrays (TPESD5431N) protect ten lead lines, including eight EEG, one reference, one right-leg drive), insulating the interface from surges and minimizing leakage (Fig. 3). The channels all have a passive first-order low-pass pre-filter to reduce high-frequency noise before amplifying and converting (Fig. 4); the cut-off frequency, given by $f = 1/(2\pi RC)$, is positioned above the dominant EEG band but still compatible with other physiological signals.

Analog Front-End and Conversion. Legend-semi LH00199 (the red rectangle in Fig. 2) analog front end provides eight simultaneous 24-bit Δ–Σ ADC channels with programmable gain and high CMRR, which is suitable for non-invasive EEG. The differential inputs (IN1P/N–IN8P/N) are amplified (PGA A1–A8) and digitized (ADC1–ADC8), with conversions synchronized via `DRDY` and streamed to the controller over SPI. With an internal reference near 4.5 V, the effective LSB ($V_{\mathrm{LSB}} = V_{\mathrm{REF}}/(2^{23} - 1)$) is on the order of $0.54\,\mu$V, suited for typical EEG amplitudes (0.5–200 μV).

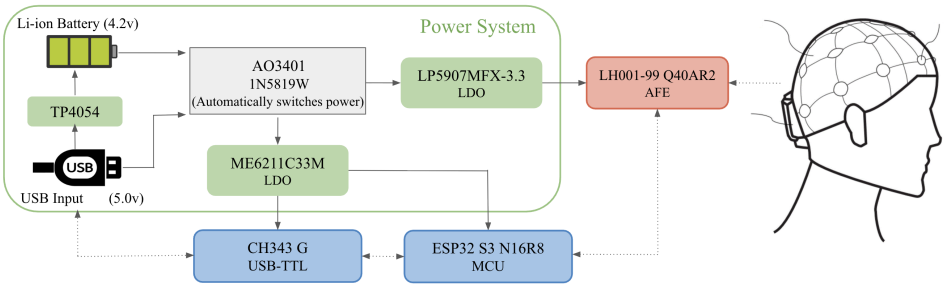


Fig. 2: EEG System Design.

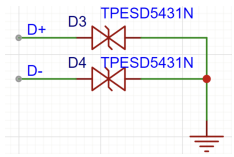


Fig. 3: Isolation circuit.

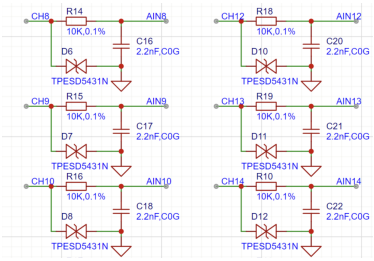


Fig. 4: Pre-filtering circuit.

Controller, I/O, and Firmware. An ESP32-S3 class microcontroller unit (MCU) controls acquisition, local buffering, and wireless telemetry; the USB–UART bridge (CH343P) facilitates firmware download and tethered logging (blue rectangles in Fig. 2). The acquisition stack is synchronized in timing with the ADC, and incorporates a packetization module (that groups sampled data into frames) for host-side processing. Safety measures include power and signal isolation, as well as a right-leg drive reference line for improved stability in EEG acquisition.
Power. The voltage supply is controlled by a 4.2 V Li-ion cell. There are separate analog and digital rails provided by low-noise LDOs: LP5907 for noise-sensitive analog regions (high power supply rejection ratio, low output noise, low quiescent current) and ME6211 for high current digital loads. There is also an extra ESD protection on the battery output.

Overall, this architecture balances fidelity, safety, and portability, delivering a simultaneous multi-channel, 24-bit EEG suitable for helmet integration and real-time inference while remaining serviceable for consumer use.

C. Real-time Inference System

We propose a hybrid architecture, EEGConvTrans, consisting of localized one-dimensional Convolutional Neural Networks (1D-CNNs) for capturing localized temporal features combined with a Transformer encoder for capturing long-range temporal structures. This combination leverages the respective inductive biases of CNNs (local stationarity) and Transformers (capturing long-range dependencies), obtaining strong performance on multi-class EEG tasks even with minimal data.

Task taxonomy. We adopt the 12-label taxonomy in Table I to represent sport-relevant cognitive and physiological task states for wearable EEG evaluation. The labels are applied consistently across all experiments for attention/emotion, verbal fluency, finger tapping, and breathing conditions, and they are not intended as clinical concussion diagnosis or severity grading. Data acquisition and preprocessing are described in Section IV.
Model architecture. The model architecture is shown in Figure 5. The normalized input window is fed to a lightweight 1D-CNN feature extractor (three conv–ReLU–BN blocks, where kernel size is 5) that maps C channels to a latent dimension d_{model}. This resulting sequence in $T \times d_{\text{model}}$ is fed to an (L)-layer Transformer encoder (multi-head self-attention + position-wise feed-forward network with dropout), in order to discover long-range temporal dependencies. Global average pooling (GAP) over time yields a fixed length representation that passes through a two-layer classification head with ReLU and dropout, projecting onto the K classes.

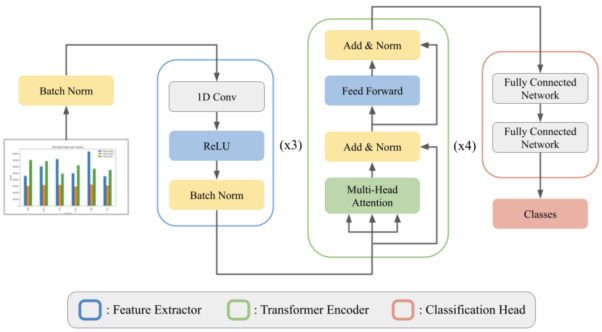


Fig. 5: EEGConvTrans Architecture Overview.

IV. Experiments

We evaluate *HiveGuard* across (i) structural safety and impact attenuation, (ii) EEG signal quality and spectral characteristics, and (iii) multi-task classification with the proposed *EEGConvTrans*.

A. Data Collection

Due to safety and ethical restrictions, we do not collect EEG data from acutely symptomatic individuals immedi-

Task	Data Simulation → Categories	Purpose
Attention & Emotion	High tension → Focused Attention	Assess cognitive and emotional states under varying conditions
	Tired → Difficulty Concentrating	
	Relaxed → Unable to concentrate	
Verbal Fluency	Casual conversation → Fluent Speech	Evaluation of language expression abilities
	Unfamiliar topics → Disfluent Speech	
	Speaking under pressure → Blocked Speech	
Finger Tapping	High-Frequency Tapping → Normal	Assess motor control and fine motor skills
	Slow Tapping → Medium	
	Inability to perform Tapping → Abnormal	
Breathing Conditions	Resting → Normal	Investigate the impact of respiratory regulation on physiological and cognitive functions
	Heavy Breathing → Medium	
	Difficulty Breathing → Abnormal	

TABLE I: Task Taxonomy of Cognitive and Physiological State Labels.

ately after head trauma. Instead, data were obtained in a controlled, simulated environment across four domains: attention/emotion, verbal fluency, finger tapping, and breathing conditions (as shown in Table I). Helmet-obtained EEG signals were stored as time-stamped per-channel voltages. The corpus contains 12 labels and approximately 500k time-stamped samples (93.7 MB) with 16 channels per recording.

B. Data Processing

Filtering. All channels are filtered with a fourth-order Butterworth band-pass filter (7.3–15.5,Hz) to improve robustness in a motion-prone wearable setting by reducing low-frequency drift and high-frequency EMG noise while emphasizing alpha/mu and low-beta activity relevant to attention and motor tasks. Task-specific or adaptive filtering may further improve performance and will be explored in future work.

Temporal normalization. Sequences are zero-padded or cropped to a fixed window of length $T = 5000$ samples per example to have a fixed input dimensionality.

Channel-wise standardization. Single-channel EEG data are standardized to zero mean and unit variance using statistics computed on the *training* split, and the derived parameters are applied to the validation and test sets to avoid leakage and maintain consistent scaling across sessions.

Tensorization. After pre-processing, the data takes the form of an N $\times$ T $\times$ C tensor where N represents the number of valid samples, T is 5000, which is the fixed length of the sequence, and C is 16 which is the number of EEG channels.

C. Helmet Impact and Structural Evaluation

Geometric Structure Comparison. To investigate how geometric structure impacts energy absorption, three samples sized $58 \times 58 \times 15$ mm (circular, honeycomb, solid) were 3D printed (mean weight $\cong$ 16 g). We released a steel ball of 303 g from a height of 90m above a given sample positioned on a thin-film pressure sensor; the absorbed impacted forces were recorded by Newtons. We examined two orientations, vertical (standing) and horizontal (flat).

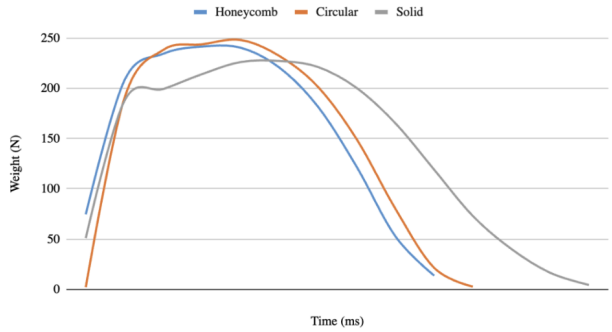
In the horizontal case, the solid sample absorbed the highest amount of force ($\sim$225 N), which is expected given the continuous material distribution of the solid sample over the ones containing gaps (Fig. 6a). For vertical impact, the honeycomb sample experienced the lowest maximum force ($\sim$150 N), superior to the circular ($\sim$170 N) and solid ($>$200 N) samples (Fig. 6b). The ability of the honeycomb structure to deform upon impact allows for more energy dissipation in this direction, aligning with the predominant orientation encountered in sports-related impacts.

Finite-Element Analysis (FEA). We performed FEA with two load cases—top-down and front-to-back—using a 500 N applied load, and studied the distributions of von Mises stress. Top-down loading resulted in widely distributed stresses with no sudden localizations (Fig. 7a), while front-to-back loading resulted in concentrations along the honeycomb cell borders and the front area (Fig. 7b). These distributions validate the empirical result that honeycomb structure enhances energy dissipation but show particular areas experiencing high levels of stress where material reinforcement would be beneficial.

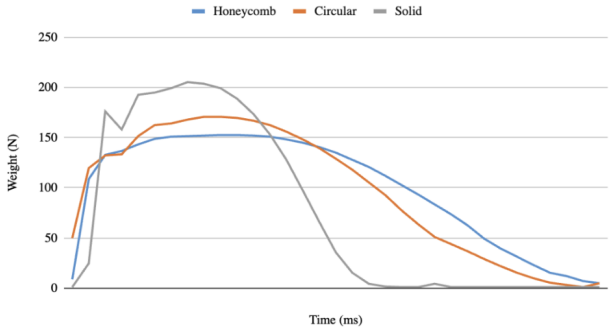
D. Classification Results with EEGConvTrans

We built independent classifiers for each task family (attention/emotion, verbal fluency, finger tapping, breathing conditions) on the preprocessing of Section IV-B. Unless indicated, we provide accuracy and loss traces of all the tasks.

Attention & Emotion. The training and validation curves are shown in Figure 8. The loss fell sharply within 10

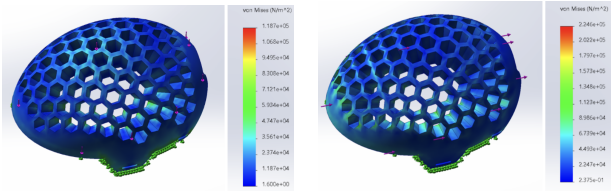


(a) Horizontal orientation.



(b) Vertical orientation.

Fig. 6: Absorbed force comparison across different geometric structures and orientations.



(a) Horizontal orientation. (b) Vertical orientation.

Fig. 7: Von Mises stress distributions tests.

epochs and converged by epoch 20, with the validation loss remaining slightly higher, showing steady learning. The accuracy on the training set attained nearly 100% by epoch 15, and the validation accuracy converged above 90%. The small train–validation gap indicates good generalizability, although variability observed in later epochs is likely due to inter-session variability. In general, the *EEGConvTrans* accurately classified focused attention, difficulty concentrating, and the inability to concentrate states, indicating its ability for real-time cognitive assessment.

Verbal Fluency. The network rapidly acquired discriminative speech category features, causing the training loss to decrease rapidly in the first 10 epochs, showing fast convergence, and stabilized after epoch 15. The validation loss showed oscillation from epochs 3–7 before settling down, likely due to restricted sample variability. The

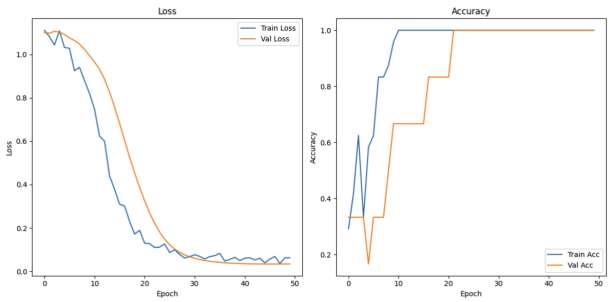


Fig. 8: Attention/emotion task: loss and accuracy.

accuracy increased steadily, with the training accuracy achieving 100% and validation stabilizing above 95% by epoch 12 (Fig. 9). The gap being small in later epochs indicates better generalization with low overfitting. The model generally does a good job of differentiating fluent, disfluent, and blocked speech conditions with robust performance achieved regardless of early instability.

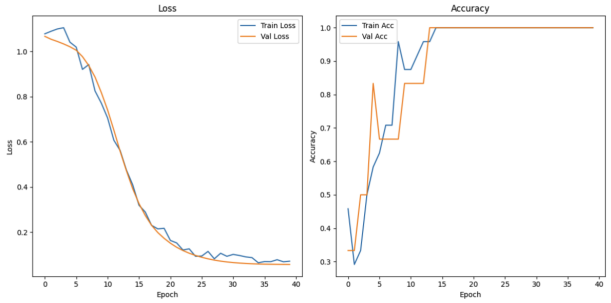


Fig. 9: Verbal fluency task: loss and accuracy.

Finger Tapping. As Fig. 10 shows, the training loss fell consistently and reached low values after epoch 40, indicating successful motor pattern learning. Validation loss, however, had large variations in later epochs, with larger variability across sessions and potential overfitting. Training accuracy achieved 100% at epoch 30, while validation accuracy fluctuated between 80–100%, with unstable generalization. These results show that additional regularization or data augmentation may be required to improve robustness. After 30 epochs, the train–validation curves start to drift apart, which is typical of overfitting when session diversity is limited. We therefore report the best-validation checkpoint (early stopping), and expect stronger regularization/augmentation to improve finger-tapping generalization.

Breathing State. As Fig. 11 shows, the training loss decreased regularly, a sign of successful learning, but validation loss remained consistently higher with enormous oscillations, a sign of instability across samples. While training accuracy approached 95% by epoch 30, validation accuracy plateaued at around 80% with sudden oscillations, a sign of overfitting and an inability to

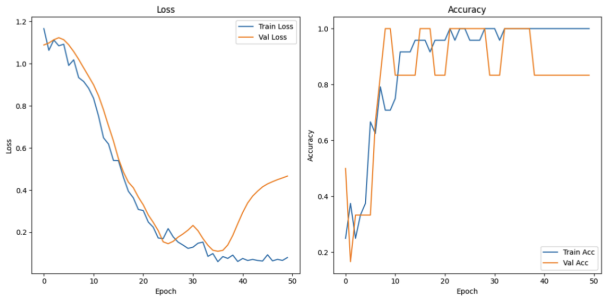


Fig. 10: Finger tapping task: loss and accuracy.

generalize breathing-pattern related features. Compared to the other tasks, this classification was harder, and it would probably require additional features or multimodal signals to be made robust.

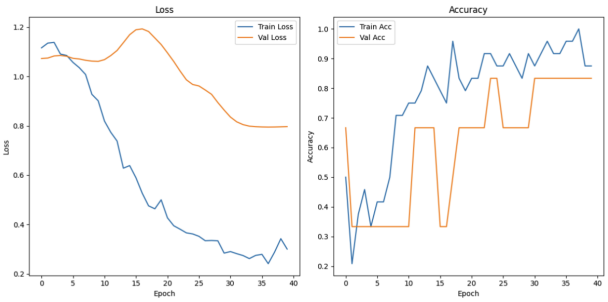


Fig. 11: Breathing state task: loss and accuracy.

V. Conclusion

We introduced the smart helmet *HiveGuard*, consisting of a honeycomb-patterned structure, a 16-channel EEG subsystem, and on-board real-time inference by *EEGConvTrans*. Sample tests and FEA demonstrate superior vertical impact absorption and more uniform stress than solid/circular samples. *EEGConvTrans* generates multi-class classification over 12 labels of concussion severity. These results validate the potential of *HiveGuard*'s multi-faceted approach to revolutionize concussion prevention and management in sports and recreation. Future work includes material testing to optimize protection, and applying advanced noise-reduction algorithms to improve EEG signal accuracy in various conditions.

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