INDUSTRIAL APPLICATION

Brain-regulated learning for classifying on-site hazards with small datasets

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Abstract
Machine vision technologies have the potential to revolutionize hazard inspection, but training machine learning models requires large labeled datasets and is susceptible to biases. The lack of robust perception capabilities in machine vision systems for construction hazard inspection poses significant safety concerns. To address this, we propose a novel method that leverages human knowledge extracted from electroencephalogram (EEG) recordings to enhance machine vision through transfer learning. By pretraining convolutional neural networks with EEG data recorded during construction hazard evaluations, we investigated three common on-site hazard classifications using small datasets. Our results demonstrated that the proposed method resulted in improved accuracy (with an 11% increase) and enhanced rationality of machine learning predictions (as revealed by network visualization analysis). This research opens avenues for further exploration and industry applications, aiming to achieve more intelligent and human-like artificial visual perception, ultimately enhancing safety and efficiency in automated hazard inspection.

1 | INTRODUCTION

In recent years, computer vision technologies have made significant advancements in hazard inspection, serving as a valuable supplement or even replacement for human inspection. These advancements primarily stem from the development of machine learning, particularly neural networks, which have achieved state-of-the-art accuracy in various prediction tasks (Rafiei & Adeli, 2016, 2017, 2018; Rafiei et al., 2017), especially within the field of vision (Li et al., 2019; C. Luo et al., 2021; Mostafa & Hegazy, 2021; Paneru & Jeelani, 2021; Valikhani et al., 2021). Nevertheless, training neural networks requires a substantial quantity of labeled samples (H. Luo & Paal, 2021), which necessitates significant manual effort and financial resources for annotation. Moreover, machine algorithms are susceptible to biases and can be easily misled when presented with highly cluttered or manipulated samples (van Dyck & Gruber, 2020; H. Zhou et al., 2022). The pursuit of autonomous inspection and monitoring systems utilizing machine vision in construction hazard inspection is driven by the potential for increased efficiency and safety. However, the current challenge lies in the lack of robust perception capabilities in these systems, which raises significant safety concerns. Without the ability to accurately perceive and interpret hazards in the environment, there is a heightened risk of overlooking potential dangers, leading to accidents, injuries, and compromised safety measures (Johansen et al., 2023; Yan et al., 2020). Therefore, it is crucial to develop machine vision systems with robust perception capabilities to ensure effective hazard detection and prevention, ultimately enhancing overall safety on construction sites.

Inspired by human’s inherent ability to perceive and detect biases in ambiguous environments, we aimed to leverage human knowledge to bridge the gap between...
machine vision and human-level intelligence (S. K. Chen et al., 2020). Thus, we sought to develop a method that extracts human knowledge and incorporates it into machine learning models. A direct approach to accessing human perception is by recording human cortical activities through non-invasive neuroimaging techniques such as electroencephalogram (EEG). In the field of construction, EEG has been extensively explored as an effective ergonomics tool and intuitive interface for human–machine collaboration (Aryal et al., 2017; Awoolu et al., 2019; Hwang et al., 2018; Jebelli et al., 2018; Jinwoo Kim et al., 2020; Tsao et al., 2019). However, the neural signatures specific to different construction hazards are not yet well-established, and there is currently no way to bridge the human internal representations reflected in brain activity patterns and machine learning models.

To address this gap, our study introduces a novel method that utilizes EEG recordings to capture human perception and leverages the technique of transfer learning. Specifically, we utilize human brain activity recorded during the perception of the same images as the machine learning models to create a pretraining dataset for neural networks. This pretraining step aims to initialize the network parameters. While our work builds upon previous transfer learning approaches (Gao & Mosalam, 2018; H. Liu et al., 2021; Q. Liu et al., 2018; Quqa et al., 2023), we extend the methodology by incorporating a separate stream of data derived from human brain activity. This allows us to explore the potential of leveraging human perception for improved performance in image classification tasks with small datasets.

In the following sections, we provide a detailed description of the implementation of our proposed method and present a case study focusing on three common construction hazard categories (Fang et al., 2020; Han et al., 2018): unclosed electrical compartments, lack of edge protection, and unstable temporary structures. By testing the performance of the proposed method within this context, we aim to assess its potential for achieving improved image classification accuracy and reasonableness using limited datasets. The novelty and contributions of our proposed method can be summarized as follows:

1. Conversion of time-series brain signals to time-frequency representations: We utilized wavelet transformation to convert the brain signals into time-frequency representations. This transformation allows us to leverage both the temporal and spectral features of the signals for more effective signal classification.
2. Utilization of convolutional neural networks (CNNs) for brain signal classification: By representing the time-frequency representations of brain signals in image format, we can employ CNNs, which have demonstrated exceptional performance in image classification tasks. This application of CNNs enhances the accuracy of brain signal classification.
3. Case study involving construction workers’ cortical activities: We conducted a case study where we recorded the cortical activities of construction workers via EEG while they evaluated the risk status of the same images used for classification by CNN. This empirical investigation provides valuable neurophysiological insights underlying hazard recognition, establishing a connection between human perception and machine learning.
4. Identification of specialized brain areas for hazard recognition: Through a comparison of brain activation patterns induced by different hazard categories, we identified the specific brain areas that exhibit specialization in recognizing construction hazards. This analysis provides evidence regarding the existence of high-level cognitive processing in hazard recognition and helps pinpoint the brain areas and associated cognitive functions responsible for recognizing specific hazards.
5. Exploitation of transfer learning using time-frequency representations: The time-frequency representations of brain signals, which have been transformed into a two-dimensional (2D) image format, serve as the source dataset for a transfer learning strategy. This approach capitalizes on the format similarities between brain signals and construction images, facilitating knowledge transfer and improving the classification performance of the model.
6. Interpretability through visualization techniques: To enhance interpretability, we employed visualization techniques that shed light on the decision-making process of the models. By evaluating the performance of the proposed approach not only on quantitative metrics but also on the rationality of machine learning predictions, we provide a comprehensive evaluation that fosters human trust in automation and ensures the reliability of the proposed method.

2 RELATED WORK

2.1 Using human brain activity to guide machine learning

The direct harnessing of internal representations in the human brain to guide machine learning represents a highly promising and novel approach that expands upon
the existing body of literature. Although previous research has extensively utilized measures of human behavior to enhance machine learning through various methods such as demonstration learning (C.-J. Liang et al., 2020), active learning (Jinwoo Kim et al., 2020), structured domain knowledge (Dash et al., 2022), and discriminative feature selection (Deng et al., 2015), this study highlights the unique advantage of directly leveraging human brain activity. By directly accessing the neural processes underlying human perception and cognition, this approach offers a distinct pathway for accelerating the development of automated vision-based hazard detection technologies, bringing them closer to achieving human-level intelligence. This interdisciplinary integration of machine learning and neuroscience holds great potential in advancing the field and paving the way for more sophisticated and effective hazard detection systems.

Prior studies have introduced methods to incorporate human brain activity into machine learning models. For example, one notable approach weighed the importance of training samples based on the effort exerted by the human brain in recognizing each sample, using functional magnetic resonance imaging (fMRI) to measure voxel responses to images (Fong et al., 2018). Another study employed transfer learning to combine feature representations learned from human brain activation patterns recorded by fMRI with deep visual features extracted from images, resulting in improved performance for an audiovisual pattern recognition task (Nishida et al., 2020). Although these methods demonstrated impressive performance by incorporating human brain representations, they face challenges in practical application due to the high costs and limited portability of fMRI.

In contrast, EEG offers a non-invasive, wearable, low-cost, and user-friendly alternative, making it more promising for widespread adoption (Saedi et al., 2022). However, the methods developed for voxel responses recorded by fMRI are not directly applicable to EEG signals due to the fundamental differences in their measurement principles and signal characteristics. The nature of fMRI voxel responses, primarily related to blood oxygenation level-dependent changes, differs from the power levels of EEG signals, which contain valuable frequency-domain information associated with brainwave activity. Therefore, a new method is required to extract human knowledge from recorded EEG signals and effectively integrate it into machine learning models. Additionally, identifying the critical brain regions involved in hazard recognition is of great practical significance as it allows for the reduction of electrodes required in EEG headset development, thus reducing costs associated with its implementation.

### 2.2 Human brain activity recording in construction

In construction tasks, where human assistance is often required due to the unstructured and dynamic nature of construction sites, effective communication between humans and robots is crucial for maintaining safety and productivity. To facilitate sustainable and safe human–robot collaboration, there is a growing emphasis on the development of intuitive user interfaces that minimize the cognitive effort required for communication with robots (Y. Liu et al., 2021). In this regard, researchers have explored the potential of neurophysiological sensing, which involves capturing and interpreting electrical charges generated by brain activity to infer cognitive-related information.

Among the various recording modalities, EEG has emerged as a popular choice due to its non-invasiveness and high temporal resolution, allowing for the capture of fast fluctuations in brain activity on a millisecond time scale (Bressler, 2002). By leveraging advanced signal processing and machine learning techniques, researchers have successfully decoded workers’ intentions and cognitive states in real time from continuously collected EEG signals, establishing an intuitive and implicit communication pathway between robots and human workers. For instance, mental imagery tasks have been used to classify brain signals and decode movement intentions (Feng et al., 2021; Hassanpour et al., 2019), enabling direct control of robots (Y. Liu et al., 2021) or rehabilitation devices (Burns et al., 2020; Z. Yang et al., 2018). Additionally, EEG-based wearables have demonstrated utility in diagnosing disorders (Bilgen et al., 2020; Nogay & Adeli, 2020; Oalamat et al., 2022), recognizing emotions (Cai et al., 2022), assessing mental states (Jebeelli et al., 2017, 2018; Wang et al., 2017), and monitoring workers’ abnormal conditions, allowing robots to trigger appropriate adjustments to better support their human counterparts in collaborative tasks (Y. Liu et al., 2022; Shayesteh & Jebeelli, 2022). This EEG-based communication pathway, which involves continuous monitoring of EEG signals and enables robots to react accordingly, serves as the foundation for a worker-centered human–robot collaboration framework (Y. Liu et al., 2021). This approach is often referred to as an adaptive automated system (Ijtsma et al., 2022) or a “keep human in the loop” approach in the literature (Eskandar et al., 2020). Its primary goal is to foster human trust in automation and facilitate a harmonized human–robot collaboration.

In practical applications, the integration of EEG-based sensor systems into smart safety headsets has revolutionized the evaluation of workers’ mental states (Jebeelli
et al., 2020). By continuously monitoring EEG signals, these systems can promptly detect abnormalities and trigger adaptive aiding or prevention warnings. This real-time assessment of workers’ cognitive states significantly enhances safety and promotes a proactive approach to addressing potential risks. Looking ahead, EEG-based wearables hold tremendous market potential due to the widespread recognition of neurophysiological sensing as a powerful tool for ergonomics (Abuwarda et al., 2022; Saedi et al., 2022). Moreover, the intuitive communication facilitated by EEG-based technology has also emerged as a vital aspect of integrated human–robot interaction. The seamless exchange of information between humans and robots through EEG-based wearables fosters efficient collaboration and enhances the overall productivity and safety of construction environments. As the field advances, EEG-based wearables have the potential to become ubiquitous real-world applications, with extensive EEG signal collections serving as valuable data pools for algorithm development. These datasets enable researchers to explore new frontiers in EEG signal analysis and unlock the full potential of EEG-based technologies. This has the capacity to revolutionize various industries by leveraging the rich information encoded in human brain activity.

2.3 Spatial, temporal, and spectral features of EEG signals for hazard recognition

Our proposed method is grounded in a hypothesis that cortical activities measured through neuroimaging techniques contain valuable information about object categories. Previous studies have extensively explored how the human brain responds to various objects, including human faces, body parts, and natural scenes (Muret et al., 2022; Peelen & Downing, 2017). Specialized cortical regions dedicated to processing these objects, such as the temporal lobe for human face processing (Jonas et al., 2016), have been well-characterized. However, the neuropsychological evidence regarding construction hazards is limited. Only a few studies have utilized EEG recordings and event-related potentials to investigate the neurophysiological signatures associated with hazard recognition. For instance, the presence of P300 components in the frontal and parietal areas has been observed when participants viewed hazardous images (J. Chen et al., 2022; Q. Liu, 2018; Ma et al., 2014). Although these studies identified critical spatial and temporal features of brain activity induced by hazardous conditions, compared to safe conditions, they did not explore how the human brain responds differentially to various hazard categories. In fact, previous field observations and questionnaire-based studies have suggested that the recognition of different hazards involves distinct cognitive processes (Albert et al., 2017; Han et al., 2018). The lack of clear neuropsychological correlates for hazard recognition and the limited understanding of how the human brain responds differently to various hazard categories limits our ability to leverage human knowledge for improving machine learning algorithms in this domain.

Furthermore, in the field of EEG-based sensor system applications, feature extraction and classification are crucial steps following signal acquisition and preprocessing. Traditionally, EEG studies in construction have utilized various types of features, including time-domain features (e.g., average amplitude), frequency-domain features (e.g., power spectral density in specific frequency bands), and time-frequency domain features (e.g., valence and arousal) as inputs to machine learning classifiers such as linear discriminant analysis, support vector machines, and k-nearest neighbor (Jeon & Cai, 2021; Saedi et al., 2022). These approaches have shown impressive performance, but they require expertise in both EEG signal features and the specific engineering task being investigated, posing a technical barrier that may impede the future exploration of EEG-based applications.

To overcome the limitations of handcrafted EEG features, researchers have turned to deep learning techniques for end-to-end analysis. By leveraging deep learning, the need for manual feature extraction is alleviated, leading to exceptional classification performance in various cognitive tasks involving EEG signal classification (Craik et al., 2019; Schirrmeister et al., 2017). In the quest for an appropriate neural network structure for EEG signal classification, researchers have also explored the paradigm of transfer learning, which allows them to harness well-established computer vision models from the existing literature for image classification tasks. Moreover, prior research has demonstrated the superiority of transfer learning over traditional classifiers in the classification of EEG signals (Zhang et al., 2020). Building upon these findings, this study adopts a transfer learning approach to classify EEG signals induced by different hazard categories.

To preprocess the raw EEG signals and prepare them as inputs for CNNs, this study draws inspiration from previous works that utilized wavelet transformation to convert the raw brain signals into the time-frequency domain, enabling the extraction of spatial–spectral–temporal EEG representations (Hajinoroozi et al., 2016; Tabar & Halici, 2017). In addition, this study extends the frequency range of interest to include a broader spectrum, aligning with prior research on the neurocognitive mechanisms of construction hazard recognition based on brain activation patterns (Liao et al., 2022). This extension surpasses the analysis of features extracted solely from a single frequency band as
seen in previous studies (W. Liu et al., 2018; Nicolae et al., 2020; Nogay & Adeli, 2020).

3 | METHODOLOGY

3.1 | EEG data acquisition

The EEG data used in this study are a subset of the data from a previously published study that investigated construction hazard recognition (J. Chen et al., 2022). Seventy-seven male construction workers (all right-handed, with normal or corrected-to-normal vision) were recruited from the real estate management office at Tsinghua University, China, to participate in the experiment. One participant was excluded due to excessive artifacts in his EEG signals. All participants provided written informed consent and received 100 RMB as compensation for their participation. The study was approved by the Department of Civil Engineering at Tsinghua University.

The experimental task was an image-based hazard recognition task (see Figure 1a). Images of on-site construction scenes were displayed on a monitor screen using Tobii Pro Lab software. The images were retrieved from a database (Q. Xu et al., 2019) that collects pictorial recordings and descriptions of construction hazards identified during safety inspection, along with corresponding pictorial recordings of corrected scenes after rectification.

During the experiment, participants were seated approximately 0.8 m from the monitor in a sound-attenuated room. The trial procedure was as follows: A fixation (a cross) appeared at the center of the monitor for 500 ms to instruct participants to focus their attention. The duration of the fixation was typically 500–800 ms to balance visibility and avoidance of distraction. Subsequently, an image depicting a construction scene was presented for up to 3000 ms. Participants could press any key to end the display early if they had already made a judgment decision regarding the scene’s risk status within 3000 ms; otherwise, it remained on-screen for the full duration. A blank screen appeared for 500 ms after the image, followed by a response screen where participants reported the risk assessment of the previously presented construction scene by pressing a corresponding key on the keyboard (“0” for safe, “1” for hazardous). The 500 ms blank screen served as an interstimulus interval, delaying the presentation of the next screen to prevent participant overwhelm and ensure a smoother experimental process.

The experiment consisted of three sessions: training, formal, and validation. In the training session, participants were familiarized with the experimental protocol and performed 10 practice trials. The practice session continued until participants reported feeling comfortable with the experimental setup. The images used in the training session were different from those used in the formal session. In the formal session, a 1-min break followed every 30 trials to alleviate fatigue. During the break, participants were instructed to relax with their eyes closed. The validation session included 30 randomly selected trials from the previous trials to assess the consistency of participants’ responses. Participants with a consistency rate below 50% were excluded from further analysis. Consequently, five participants were excluded.

EEG signals were recorded using a 32-channel electrode cap at a sampling rate of 250 Hz. The electrodes were arranged according to the 10–20 system. Before recording the EEG signals, electrically conductive adhesives were injected into the gaps between each electrode and the participant’s scalp. The electrode impedance was visually monitored using computer-aided visualization, and the EEG signals were not recorded until the impedance of all channels was below 20 kΩ.

3.2 | Dataset

The dataset for each participant consisted of 120 color images of real construction scenes, which were presented while their brain activities were recorded using EEG (refer to J. Chen et al., 2022, for detailed information on the dataset). The images represented various hazard categories, including overhead power lines, unprotected electrical panels, open electrical compartments, suspended platforms without edge protection, unstable temporary structures (e.g., scaffolding and frameworks), lack of safety helmets, floor obstacles causing tripping, and improper storage of flammable or explosive chemicals. For this study, we focused on a subset of these categories, specifically electric leakage, lack of edge protection, and structural instability, with each category consisting of 10 samples (see Figure 1b). These images were used as visual stimuli for both EEG data collection and training data for machine learning experiments.

3.3 | EEG data preprocessing

The EEG signals underwent initial bandpass filtering from 0.1 to 40 Hz. Subsequently, possible artifacts, such as heartbeats, eye movements, and respiration responses, were identified and removed using independent component analysis (Makeig et al., 1996). The EEG signals were then segmented into trial-based epochs of [−200 ms, 1000 ms], with a baseline of [−200 ms, 0 ms] (0 ms denoting the stimulus onset). Epochs containing values exceeding ± 100 µv for any recording electrode were
FIGURE 1  (a) Neuropsychological experiment investigating a construction hazard recognition task with electroencephalogram (EEG) data being collected. (b) Visual stimuli depicting hazard categories (A: electric leakage, B: lack of edge protection, C: structural instability) and conditions (1: hazardous, 2: safe). (c)–(e) Examples of raw EEG signals and time-frequency maps of EEG representations after wavelet transformation for the three hazard categories. (f) Example of a time-frequency map generated by time-frequency analysis of the EEG signals. The color bar indicates the magnitude of oscillatory power. (g) Gradient-weighted class activation mapping (Grad-CAM) localizations for the “electric leakage” category using the ImageNet-pretrained visual geometry group (VGG)-16 model, along with predicted labels and their respective probabilities. (h) Grad-CAM feature heatmaps highlighting important regions for model prediction and original construction scene images for the “lack of edge protection” category. The original images and their corresponding feature heatmaps are displayed from top to bottom. The red-to-blue gradient signifies the model’s focus on specific areas. CNN, convolutional neural network.

3.4 EEG time-frequency representation analysis

To serve as 2D inputs for the CNN, all raw EEG signals were transformed into the time-frequency domain (Tallon-Baudry et al., 1996; see Figure 1c–e). The method employed for quantifying changes in brain signal amplitude is based on a time-frequency wavelet decomposition of the signals (Tallon-Baudry et al., 1997). This method offers a better compromise between time and frequency resolution (Sinkkonen et al., 1995), compared with short-term Fourier transforms (Makeig, 1993). It provides a time-varying energy of the signal in each frequency band, resulting in a time-frequency representation of the signal. Each trial was convoluted with complex Morlet’s wavelets, as denoted as \( w(t, f_0) \) (Kronland-Martinet et al., 1988), which have a Gaussian shape in both the time domain (\( \sigma_t \)) and the frequency domain (\( \sigma_f \)) around their central frequency (\( f_0 \)), as in

\[
 w(t, f_0) = A \exp \left( -\frac{t^2}{2\sigma_t^2} \right) \exp \left( 2i\pi f_0 t \right)
\]

with \( \sigma_f = 1/2 \pi \sigma_t \). Wavelets are normalized so that their total energy is 1, the normalization factor \( A \) being equal to \( (\sigma_t \sqrt{\pi})^{-1/2} \).

The time-varying energy \( [E(t, f_0)] \) of the signal in a frequency band is the square norm of the result of the convolution of a complex wavelet \( [w(t, f_0)] \) with the signal \( [s(t)] \) as in

\[
 [E(t, f_0)] = |w(t, f_0) \times s(t)|^2
\]
TABLE 1  Details of each layer in the proposed convolutional neural network model.

| Layer type  | No. of filters | Kernel size | Output shape | No. of trainable parameters |
|-------------|----------------|-------------|--------------|----------------------------|
| Input       | /              | /           | 150 × 150    | /                          |
| Conv2D      | 16             | (3,3)       | 148 × 148    | 448                        |
| MaxPooling  | 16             | (2,2)       | 74 × 74      | 0                          |
| Conv2D      | 32             | (3,3)       | 72 × 72      | 4640                       |
| MaxPooling  | 32             | (2,2)       | 36 × 36      | 0                          |
| Conv2D      | 64             | (3,3)       | 34 × 34      | 18,496                     |
| MaxPooling  | 64             | (2,2)       | 17 × 17      | 0                          |
| Flatten     | /              | /           | 18496        | 0                          |
| Dense       | /              | /           | 512          | 9,470,464                  |
| Dense       | /              | /           | 3            | 1539                       |

t represents a continuum of real values over a specified time interval. The time-frequency representation of the signal is obtained through the convolution of the signal by a family of wavelets. In line with a previous study (Harada et al., 2020), the Hanning taper was used to generate the time-frequency representations of the EEG data. A sliding window of 500 ms with 50 ms time steps was applied. The period of interest for the analysis was chosen as the 0−0.9 s post-stimulus period based on previous findings highlighting the relationship between brain activities and the processing of visual information related to construction hazards (X. Zhou et al., 2022). The time-frequency analysis of the EEG data was performed using the FieldTrip toolbox in MATLAB.

3.5 Experimental design

We adopted a CNN learning framework in accordance with a CNN structure designed for a similar task of classifying transformed EEG images (M. Xu et al., 2020). The CNN architecture consisted of an input layer, three convolution layers with rectified linear units (ReLUs), max-pooling, two fully connected layers, and a softmax output layer for classification. Refer to Table 1 for detailed information on the CNN architecture.

The experiments were conducted using Keras (version 2.4.3) with TensorFlow (version 2.3.1) as the backend. When training on the EEG data, the parameters of the CNNs were randomly initialized from Gaussian distributions and trained with a batch size of one image instance. Convolution stride was applied in each dimension, and the “SAME” mode was used for spatial padding. The ReLU activation was followed by a pooling layer with a side length of 0, filled with a zero, and a moving step size of 2. Adamax optimization (Kingma & Ba, 2014) with a learning rate of 0.0001 was employed, and categorical cross-entropy was used as the loss estimation metric.

The models were tested using five-fold cross-validation. The full dataset was split into five equal-sized portions, with four portions used for training and one for testing in each iteration. This process was repeated five times to ensure that each portion was used for testing exactly once. Due to the small size of the dataset, we trained the models for up to 20 epochs and implemented early stopping to prevent overfitting. Early stopping was applied when the loss on the validation set did not decrease for three consecutive epochs. The CNN was then fine-tuned on the construction image dataset, using the same training–testing splits as the EEG images.

For the baselines, we implemented the same CNN architecture from scratch on the construction image dataset. Additionally, we employed a mainstream pretrained model, namely, the visual geometry group (VGG)−16 (Simonyan & Zisserman, 2014). This 16-layer CNN includes a series of convolutional layers followed by a max-pooling layer. The VGG-16 model was pretrained on the ImageNet dataset, which contains over 1.2 million 256 × 256 natural images categorized into 1000 classes (Deng et al., 2009). Examples of object categories in ImageNet include “bonnet,” “chainlink fence,” “castle,” and “garbage truck.” ImageNet consists of a wide range of object categories, making it a commonly used dataset for implementing transfer learning.

To adapt the VGG-16 model, we followed a customary approach from a previous study (Oquab et al., 2014): We replaced the top fully connected layer with a new layer consisting of 512 activation units and a final softmax activation layer for predictions on our dataset’s three preexisting categories. In the fine-tuning process, the early layers of the VGG-16 model were kept fixed, and only the newly introduced layers were trained using an Adamax optimizer (Kingma & Ba, 2014) with a learning rate of 0.0001.
This approach leverages the generic features generated by the earlier layers, while the higher-level layers focus on task-specific features for differentiating between object categories (Bengio et al., 2013).

3.6 Visualization via gradient-weighted class activation mapping (Grad-CAM)

To assess the interpretability of the machine learning predictions, we employed the Grad-CAM technique to produce a visual explanation for decisions from the CNN models (Selvaraju et al., 2020), inspired by Melching et al. (2022), Y. Yang et al. (2022), and Selvaraju et al. (2020). Grad-CAM generates a coarse localization map that highlights the regions in the image that the CNN relies on to make its predictions. By analyzing the gradients of the target object parts flowing into the final convolutional layer, Grad-CAM assigns importance weights to each neuron, capturing the semantic class-specific information relevant to the particular decision of interest. This visualization technique aids in localizing discriminative image regions and provides valuable insights into network interpretability, enabling the diagnosis of failure modes and explanations for seemingly unreasonable predictions.

4 RESULTS

After the time-frequency analysis of the EEG signals, the time course of signal energy in each frequency band from a representative electrode is shown in Figure 1f. The time-frequency representations of the EEG signals were obtained using a 100-ms and 2-Hz time-frequency sliding window. This is equivalent to extracting the value of each pixel in the time-frequency map (Figure 1f) and averaging over the time-frequency window to get the time-frequency features of EEG signals.

As suggested by Cohen and Gulbinaite (2013), the time-frequency representations of EEG signals are afterward denoted as “power”—the squared amplitude of frequency-band-specific time series—to concisely reflect the mathematical procedure of extracting the energy of a frequency band-specific signal. Because the power induced by the visual stimuli of each hazard category did not follow normal distributions (Lilliefors test, \( p < 0.05 \)), a Kruskal–Wallis test was conducted to compare the power induced by the three hazard categories. The statistical analysis employed a two-tailed test with a significance level of 0.05.

In previous neurophysiology studies, three brain regions—the frontal cortex, posterior parietal cortex, and temporal cortex—are mainly examined because they have been widely recognized for their crucial roles in the cognitive processes related to object recognition (Linden et al., 2012). We observed that the differences in power induced by the three hazard categories were most prominent in the left frontal cortex (see Figure 2). This is consistent with the findings of previous neuropsychological studies on construction hazard recognition that suggest the left frontal cortex is actively involved to enable category-related semantic analysis (Jeon & Cai, 2021; X. Zhou et al., 2021). The results also align well with cognitive theories that the left frontal cortex is a vital region for object vision in remembering “what” an object is (Wilson et al., 1993). Therefore, brain activities recorded from the F3 electrode were considered optimal for capturing the semantic information of the hazard categories encoded in the internal representations of the human brain and were chosen for the subsequent machine learning experimentation.

For the participant, we generated the time-frequency map of the artifact-free EEG signals on a trial basis. These maps were then averaged across trials of each hazard category and normalized by calculating the relative change from the baseline. The averaged time-frequency maps of the three hazard categories are shown in Figure 1c–e. Notably, we observed that spectral power in recognizing structure-related hazards was most pronounced in the gamma band, whereas edge protection-related hazards induced stronger beta-band oscillatory activities. The cognitive functions associated with these findings are discussed in Section 5.

The time-frequency maps of EEG signals, generated on a trial basis, served as the source dataset for deploying the transfer learning strategy. Pretraining the CNN on these maps resulted in an average accuracy of 33% for classifying the EEG signals induced by the three hazard categories. Subsequently, the CNN was fine-tuned on the construction images, and the performance was evaluated using accuracy, precision, recall, and F1 score (see Figure 3).

The results demonstrate that the EEG-pretrained CNN outperforms the CNN from scratch, exhibiting improved accuracy, recall, and F1 score. This improvement can be attributed to the integration of neurophysiological insights, which enhance the model’s feature extraction capabilities and enable more accurate hazard classifications. These findings validate the efficacy of utilizing EEG data as an additional side-source for regularization, resulting in a better set of model weights that capture hazard category information carried in human brain activities and compensating for the limited training samples.

Additionally, the ImageNet-pretrained VGGNet demonstrates competitive performance in the hazard classification task. The pretraining on the large-scale ImageNet dataset equips the VGGNet with strong feature extraction capabilities, which are reflected in its higher accuracy,
FIGURE 2 Results comparing EEG powers induced by three hazard categories in multiple electrodes for each time-frequency window (time: 0–100, 100–200, 200–300, 300–400, 400–500, 500–600, 600–700, 700–800, and 800–900 ms; frequency: 2–4, 6–8, 10–12, 14–16, 18–20, 22–24, 26–28, 30–32, 34–36, and 38–40 Hz). Blocks filled in black denote corresponding \( p < 0.05 \).

FIGURE 3 Classification performance metrics. CNN, convolutional neural network.

recall, precision, and F1 score, compared to the CNN from scratch. This highlights the benefits of leveraging pretrained models in image classification tasks.

A notable comparison arises between the EEG-pretrained method and the ImageNet-pretrained VGG-16. Based on quantitative evaluation metrics, the ImageNet-pretrained VGG-16 performs better in hazard classification. The underlying mechanism could be that the EEG-pretrained method leverages domain-specific knowledge encoded in EEG signals, allowing it to more effectively capture hazard-related patterns. In contrast, the ImageNet-pretrained VGG-16 capitalizes on its broad knowledge of visual features from the ImageNet dataset, contributing to its competitive performance. This contrast emphasizes the significance of considering different sources of prior knowledge when designing classification models.

Moreover, despite the superior quantitative performance of the ImageNet-pretrained VGG-16, further visualization analysis raises concerns about its true understanding of the scene and reliance on correct features for predictions. Figure 1g shows that VGG-16 misclassifies the electrical compartment as a gas pump instead of recognizing it as the dominant object. In another case, it misrepresents green plants in the environment, assigning a high probability (> 0.7) to “greenhouse” as the output label. Similarly, for the “lack of edge protection” category in Figure 1h, the ImageNet-pretrained VGG-16 falsely predicts “maze” and “prison” as the labels for Examples A and B, respectively. In contrast, the EEG-pretrained CNN accurately localizes the edge even in the absence of the key element, railway, demonstrating higher robustness regardless of scene conditions and visual clutter.

The qualitative results from the visualization analysis emphasize the importance of understanding how models
make decisions in addition to quantitative metrics to ensure the reliability and accuracy of hazard recognition systems. Establishing appropriate trust in automation requires interpretability of the models. Although deep neural network models sacrifice interpretability for greater performance, gaining insights into the rationality of machine learning predictions is crucial for evaluating their reliability and building human trust in machine intelligence. In this regard, our proposed method successfully incorporates the advantages of human vision, which is less biased by highly cluttered environments. This is critical for automated hazard detection techniques to function effectively on unstructured and dynamic construction sites, bringing machine vision closer to human-level intelligence.

5 | DISCUSSION

Our study demonstrates the feasibility of accessing human perception using EEG and transferring human internal representations to a machine learning algorithm through transfer learning, leading to more accurate and reasonable classification for a few-shot hazard image classification task. While these preliminary results are promising, further research is needed to confirm the efficacy of this approach and explore its potential applications in automated hazard detection.

The identification of neurophysiological signatures for hazard recognition also provides valuable insights into human visual perception and processing systems, offering actionable information for effective safety training programs and interventions. Specifically, our findings reveal that the recognition of “lack of edge protection” is associated with stronger beta-band activity in the left frontal cortex, indicating heightened cognitive control beyond anticipating potential falls. Furthermore, it was observed that the gamma-band oscillatory activity was stronger when participants perceived an “unstable structure,” suggesting the involvement of higher-order sensory processing, such as visuospatial working memory maintenance and selective attention modulation. These results underscore the importance of prioritizing hazard “unstable structure” in safety training programs to facilitate the construction of mental schemas among workers and improve their hazard recognition capacities. By bridging the neural correlates of hazard recognition and associated cognitive functions, our research provides a foundation for developing targeted interventions that enhance workers’ hazard perception and mitigate workplace accidents. Future research should continue to explore the potential applications of neurophysiological signatures for improving safety training and develop evidence-based strategies to optimize hazard recognition in various occupational settings.

Furthermore, the proposed method presented in this study offers a promising approach to image labeling by directly decoding category information from recorded brain activities, thereby potentially revolutionizing the traditional manual annotation process. The ability to decode brain activities and leverage them for image labeling opens new possibilities for automating and enhancing the annotation process, reducing reliance on human annotators. Moreover, the pretraining of the CNN on human brain activity is hypothesized to result in a better set of model weights as evidenced by the improved classification performance in a few-shot image classification task. This approach underscores the potential for integrating human knowledge into machine learning and reducing the dependency on extensive labeled datasets for neural network training. While our study focused on construction hazard images, the framework is applicable beyond hazards and the construction context. By incorporating insights from human brain activity, we can mitigate the manual efforts and resources required for image labeling, paving the way for more efficient and scalable machine learning algorithms in various domains.

Moreover, our findings strongly support the practical implementation and translation of our approach into real-world applications. The identification of the left cortex as a superior region for capturing hazard-related category information provides a crucial foundation for the development of more efficient and cost-effective EEG-based wearable devices. By leveraging the left cortex as a focal recording site, we can reduce learning time and mitigate the risk of overfitting when analyzing high-dimensional EEG data. Focusing on the most informative brain regions allows us to streamline the data analysis process and enhance the efficiency of model pretraining. Additionally, minimizing the development costs associated with EEG-based wearables enables improved accessibility and commercial viability.

Last, the findings of this study demonstrate the potential of our proposed method to facilitate intuitive communication of human perceptions regarding hazard-category information. This novel communication channel holds the promise of replacing traditional verbal communication or button-press interfaces in device design, opening up new possibilities for seamless human–machine collaborations in ubiquitous hazard identification. By harnessing the rich information encoded in human brain activities, semi-automated navigation and perception systems can be better guided by human cognition, leading to more efficient and accurate hazard identification. The implications of this study extend beyond hazard identification and have broader applications in the development of advanced
human–machine interfaces. This research highlights the transformative role of neurophysiological insights in shaping the future of human–machine interaction, driving innovations in various tasks.

The initial implementation of the proposed paradigm has several limitations, which warrant further research for their resolution. First, the CNN architecture used in this study was adapted from a previous work on EEG image classification, chosen for its computational efficiency (Arco et al., 2022; Y. Liang et al., 2022). Future studies should explore neural architecture search methods to automatically design an optimal network structure, potentially leading to improved performance (Xue et al., 2021).

Second, the EEG data in this study were collected during a binary discrimination task, focusing solely on the presence or absence of hazards. To gain deeper insights into human brain functioning during hazard recognition, it is recommended that future research employs a multiple-choice design. By allowing participants to engage in comprehensive scene understanding and risk assessment, this approach would enable monitoring of brain regions involved in more complex cognitive functions. Furthermore, providing feedback to participants during the experiment can facilitate learning and encourage accurate responses, thereby minimizing noise from false trials (Grill-Spector et al., 2000). This expanded experimental design would enable investigation into whether recorded brain activity, obtained in more realistic settings, encodes superior domain knowledge. Consequently, the potential for enhancing machine learning algorithm performance using this methodological framework can be explored.

Third, it is important to note that the proposed method was tested on EEG data acquired from a single participant, and the performance improvement of the EEG-pretrained CNN model was observed. Although this finding demonstrates the feasibility and potential benefits of our approach, it is crucial to conduct further studies with larger and more diverse participant samples to validate and generalize these results. Future research can also expand upon this work by investigating individual differences in hazard recognition processes, leading to the development of more personalized services for EEG headset users.

Last, as commercially available EEG devices become more widespread, novel paradigms for EEG data sharing are emerging, including blockchain platforms supported by cryptoeconomic incentives. The future holds potential for workers’ EEG data to be shared in a more open and transparent manner, allowing for broader utilization. Additionally, we plan to release the EEG dataset used in this study to the public, contributing to the advancement of research in this field.

6 | CONCLUSION

Consensus has been achieved that machine vision can benefit from learning from biological vision, and research effort has been devoted to characterizing the neural processes underlying construction hazard identification. However, there remains a gap in directly transferring knowledge between human visual recognition and machine vision models. In this study, we introduce a novel paradigm of brain-regulated machine learning, where a neural network is pretrained using wearable EEG data recorded from human subjects viewing the same images as the machine vision algorithms. We selected EEG to record brain signals owing to its high temporal resolution, portability, and commercial viability (Liao et al., 2022). The transfer learning paradigm was utilized as it has been proven effective in multiple cross-modality image settings in previous studies (Jia et al., 2021). To evaluate the performance of the proposed EEG-pretrained method, we compared it with the performance of the randomly initialized and ImageNet-pretrained methods on a three-class construction hazard classification task with a small-scale dataset. Our results demonstrated that the EEG-pretrained method outperforms the other methods in terms of classification accuracy and the overall reasonableness of the predictions as revealed by the network visualization technique. By pretraining the CNN models on EEG data, we effectively extract and incorporate human knowledge of hazard recognition from recorded brain activities into the models. This approach represents a significant advancement in bridging the gap between human visual capabilities and machine learning algorithms. Our work holds great potential for enhancing the practical implementation of machine vision in improving the performance and reliability of automated hazard detection systems. By leveraging the insights gained from our study, we envision that our findings will inspire further research and industry applications in the pursuit of more intelligent and human-like artificial visual perception across various domains.

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