# THE HALLMARK OF COLOUR IN EEG SIGNALS

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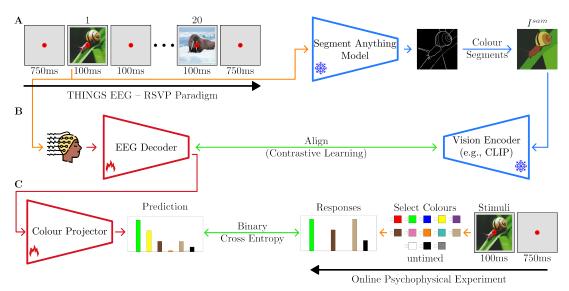
# **ABSTRACT**

Our perception of the world is inherently colourful, and colour has well-documented benefits for vision: it helps us recognise objects more quickly and remember them more effectively. We hypothesised that colour is not only central to perception, but also a rich and decodable source of information in electroencephalography (EEG) signals recorded non-invasively from the scalp. Previous studies have shown that colour can be decoded from neuroimaging brain signal to simple, uniformly coloured stimuli, but it remains unclear whether this extends to natural, complex images where colour is not explicitly cued. To investigate this, we analysed the THINGS-EEG dataset, in which 64-channel EEG was recorded while participants viewed over 1,800 distinct objects presented for 100 ms each in a rapid serial visual presentation paradigm. We established a perceptual colour ground truth through an online psychophysical experiment, where participants briefly viewed each image and selected all perceived colours from a palette of thirteen options. We then trained an artificial neural network to predict these scene-level colour distributions directly from EEG signals, and we found that colour information was robustly decodable (average F-score about 0.5). We next asked whether colour could enhance EEG-based object decoding. Given the strong link between colour and object perception, we segmented images using the Segment Anything Model (SAM), assigned each object a representative colour based on its average pixel values, and extracted features from these colouraugmented images with CLIP vision encoders. We trained an EEG encoder—CUBE (ColoUr and oBjEct decoding)—to align features not only in object space but also in colour space. Across both THINGS EEG and MEG datasets, in a 200-class object recognition task, integrating colour features improved decoding accuracy for all participants by about 5% across architectures. Together, these results demonstrate that EEG signals carry substantial colour information during natural vision and that modelling colour explicitly can strengthen neural decoding frameworks. This work highlights a new way to study the neural representation of colour and its role in supporting visual cognition.

### 1 How strong is the colour signal in neuroimaging?

Our visual system makes sense of a scene with remarkable speed. In just a fleeting glance, as brief as 13 ms, we can attach a simple description such as "green tree" to what we have seen (Potter et al., 2014). This raises an important question: what kind of rich representations arise in the brain within such a short window, and can these be detected in neuroimaging signals? Here we turn our attention to colour, an effortless and ever-present aspect of vision. Colour not only shapes how we perceive objects (Tanaka et al., 2001; Bramão et al., 2011), but also enhances memorability (Gegenfurtner & Rieger, 2000; Wichmann et al., 2002) and speeds up recognition (Møller & Hurlbert, 1996; Rosenthal et al., 2018).

Research into colour decoding from neuroimaging has a long history (Regan, 1970; Paulus et al., 1984). Studies have shown that signals carry information about chromaticity, luminance, and saturation (Sutterer et al., 2021; Hermann et al., 2022; Pennock et al., 2023; Rozman et al., 2024), the hue circle (Hajonides et al.,



**Figure 1:** The schematic framework of **CUBE** (ColoUr and oBjEct decoding). **A:** The RSVP paradigm used to collect the THINGS EEG dataset (Gifford et al., 2022). **B:** An EEG encoder aligns brain activity with features from a pretrained vision encoder applied to colour-segmented images. **C:** A linear projection layer maps the aligned representation to thirteen-dimensional behavioural colour responses.

2021), the geometry of colour space (Rosenthal et al., 2021), and even unique hues (Chauhan et al., 2023). Fewer studies, however, have examined how colour interacts with object processing. One study suggests that while both shape and colour can be decoded from as early as 60–70 ms after stimulus onset, shape—colour congruency only appears much later, around 200 ms (Teichmann et al., 2020). These insights are valuable, yet they mostly come from simplified displays of uniform coloured shapes on plain backgrounds. What remains unclear is whether colour can also be reliably decoded from non-invasive brain signals when people view rich, natural scenes. This is the challenge we take on in the present study.

In recent years, progress in decoding has accelerated thanks to artificial intelligence and the availability of large datasets. The NSD dataset (Allen et al., 2022), for example, offers large-scale fMRI data covering about 10,000 natural images. Similarly, the THINGS EEG (Gifford et al., 2022) and MEG (Hebart et al., 2023) datasets provide recordings of comparable scale, creating new opportunities to investigate how natural images are represented in the brain. Alongside these resources, contrastive learning (Radford et al., 2021) has emerged as a powerful tool for decoding. It has already shown strong performance across modalities, from speech recognition (Défossez et al., 2023) to visual object recognition in fMRI (Scotti et al., 2024), EEG (Song et al., 2024), and MEG (Wu et al., 2025).

# 1.1 **CUBE** (**C**OLO**U**R AND O**B**J**E**CT DECODING)

We adopted the same general framework of large datasets and contrastive learning to investigate how colour is represented in brain signals during natural image viewing. Our focus here is on EEG, which, despite its low spatial resolution, offers high temporal resolution, affordability, portability, and the possibility of real-time decoding (Benchetrit et al., 2023; Robinson et al., 2023). Instead of collecting a new dataset, we created colour annotations for the THINGS EEG dataset (Gifford et al., 2022) through a large-scale psychophysical experiment designed to mimic the conditions of the original recordings. Participants viewed an image for 100 ms and then selected all perceived colours from a palette of 13 options (see Figure 1, panel C).

We trained an EEG decoder, implemented as a simple artificial neural network (ANN) with two linear layers and a residual connection, to align EEG representations with visual features extracted from pretrained CLIP networks. To better capture perceptual colour structure, which operates at the object rather than pixel level (Gegenfurtner, 2025), we processed each image  $I^{org}$  using the Segment Anything Model (SAM) (Kirillov et al., 2023). For each segmented region, we averaged pixel colours to create uniformly colour-segmented images  $I^{sam}$  (see Figure 1, panel B), providing a closer approximation to colour perception at a glance.

To evaluate colour decoding from EEG signals, we added a linear projection layer atop the CLIP-aligned features to output a 13-dimensional vector matching the behavioural colour palette. Performance was measured with the F-score for this multi-class task. Results show reliable decoding, with an average F-score of 0.50 across participants—well above chance (0.17). This constitutes our first contribution: demonstrating colour decoding from EEG during natural image viewing with 100 ms exposure. Notably, the noise ceiling in this RSVP paradigm is 0.64, indicating the decoder approaches average human agreement.

Encouraged by these results, we hypothesised that incorporating colour features into the contrastive alignment framework could enhance object recognition decoding. Prior work shows that colour and object perception are closely intertwined, both in behavioural studies (Bramão et al., 2011; Gegenfurtner, 2025) and at the neuronal level (Rosenthal et al., 2018; Tanaka et al., 2001). To model this, we aligned the EEG decoder simultaneously to CLIP features from the original images  $I^{org}$  and from colour-segmented images  $I^{sam}$  (Figure 2). These segmented images capture object—colour associations more directly, particularly under the brief 100 ms exposure used in our experiment.

We term this framework **CUBE** (ColoUr and oBjEct decoding), as it explicitly leverages the interaction between colour and object representations in the brain. Experimentally, CUBE improves state-of-the-art object recognition decoding by a consistent 5% across all participants and in both EEG and MEG. This underscores the importance of colour—object interactions in neuroimaging decoding and points to a strongly shared representational space for colour and object in the brain.

### 2 Method

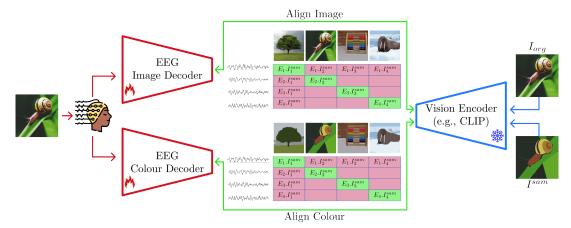
### 2.1 NEUROIMAGING DATASETS

We primarily focused on the THINGS EEG dataset and secondarily on the MEG dataset, both using a subset of the THINGS collection (Hebart et al., 2019), a high-quality set of 1,854 diverse object concepts.

**THINGS EEG dataset** (Gifford et al., 2022): Recordings were collected from 10 participants using a rapid serial visual presentation (RSVP) paradigm (Intraub, 1981), where each image was shown for 100 ms, followed by a 100 ms blank (Figure 1, Panel A). EEG was recorded with a 64-channel cap. The training set included 1,654 concepts (10 images per concept, 4 repetitions per image), and the test set 200 unseen concepts (1 image per concept, 80 repetitions per image). Preprocessing followed the original paper: signals were epoched 0–1000 ms post-stimulus, downsampled to 250 Hz, and reduced to 17 occipito-parietal channels most relevant to vision<sup>1</sup>. To improve signal-to-noise ratio, repetitions of the same image were averaged, yielding 16,540 training samples and 200 test samples per participant.

**THINGS MEG dataset** (Hebart et al., 2023): Recordings from 4 participants, with each image presented for 500 ms followed by a  $1000 \pm 200$  ms interval. MEG was recorded with 271 channels. The training set comprised 1,854 concepts (12 images per concept, 1 repetition each), with 200 forming the test set (1 image per concept, 12 repetitions each). Test concepts were excluded from training to match the zero-shot evaluation of EEG. Preprocessing followed the same strategy as EEG, except MEG signals were downsampled to 200 Hz.

<sup>&</sup>lt;sup>1</sup>P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, PO3, POz, PO4, PO8, O1, Oz, O2



**Figure 2:** The colour-aware CUBE framework for object decoding from brain signals. Two EEG decoders are trained to align with (1) the original RGB images viewed by participants and (2) colour-segmented versions of the same images. Colour alignment follows contrastive learning (Radford et al., 2021), while image alignment employs the Uncertainty-aware Blur Prior algorithm (Wu et al., 2025).

### 2.2 PSYCHOPHYSICAL EXPERIMENT ON COLOUR PERCEPTION UNDER BRIEF EXPOSURE

When an image is shown for only 100 ms, a key question is how much of the scene can be understood and accessed consciously (Keysers et al., 2001). To approximate participants' colour perception in the EEG experiment, we conducted a psychophysical study with a similar presentation rate. A blank screen with a central fixation cross was shown for 750 ms, followed by the image for 100 ms. Participants, instructed via written guidelines, selected all perceived colours from a thirteen-colour palette (Figure 1, Panel C).

To annotate the full THINGS EEG dataset (16,740 images), the experiment was run online via Prolific (Palan & Schitter, 2018). Each participant saw 450 images. For training images, participants had 5 seconds per trial due to the large volume; for test images, no time limit was imposed to capture all perceived colours. In total, 133 participants from diverse cultural and linguistic backgrounds participated and were compensated monetarily.

Subjectively, this fast-paced paradigm shows that participants tend to recall only a few foreground objects and their colours. Strong colour-object associations emerge, while background colours are poorly remembered unless covering large uniform regions. This is reflected in the responses: participants selected on average 2.1 colours per image. Beyond the THINGS EEG colour annotations, this large-scale experiment provides a valuable dataset for studying colour perception under brief exposures in ecologically relevant settings, which will be released for the community.

### 2.3 VISUAL NEURAL DECODING

To decode colour and object from neuronal data, we adopted a contrastive learning paradigm (Radford et al., 2021), which has been widely used in neuroimaging research (Song et al., 2024; Li et al., 2024; Scotti et al., 2024). In this framework, an EEG decoder is trained to align its output representations with those of a pretrained vision encoder, often a variant of CLIP (Figure 2). Similar strategies have also been applied with other modalities, such as language encoders (Akbarinia, 2024) and depth encoders (Zhang et al., 2025).

Formally, let  $\mathbf{z}_i^{EEG}$  denote the feature representation predicted by the EEG decoder for sample i, and  $\mathbf{z}_i^{IMG}$  the corresponding representation from the vision encoder. The goal of contrastive learning is to maximise the

similarity between matching pairs ( $\mathbf{z}_i^{EEG}, \mathbf{z}_i^{IMG}$ ) while minimising similarity with all other non-matching pairs in the batch. This is achieved with a symmetric cross-entropy objective:

$$\mathcal{L}_{\text{CLIP}} = -\frac{1}{N} \sum_{i=1}^{N} \left[ \log \frac{\exp\left(\text{sim}(\mathbf{z}_{i}^{EEG}, \mathbf{z}_{i}^{IMG})/\tau\right)}{\sum_{j=1}^{N} \exp\left(\text{sim}(\mathbf{z}_{i}^{EEG}, \mathbf{z}_{j}^{IMG})/\tau\right)} + \log \frac{\exp\left(\text{sim}(\mathbf{z}_{i}^{IMG}, \mathbf{z}_{i}^{EEG})/\tau\right)}{\sum_{j=1}^{N} \exp\left(\text{sim}(\mathbf{z}_{i}^{IMG}, \mathbf{z}_{j}^{EEG})/\tau\right)} \right], (1)$$

where N is the batch size,  $\tau$  is a learnable temperature parameter, and  $sim(\cdot, \cdot)$  denotes the cosine similarity. This loss encourages the EEG and image representations of the same stimulus to be close in the embedding space, while separating them from mismatched pairs.

One persistent challenge in neuroimaging applications is dataset size: current datasets are relatively small for deep learning, leading to overfitting during training and poor generalisation at test time. A recently proposed technique, the *Uncertainty-aware Blur Prior* (Wu et al., 2025), mitigates this by introducing a foveated blur to the original images  $I^{org}$ , simulating how participants perceive stimuli. By suppressing high-frequency details, this strategy reduces one of the main drivers of overfitting. We adopt this approach in our training framework, processing  $I^{org}$  with the foveation blur described in Wu et al. (2025).

Building on this idea, we propose a *colour-aware contrastive learning framework*, in which the decoder is also aligned with CLIP features extracted from segmented images, denoted  $I^{sam}$ . These are obtained from  $I^{org}$  using SAM-1 (Kirillov et al., 2023) with default global segmentation parameters, except for 64 points per side and a stability score threshold of 0.92. We hypothesise that colour-segmented images better capture perceived colours and object associations during brief exposures (100 ms). To evaluate this, pilot experiments showed participants  $I^{org}$  for 100 ms, followed by a 750 ms grey screen, after which  $I^{sam}$  was presented alone or alongside a greyscale version of  $I^{org}$ . Participants were asked to click mismatched pixels relative to the original scene. Very few mismatches were reported, suggesting that colour-segmented images closely approximate perception under 100 ms viewing.

The *EEG Decoder* in CUBE follows Wu et al. (2025): two linear layers with GELU activation and a residual connection. The *Colour Projector* comprises two linear layers with ReLU, mapping CLIP-aligned features to a thirteen-colour palette. In all experiments, OpenCLIP (Cherti et al., 2023) was used to extract features from different vision encoders. Networks were trained for 50 epochs with batch size 1024 using the AdamW optimiser (Loshchilov & Hutter, 2017), with learning rate  $1 \times 10^{-4}$  and weight decay  $1 \times 10^{-4}$ . Other configurations followed Wu et al. (2025).

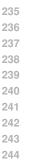
For all experiments, two types of networks were trained. *Intra-participant* networks were trained and evaluated on the EEG data of the same participant, whereas *inter-participant* networks were trained on all participants except one, which was held out for testing.

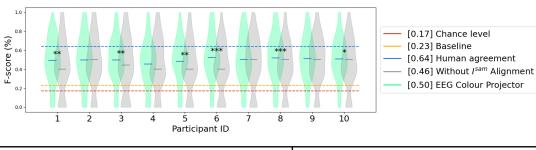
#### 3 Colour decoding

Colour decoding is a multi-class task, as multiple colours may co-occur in a single image, and substantial variation exists across participants, particularly under brief viewing (Bosten, 2022); for example, one participant may label wood as *brown*, another as *beige*. Agreement between two human responses was quantified using the F-score:

$$F = \frac{TP}{TP + \frac{1}{2}\left(FP + FN\right)},\tag{2}$$

where TP, FP, and FN denote true positives, false positives, and false negatives. The same metric evaluated EEG colour decoding. As average human responses and model predictions are not binary, both were thresholded. All reported F-scores use a threshold of 0.33, based on the rationale that at least one-third of participants should agree on a colour for a given image.





Method		Intra-participant										Inter-participant										
	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	AVG	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	AVG
CUBE	.484	.495	.502	.460	.486	.530	.512	.523	.513	.520	.502	.318	.400	.282	.341	.322	.276	.332	.335	.324	.363	.329

**Figure 3:** Colour decoding performance of CUBE. **Top**: F-score distributions over 200 test images. Chance level is shown in red and the noise ceiling from behavioural agreement in blue. Asterisks mark significant differences between models with and without  $I^{sam}$ . **Bottom**: Average F-scores for within- (intra) and across-participant (inter) training. Table cells are colour-coded from green to yellow as F-scores decline.

The results of colour decoding on the THINGS EEG dataset are shown in Figure 3. Overall, the CUBE model achieves an F-score slightly above 0.50, markedly exceeding chance (0.17), computed over 10,000 iterations with two randomly selected colours per trial, matching the average number of colours chosen per participant. Performance is also well above the baseline (0.23), calculated similarly but sampling colours from the training set distribution rather than uniformly. The noise ceiling, the average agreement among all participants, is 0.64. These results demonstrate that CUBE extracts meaningful colour information directly from EEG signals, approaching the level of average human responses—a remarkable achievement given the noisy, low-dimensional nature of EEG data. Inter-participant networks yield lower F-scores (0.33) but still far exceed chance, indicating a shared representation of colour across individuals (Gegenfurtner, 2003). Qualitative examples are provided in Appendix Figures 6 and 7.

Decoding performance drops to 0.46 when the EEG decoder is trained only on colour ground truth, without alignment to  $I^{sam}$  features, a reduction that is statistically significant for most participants (Student's t-test). While results are reported using the CoCa-ViT-L-14 architecture (Yu et al., 2022), no significant differences were observed with alternative architectures.

Although F-scores vary by 7% between the best (participant 06) and worst (participant 04), the overall distribution across the 200 test images is similar for all participants. This consistency is partly due to the colour ground truth reflecting average human responses, which cannot fully capture individual colour perception (Bosten, 2022) during the EEG experiment.

# 4 Object recognition decoding

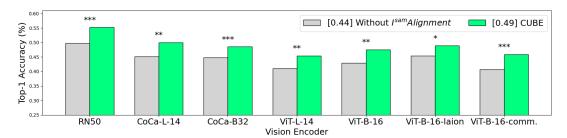
Object decoding networks were evaluated in a zero-shot setting: among 200 possible images, the one with the highest cosine similarity was taken as the decoded object.

### 4.1 EEG

Object recognition accuracies of CUBE and several comparison models are reported in Table 1. By incorporating colour-aware alignment, CUBE improves both top-1 and top-5 accuracy in intra-participant evaluation by about 6%. Notably, this improvement is consistent across all objects, indicating robust gains from the

**Table 1:** Object decoding performance of CUBE on the THINGS EEG dataset (Gifford et al., 2022) across 200 possible classes. Comparison methods from the literature include BraVL (Du et al., 2023), NICE (Song et al., 2024), ATM (Li et al., 2024), VE-SDN (Chen et al., 2024), and UBP (Wu et al., 2025). Table cells are colour-coded from green to yellow as accuracies decrease.

	Top-1									Тор-5												
Method	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	AVG	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	AVG
										In	tra-pa	rticipa	nt									
BraVL	.061	.049	.056	.050	.040	.060	.065	.088	.043	.070	.058	.179	.149	.174	.151	.134	.182	.204	.237	.140	.197	.175
NICE	.132	.135	.145	.206	.101	.165	.170	.229	.154	.174	.161	.395	.403	.427	.527	.315	.440	.421	.561	.416	.458	.436
ATM	.256	.220	.250	.314	.129	.213	.305	.388	.344	.291	.285	.604	.545	.624	.609	.430	.511	.615	.720	.515	.635	.604
VE-SDN	.326	.344	.387	.398	.294	.345	.345	.493	.390	.398	.372	.637	.699	.735	.720	.586	.688	.683	.798	.696	.753	.699
UBP	.412	.512	.512	.511	.422	.575	.490	.586	.451	.615	.509	.705	.809	.820	.769	.728	.835	.799	.858	.762	.882	.797
CUBE	.460	.565	.615	.605	.450	.595	.530	.630	.555	.655	.566	.770	.855	.895	.835	.790	.880	.845	.920	.855	.930	.858
	Inter-participant Control of the Con																					
BraVL	.023	.015	.014	.017	.015	.018	.021	.022	.016	.023	.018	.080	.063	.059	.067	.056	.072	.081	.076	.064	.085	.070
NICE	.076	.059	.060	.063	.044	.056	.056	.063	.057	.084	.062	.228	.205	.223	.207	.183	.222	.197	.220	.176	.283	.214
ATM	.105	.071	.119	.147	.070	.111	.161	.150	.049	.205	.118	.268	.248	.338	.394	.239	.358	.435	.403	.227	.465	.337
UBP	.115	.155	.098	.130	.088	.117	.102	.122	.155	.160	.124	.297	.400	.270	.323	.338	.310	.238	.322	.405	.435	.334
CUBE	.140	.175	.080	.140	.135	.130	.095	.125	.195	.155	.137	.335	.410	.235	.350	.310	.355	.335	.385	.415	.420	.355



**Figure 4:** Encoder type experiment.

additional colour features introduced in CUBE. Performance peaks at a top-1 accuracy of 66% and a top-5 accuracy of 93% for the best participant—remarkable decoding performance given the noisy nature of EEG signals. For inter-participant evaluation, the improvement is more modest at just over 1%, likely reflecting substantial individual variability in visual processing (De Haas et al., 2019).

We further examined whether CUBE's improvements generalise across different visual encoders. Results are shown in Figure 4. Across seven encoders with diverse architectures and pretraining datasets, colour-aware alignment consistently improves performance by approximately 5%, with all gains statistically significant (Student's t-test). These findings confirm that incorporating colour alignment enhances EEG decoding across a wide range of feature spaces. Intuitively, this is expected: when viewing an image for as briefly as 100 ms, colour is one of the first visual attributes to stand out.

# 4.2 MEG

We also tested CUBE on the MEG dataset. The results closely mirror the EEG findings: intra-participant accuracy improves by about 5% and inter-participant accuracy by about 1%. These results indicate that colour-aware contrastive alignment generalises beyond EEG and is equally effective with other neuroimaging modalities.

**Table 2:** Object decoding performance of CUBE on the THINGS MEG dataset (Hebart et al., 2023) across 200 possible classes. Comparison methods from the literature include BraVL (Du et al., 2023), NICE (Song et al., 2024), and UBP (Wu et al., 2025). Table cells are colour-coded from green to yellow as accuracies decrease.

			Top-5											
Method	S01	S02	S02 S03		AVG	S01	S02	S03	S04	AVG				
		Intra-participant												
NICE	.096	.185	.142	.090	.128	.278	.478	.416	.266	.360				
UBP	.150	.460	.273	.185	.267	.380	.805	.590	.435	.552				
CUBE	.165	.520	.335	.235	.314	.435	.850	.625	.480	.598				
Inter-participant														
UBP	.020	.015	.027	.025	.022	.057	.172	.100	.080	.104				
CUBE	.020	.050	.035	.025	.033	.075	.175	.100	.105	.114				

## 5 DISCUSSION

EEG is remarkably noisy, with core technology dating back a century (Berger, 1929). Recorded non-invasively over the scalp, it reflects the combined electrical activity of billions of neurons as tiny differences in ionic potentials (Azevedo et al., 2009; Goriely, 2025). Spatial resolution is also very limited (e.g., 17 electrodes at 250 Hz in this study, equals to a single-channel image of size 65). Despite these constraints, meaningful information can be extracted. For instance, decoding speech from three seconds of EEG can reach 41% accuracy among 1000 choices (Défossez et al., 2023). Similarly, object recognition in our study achieves 57% accuracy—far above the chance level of 1/200—from just one second of EEG, where each image was presented for 100 ms and the signal is already intermixed with four subsequent images.

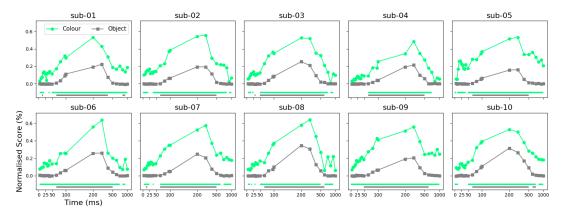
Equally remarkable is that we can now predict the perceived colours in natural images with high accuracy (F-score = 0.5). Importantly, the EEG data were collected without any explicit cues about colour, reflecting participants' natural viewing. It is striking that such noisy signals can carry such rich information—it is, in a sense, even beautifully colourful. Qualitative examples in Appendix Figures 6 and 7 show that, even in less accurate cases, the network generally captures the dominant colours in a scene, though it occasionally misclassifies neighbouring shades (e.g., beige for brown) or misestimates their relative prominence.

Comparing colour and object decoding is not straightforward. First, the metrics differ: F-score is used for multi-class colour, while accuracy is used for single-class objects. Second, the ground truths differ: object labels are objective ("this is a snail"), whereas colour annotations are subjective averages. Third, object and colour are intertwined, introducing potential confounds. For example, colour-diagnostic objects can boost colour decoding (e.g., a banana is yellow), while natural colour statistics can bias object recognition (e.g., a spherical orange may be decoded as an orange, a striped version as a volleyball) (Tanaka & Presnell, 1999; Therriault et al., 2009). Fourth, material properties add complexity (Schmidt et al., 2025), e.g., wood is typically brown with distinctive texture. Nevertheless, colour decoding performs relatively better when normalised to chance and noise ceilings: with a human agreement of 0.64, an F-score of 0.50 corresponds to 0.70, while object decoding remains at 0.57.

#### 5.1 TIME FRAME OF DECODING POWER

One important question in neuroscience is the time frame in which specific features can be decoded. To address this, we analysed object and colour decoding when training a network on only 100 ms of EEG from different intervals, e.g., [0, 100), [100, 200), and [900, 1000). We also examined very short windows (less than 100 ms) by training networks from stimulus onset until time t. All other training configurations matched those of CUBE trained on the full 1 s EEG data. Results are shown in Figure 5.

Although individual differences can be observed, across participants we find significantly decodable information in both colour and object signals from about 75 ms to 500 ms. This aligns with previous reports (Teichmann et al., 2020). Importantly, colour decoding above chance emerges earlier—in many subjects



**Figure 5:** CUBE decoding of colour and object across temporal epochs. The x-axis (0 ms) marks stimulus onset; the y-axis shows normalised F-scores (colour) and top-1 accuracy (object), scaled by chance level and noise ceiling. Data points after 100 ms use EEG intervals [t-100,t), and points before 100 ms from [0,t). Significance lines indicate intervals with decoding above chance (p < 0.05).

immediately after stimulus onset—suggesting that colour information may precede object information in natural image perception. This contrasts with earlier findings suggesting that colour and object signals arise at roughly the same time (Teichmann et al., 2020).

### 5.2 Limitations of the EEG decoding

What are the limitations of current EEG decoding frameworks, both in the literature and in the present work? A first and central issue is inter-participant performance, which remains much lower than within-participant decoding. This is perhaps not surprising. On the one hand, there are large individual differences across several dimensions of visual perception (De Haas et al., 2019; Bosten, 2022). On the other hand, EEG signals are inherently dynamic: the same stimulus may elicit different responses depending on the participant's cognitive state at a given moment. Moreover, the quality of the recorded signal is affected by technical factors such as electrode placement and impedance, which can vary across sessions and participants.

One proposed solution is to pretrain models on large, diverse EEG datasets (Wang, 2025), in analogy to large language models, and then fine-tune them for individual participants. This approach may help bridge the gap between generalisation and personalisation. Such strategies could be especially valuable for practical applications of neuroimaging decoding, for example in brain–machine interfaces for individuals with severe motor disabilities (Chaudhary et al., 2015).

## 6 CONCLUSION

In this article, we introduced **CUBE** (ColoUr and oBjEct decoding) and highlighted the importance of jointly decoding colour and object information. Our results demonstrate that EEG signals contain decodable colour information, even when recorded during object recognition tasks without explicit colour references and under very brief viewing conditions (100 ms). We further showed that incorporating colour feature alignment into standard contrastive learning frameworks for neuroimaging-based object decoding improves performance by about 5% across participants in both EEG and MEG modalities. Overall, our findings establish a novel approach for decoding colour from neuroimaging signals, underscoring its potential applications for brain–computer interfaces and the study of colour representation under naturalistic conditions.

# REFERENCES

- Arash Akbarinia. Optimising eeg decoding with refined sampling and multimodal feature integration. *arXiv* preprint arXiv:2409.20086, 2024.
- Emily J Allen, Ghislain St-Yves, Yihan Wu, Jesse L Breedlove, Jacob S Prince, Logan T Dowdle, Matthias Nau, Brad Caron, Franco Pestilli, Ian Charest, et al. A massive 7t fmri dataset to bridge cognitive neuroscience and artificial intelligence. *Nature neuroscience*, 25(1):116–126, 2022.
- Frederico AC Azevedo, Ludmila RB Carvalho, Lea T Grinberg, José Marcelo Farfel, Renata EL Ferretti, Renata EP Leite, Wilson Jacob Filho, Roberto Lent, and Suzana Herculano-Houzel. Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain. *Journal of Comparative Neurology*, 513(5):532–541, 2009.
- Yohann Benchetrit, Hubert Banville, and Jean-Rémi King. Brain decoding: toward real-time reconstruction of visual perception. *International Conference on Representation Learning*, 2023.
- Hans Berger. Über das elektroenkephalogramm des menschen. Archiv für psychiatrie und nervenkrankheiten, 87(1):527–570, 1929.
- Jenny M Bosten. Do you see what i see? diversity in human color perception. *Annual review of vision science*, 8(1):101–133, 2022.
- Inês Bramão, Alexandra Reis, Karl Magnus Petersson, and Luís Faísca. The role of color information on object recognition: A review and meta-analysis. *Acta psychologica*, 138(1):244–253, 2011.
- Ujwal Chaudhary, Niels Birbaumer, and Marco Rocha Curado. Brain-machine interface (bmi) in paralysis. *Annals of physical and rehabilitation medicine*, 58(1):9–13, 2015.
- Tushar Chauhan, Ivana Jakovljev, Lindsay N Thompson, Sophie M Wuerger, and Jasna Martinovic. Decoding of eeg signals reveals non-uniformities in the neural geometry of colour. *NeuroImage*, 268:119884, 2023.
- Hongzhou Chen, Lianghua He, Yihang Liu, and Longzhen Yang. Visual neural decoding via improved visual-eeg semantic consistency. *arXiv* preprint arXiv:2408.06788, 2024.
- Mehdi Cherti, Romain Beaumont, Ross Wightman, Mitchell Wortsman, Gabriel Ilharco, Cade Gordon, Christoph Schuhmann, Ludwig Schmidt, and Jenia Jitsev. Reproducible scaling laws for contrastive language-image learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2818–2829, 2023.
- Benjamin De Haas, Alexios L Iakovidis, D Samuel Schwarzkopf, and Karl R Gegenfurtner. Individual differences in visual salience vary along semantic dimensions. *Proceedings of the National Academy of Sciences*, 116(24):11687–11692, 2019.
- Alexandre Défossez, Charlotte Caucheteux, Jérémy Rapin, Ori Kabeli, and Jean-Rémi King. Decoding speech perception from non-invasive brain recordings. *Nature Machine Intelligence*, 5(10), 2023.
- Changde Du, Kaicheng Fu, Jinpeng Li, and Huiguang He. Decoding visual neural representations by multimodal learning of brain-visual-linguistic features. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(9):10760–10777, 2023.
- Karl R Gegenfurtner. Cortical mechanisms of colour vision. *Nature Reviews Neuroscience*, 4(7):563–572, 2003.

Karl R. Gegenfurtner. The verriest lecture: Color vision from pixels to objects. J. Opt. Soc. Am. A, 42(5): B313-B328, May 2025. doi: 10.1364/JOSAA.544136. URL https://opg.optica.org/josaa/abstract.cfm?URI=josaa-42-5-B313.

Karl R Gegenfurtner and Jochem Rieger. Sensory and cognitive contributions of color to the recognition of natural scenes. *Current Biology*, 10(13):805–808, 2000.

Alessandro T Gifford, Kshitij Dwivedi, Gemma Roig, and Radoslaw M Cichy. A large and rich eeg dataset for modeling human visual object recognition. *NeuroImage*, 264:119754, 2022.

Alain Goriely. Eighty-six billion and counting: do we know the number of neurons in the human brain? *Brain*, 148(3):689–691, 2025.

Jasper E Hajonides, Anna C Nobre, Freek van Ede, and Mark G Stokes. Decoding visual colour from scalp electroencephalography measurements. *NeuroImage*, 237:118030, 2021.

Martin N Hebart, Adam H Dickter, Alexis Kidder, Wan Y Kwok, Anna Corriveau, Caitlin Van Wicklin, and Chris I Baker. Things: A database of 1,854 object concepts and more than 26,000 naturalistic object images. *PloS one*, 14(10):e0223792, 2019.

Martin N Hebart, Oliver Contier, Lina Teichmann, Adam H Rockter, Charles Y Zheng, Alexis Kidder, Anna Corriveau, Maryam Vaziri-Pashkam, and Chris I Baker. Things-data, a multimodal collection of large-scale datasets for investigating object representations in human brain and behavior. *Elife*, 12:e82580, 2023.

Katherine L Hermann, Shridhar R Singh, Isabelle A Rosenthal, Dimitrios Pantazis, and Bevil R Conway. Temporal dynamics of the neural representation of hue and luminance polarity. *Nature communications*, 13(1):661, 2022.

Helene Intraub. Rapid conceptual identification of sequentially presented pictures. *Journal of Experimental Psychology: Human Perception and Performance*, 7(3):604, 1981.

Christian Keysers, D-K Xiao, Peter Földiák, and David I Perrett. The speed of sight. *Journal of cognitive neuroscience*, 13(1):90–101, 2001.

Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 4015–4026, 2023.

Dongyang Li, Chen Wei, Shiying Li, Jiachen Zou, and Quanying Liu. Visual decoding and reconstruction via eeg embeddings with guided diffusion. *Advances in Neural Information Processing Systems*, 2024.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *International Conference on Representation Learning*, 2017.

Per Møller and Anya C Hurlbert. Psychophysical evidence for fast region-based segmentation processes in motion and color. *Proceedings of the National Academy of Sciences*, 93(14):7421–7426, 1996.

Stefan Palan and Christian Schitter. Prolific. ac—a subject pool for online experiments. *Journal of behavioral and experimental finance*, 17:22–27, 2018.

WM Paulus, V Hömberg, K Cunningham, AM Halliday, and N Rohde. Colour and brightness components of foveal visual evoked potentials in man. *Electroencephalography and clinical neurophysiology*, 58(2): 107–119, 1984.

Ian ML Pennock, Chris Racey, Emily J Allen, Yihan Wu, Thomas Naselaris, Kendrick N Kay, Anna Franklin, and Jenny M Bosten. Color-biased regions in the ventral visual pathway are food selective. *Current Biology*, 33(1):134–146, 2023.

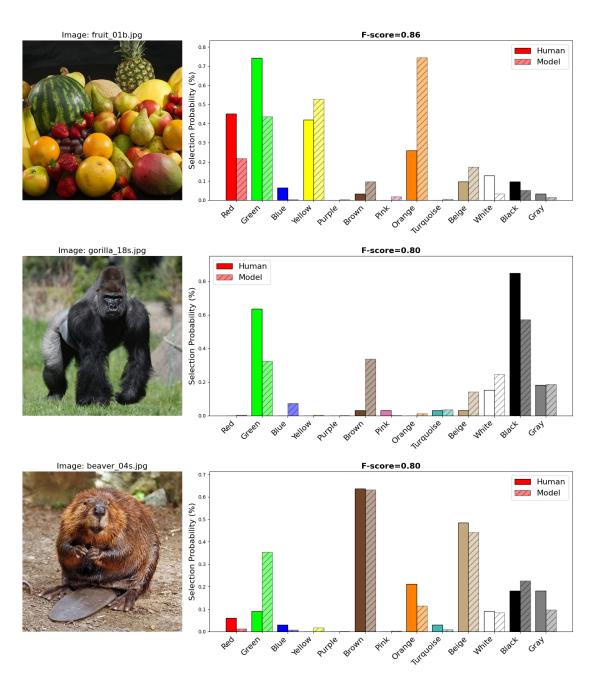
- Mary C Potter, Brad Wyble, Carl Erick Hagmann, and Emily S McCourt. Detecting meaning in rsvp at 13 ms per picture. *Attention, Perception, & Psychophysics*, 76(2):270–279, 2014.
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pp. 8748–8763. PmLR, 2021.
- D Regan. Evoked potential and psychophysical correlates of changes in stimulus colour and intensity. *Vision Research*, 10(2):163–178, 1970.
- Amanda K Robinson, Genevieve L Quek, and Thomas A Carlson. Visual representations: insights from neural decoding. *Annual Review of Vision Science*, 9(1):313–335, 2023.
- Isabelle Rosenthal, Sivalogeswaran Ratnasingam, Theodros Haile, Serena Eastman, Josh Fuller-Deets, and Bevil R Conway. Color statistics of objects, and color tuning of object cortex in macaque monkey. *Journal of vision*, 18(11):1–1, 2018.
- Isabelle A Rosenthal, Shridhar R Singh, Katherine L Hermann, Dimitrios Pantazis, and Bevil R Conway. Color space geometry uncovered with magnetoencephalography. *Current Biology*, 31(3):515–526, 2021.
- Ana Rozman, Tushar Chauhan, and Jasna Martinovic. Characterising representations of hue and saturation in the cortex using information decoding. *bioRxiv*, pp. 2024–12, 2024.
- Filipp Schmidt, Martin N Hebart, Alexandra C Schmid, and Roland W Fleming. Core dimensions of human material perception. *Proceedings of the National Academy of Sciences*, 122(10):e2417202122, 2025.
- Paul Scotti, Atmadeep Banerjee, Jimmie Goode, Stepan Shabalin, Alex Nguyen, Aidan Dempster, Nathalie Verlinde, Elad Yundler, David Weisberg, Kenneth Norman, et al. Reconstructing the mind's eye: fmri-to-image with contrastive learning and diffusion priors. *Advances in Neural Information Processing Systems*, 36, 2024.
- Yonghao Song, Bingchuan Liu, Xiang Li, Nanlin Shi, Yijun Wang, and Xiaorong Gao. Decoding natural images from eeg for object recognition. *International Conference on Representation Learning*, 2024.
- David W Sutterer, Andrew J Coia, Vincent Sun, Steven K Shevell, and Edward Awh. Decoding chromaticity and luminance from patterns of eeg activity. *Psychophysiology*, 58(4):e13779, 2021.
- James Tanaka, Daniel Weiskopf, and Pepper Williams. The role of color in high-level vision. *Trends in cognitive sciences*, 5(5):211–215, 2001.
- James W Tanaka and Lynn M Presnell. Color diagnosticity in object recognition. *Perception & Psychophysics*, 61(6):1140–1153, 1999.
- Lina Teichmann, Genevieve L Quek, Amanda K Robinson, Tijl Grootswagers, Thomas A Carlson, and Anina N Rich. The influence of object-color knowledge on emerging object representations in the brain. *Journal of Neuroscience*, 40(35):6779–6789, 2020.
- David J Therriault, Richard H Yaxley, and Rolf A Zwaan. The role of color diagnosticity in object recognition and representation. *Cognitive processing*, 10(4):335–342, 2009.

Shuai Huang · Huan Luo · Haodong Jing · Qixian Zhang · Litao Chang · Yating Feng · Xiao Lin · Chendong Qin · Han Chen · Shuwen Jia · Siyi Sun · Yongxiong Wang. Need: Cross-subject and cross-task general-ization for video and image reconstruction from eeg signals. Advances in Neural Information Processing Systems, 36, 2025. Felix A Wichmann, Lindsay T Sharpe, and Karl R Gegenfurtner. The contributions of color to recognition memory for natural scenes. Journal of Experimental Psychology: Learning, Memory, and Cognition, 28 (3):509, 2002. Haitao Wu, Qing Li, Changqing Zhang, Zhen He, and Xiaomin Ying. Bridging the vision-brain gap with an uncertainty-aware blur prior. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pp. 2246–2257, 2025.

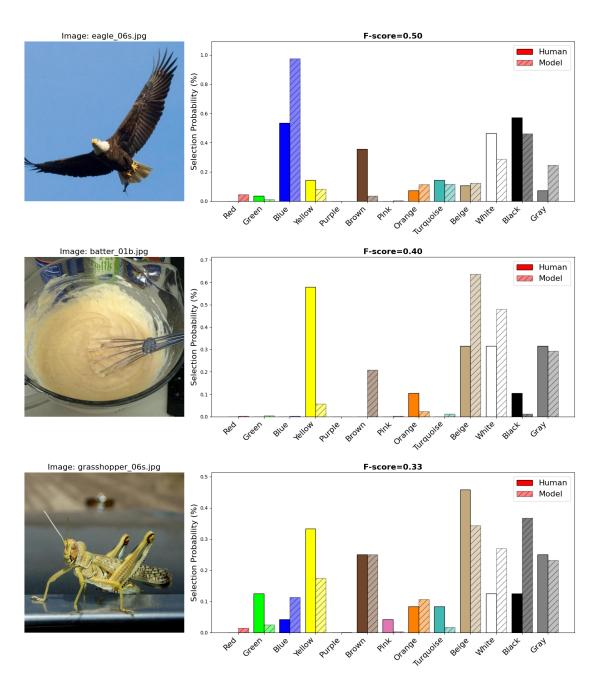
Jiahui Yu, Zirui Wang, Vijay Vasudevan, Legg Yeung, Mojtaba Seyedhosseini, and Yonghui Wu. Coca: Contrastive captioners are image-text foundation models. *arXiv preprint arXiv:2205.01917*, 2022.

Kaifan Zhang, Lihuo He, Xin Jiang, Wen Lu, Di Wang, and Xinbo Gao. Cognitioncapturer: Decoding visual stimuli from human eeg signal with multimodal information. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pp. 14486–14493, 2025.

# A QUALITATIVE EXAMPLES



**Figure 6:** High F-score examples of colours decoded from EEG alongside the corresponding colours reported in the psychophysical experiment.



**Figure 7:** Low F-score examples of colours decoded from EEG alongside the corresponding colours reported in the psychophysical experiment.