THE HALLMARK OF COLOUR IN EEG SIGNAL

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ABSTRACT

Our perception of the world is inherently colourful, and colour provides well-documented benefits for vision: it helps us see things quicker and remember them better. We hypothesised that colour is not only central to perception but also a rich and decodable source of information in electroencephalography (EEG) signal recorded non-invasively from the scalp. Previous work has shown that brain activity carries colour information for uniform patches, 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, comprising 64-channel recordings from participants viewing 1,800 distinct objects (16,740 images) for 100 ms each, totalling over 82,000 trials. We established a perceptual colour ground truth through a psychophysical experiment in which participants viewed each image for 100 ms and selected perceived colours from a 13-option palette. An artificial neural network trained to predict these scene-level colour distributions directly from EEG signals showed that colour information was robustly decodable (average F-score of 0.5). We next modelled the interaction between colour and object perception in neuroimaging decoding. Images were segmented using the Segment Anything Model (SAM), each object was assigned a representative colour, and features were extracted from these colour-augmented images using CLIP vision encoders. We trained an EEG encoder, **CUBE** (**C**olo**U**r and o**B**j**E**ct decoding), to align features in both object and colour spaces. Across EEG and MEG datasets in a 200-class recognition task, incorporating colour improved decoding accuracy by about 5%. Together, these findings demonstrate that EEG signal recorded during natural vision carries substantial colour information that interacts with object perception. Modelling this mutual interaction enhances neural decoding performance.

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).

Colour decoding from neuroimaging has a long history (Regan, 1970; Paulus et al., 1984). Brain activity carries 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., 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

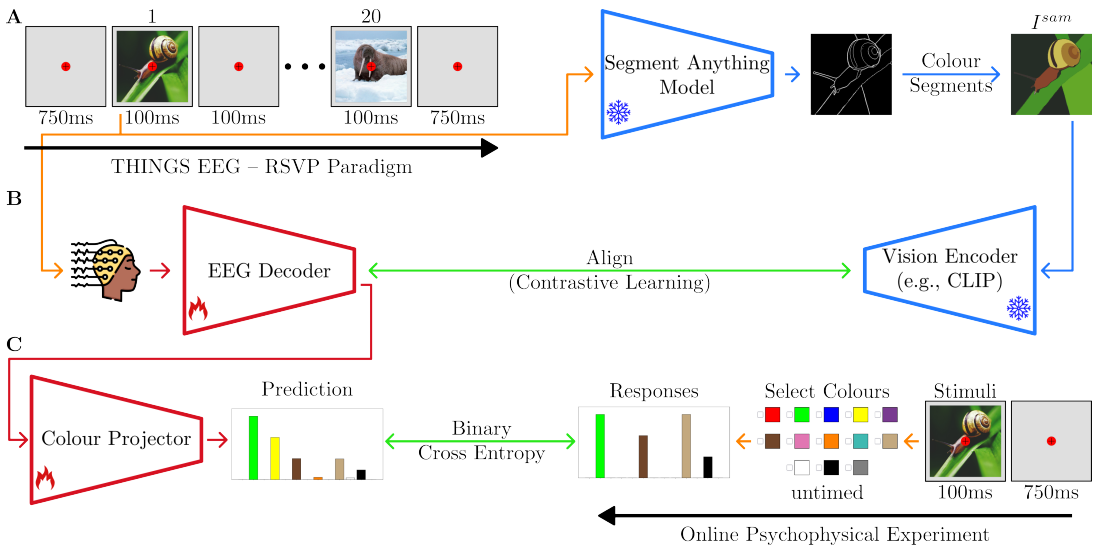


Figure 1: The schematic framework of **CUBE** (**C**olo**U**r and o**B**j**E**ct decoding). **A**: The RSVP paradigm used to collect the THINGS EEG dataset (Gifford et al., 2022). **B**: An EEG encoder aligns brain activity with features from a pretrained vision encoder applied to colour-segmented images.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

can be decoded as early as 60–70 ms after stimulus onset, shape–colour congruency emerges later, around 200 ms (Teichmann et al., 2020). These findings are valuable but mostly derive from simplified displays of uniform coloured patches on plain backgrounds. It remains unclear whether colour can be reliably decoded from brain signals when viewing rich, natural scenes—this is the challenge addressed 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 (COLOUR AND OBJECT 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 improve object recognition decoding. Colour and object perception are closely intertwined, both behaviourally (Bramão et al., 2011; Gegenfurtner, 2025) and neurally (Rosenthal et al., 2018; Tanaka et al., 2001). To model this, we algned the EEG decoder simultaneously to CLIP features from the original images I^{org} and colour-segmented images I^{sam} (Figure 2), which capture object–colour associations more directly, particularly under the brief 100 ms exposure.

We term this framework **CUBE** (**C**olo**U**r and o**BjE**ct 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

We primarily focused on the THINGS EEG dataset and, secondarily, on the MEG dataset, both derived from a subset of the THINGS collection (Hebart et al., 2019), a high-quality set comprising 1,854 diverse object concepts. We generated colour annotations for the images through an online psychophysical experiment and employed a contrastive learning framework to train our artificial neural networks[1].

2.1 NEUROIMAGING DATASETS

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[2]. 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 271 channels, each image presented for 500 ms followed by a 1000 ± 200 ms interval. The training set included 1,854 concepts (12 images per concept, 1 repetition each), and the test set comprised 200 concepts (1 image per concept, 12 repetitions each). Test concepts were excluded from training for zero-shot EEG evaluation. Preprocessing followed the same pipeline as EEG, with MEG signals downsampled to 200 Hz.

[1]The experimental materials are available on `https://arashakbarinia.github.io/projects/cube/`
[2]P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, PO3, POz, PO4, PO8, O1, Oz, O2

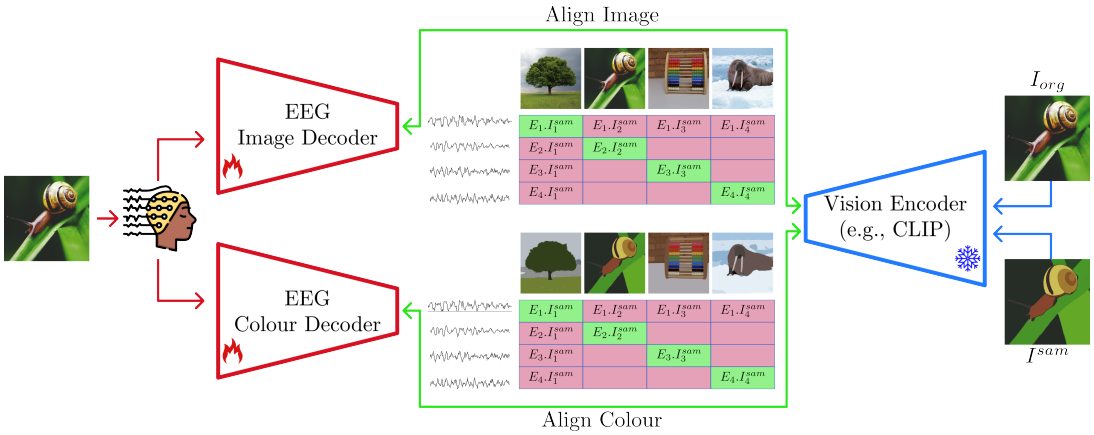


Figure 2: The colour-aware CUBE framework for object decoding from brain signals. Two EEG decoders are trained to align with (1) the original RGB images viewed by participants and (2) colour-segmented versions of the same images. Colour alignment follows contrastive learning (Radford et al., 2021), while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

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

where N is the batch size, τ is a learnable temperature parameter, and $\text{sim}(\cdot, \cdot)$ 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 additionally aligned with CLIP features extracted from colour-segmented images, denoted as I^{sam}. These images are derived from the original input I^{org} using SAM-1 (Kirillov et al., 2023) with default global segmentation parameters, except for an increased resolution of 64 points per side and a stability score threshold of 0.92. We hypothesise that colour-segmented images more closely resemble participants' perceived colours and their object associations during brief exposures (100 ms). Consequently, introducing a contrastive loss term $\mathcal{L}_{\text{CLIP}}$ between $\mathbf{z}_i^{EEG}$ and $\mathbf{z}_i^{SAM}$ is expected to boost object decoding.

To evaluate this, we conducted pilot experiments in which participants viewed I^{org} for 100 ms, followed by a 750 ms grey screen. After this interval, I^{sam} was presented either alone or alongside a greyscale version of I^{org}. Participants were instructed to click on pixels whose colour values were inconsistent with the original scene viewed for 100 ms. Only a small number of mismatches were reported, suggesting that colour-segmented images provide a close approximation of perceived colours, objects, and their associations under such brief viewing conditions.

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 1×10^{-4} and weight decay 1×10^{-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 inherently a multi-class task, as multiple colours may co-occur within a single image, and substantial variation exists across participants, particularly under brief viewing conditions (Mollon et al., 2017; Bosten, 2022). For instance, one participant may select a *brownish* tone for *wood*, whereas another may choose a more *beige* shade. This variability is a key consideration when evaluating colour perception: unlike object recognition, the ground truth is inherently subjective and may exhibit striking individual dif-

ferences (Lafer-Sousa et al., 2015). To account for this multi-class and individually variable nature of colour perception, we quantified the agreement between two human responses using the F-score:

$$F = \frac{TP}{2TP + FP + FN}, \tag{2}$$

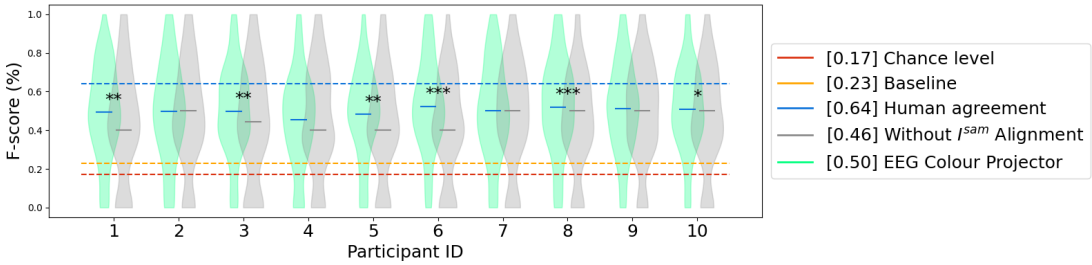
where TP, FP, and FN denote true positives, false positives, and false negatives, respectively. We opted for the F-score rather than the closely related Jaccard index (Jaccard, 1901), which is also widely used for comparing two sets, because the F-score gives a higher weight to TPs. We consider this emphasis more appropriate for colour fidelity, as it better reflects the dominant colours selected by participants. To facilitate comparison between behavioural and neural data, we applied the same metric to quantify the agreement between colours decoded from EEG and the average human responses. As neither the average human responses nor the model predictions are binary, both were thresholded. All reported F-scores use a threshold of $\frac{1}{3}$, based on the rationale that at least one-third of participants agreed on a colour for a given image.

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).

Decoding performance drops to 0.46 when the EEG decoder is trained solely on the colour ground truth, without alignment to I^{sam} features. This reduction is statistically significant for most participants (Student's *t*-test), suggesting that colour information is more effectively decoded when object and contextual features—known to influence colour perception—are taken into account (Witzel & Gegenfurtner, 2018; Tanaka & Presnell, 1999; Gegenfurtner, 2025). While the reported results use the CoCa-ViT-L-14 architecture (Yu et al., 2022), no significant differences were observed with alternative architectures.

Although the F-scores vary by 7% between the best and worst participants (53% for participant 06 and 46% for participant 04), the overall distribution across the 200 test images is similar among participants. This consistency likely arises from the colour ground truth being based on average human responses, which do not fully capture individual colour perception (Bosten, 2022) or the specific colours perceived by participants during the EEG experiment. Therefore, higher decoding accuracy may be expected if the behavioural ground truth were obtained from the same individuals who contributed the neural data.

A qualitative examination of the results—illustrated in Figure S1 in the Appendix—shows that colours decoded from EEG signals often remain plausible even in cases with relatively low F-scores. For example, regions behaviourally reported as *brownish* or *beigeish* in the *Seed* image are close to the *orangish* or *reddish* predictions by CUBE, indicating small deviations toward neighbouring colour categories. Similar mismatches appear in the red–orange tomatoes of the *Omelette* and *Fruit* images, a known challenge even for computer vision models of colour categorisation (Parraga & Akbarinia, 2023). In other cases, memory (Hansen et al., 2006) and colour constancy (Akbarinia & Parraga, 2017; Rodríguez et al., 2024) seem to guide behavioural selections. For instance, participants often selected grey for the *Elephant* image, despite predominantly brown pixels—a prediction also made by the EEG decoder. A similar effect is observed for the black–grey regions of the *Recorder* image. Overall, these results indicate that the colours decoded from EEG signals are both meaningful and perceptually coherent.



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.

4 OBJECT DECODING

Object decoding in the THINGS EEG and MEG datasets is formulated as a 200-way classification task. Performance is reported as classification accuracy. Each network is evaluated in a zero-shot setting, where among 200 candidate images, the one with the highest cosine similarity to the decoded EEG features is taken as the predicted object category.

THINGS EEG dataset (Gifford et al., 2022): Object recognition accuracies of CUBE and several comparison models are reported in Table 1. By incorporating colour-aware alignment, CUBE achieves a top-1 accuracy of 57% and a top-5 accuracy of 86% in within-subject decoding. This represents an improvement of 6% over UBP (Wu et al., 2025). Notably, this improvement is consistent across all participants, indicating that the gains conferred by colour features are robust. Performance peaks at a top-1 accuracy of 66% and a top-5 accuracy of 93% for the best participant—remarkable results given the inherently noisy nature of EEG signals. The improvement offered by CUBE in inter-participant evaluation is more modest, at just over 1% in both top-1 and top-5 accuracy, reflecting the substantial challenge of cross-subject decoding in neuroimaging due to variability in neural responses (Wei et al., 2021) and individual differences in visual processing (De Haas et al., 2019).

We further examined whether the improvements introduced by colour-aware alignment in CUBE generalise across different vision encoders. Results for seven distinct OpenCLIP encoders (Cherti et al., 2023) are shown in Figure 4. Regardless of the architecture or pretraining dataset, colour-aware alignment consistently improves object decoding performance by approximately 5%, with all gains statistically significant (Student's *t*-test). These findings demonstrate that incorporating colour alignment enhances EEG-based decoding across a wide range of feature spaces. Intuitively, this is expected: when viewing an image for as briefly as 100 ms, colour is among the earliest visual attributes to be processed, leaving a strong and measurable signature on the recorded neural signal.

THINGS MEG dataset (Hebart et al., 2023): Object recognition accuracies of CUBE and two comparison models are reported in Table 2. The results closely mirror the EEG findings: CUBE improves intra-participant accuracy by around 5% in both top-1 and top-5, and inter-participant accuracy by approximately 1%. These results indicate that colour-aware contrastive alignment generalises beyond EEG and is equally effective across other neuroimaging modalities.

Table 1: Object decoding performance of CUBE on the THINGS EEG dataset (Gifford et al., 2022) across 200 object categories. Comparison methods from the literature include BraVL (Du et al., 2023), NICE (Song et al., 2024), ATM (Li et al., 2024), IDES (Akbarinia, 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											Top-5										
Method	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	**AVG**	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	**AVG**
Intra-participant																						
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
IDES	.355	.330	.305	.365	.225	.345	.300	.440	.355	.370	.339	.645	.650	.695	.715	.570	.735	.700	.755	.705	.705	.688
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																						
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
IDES	.090	.165	.090	.135	.085	.100	.075	.135	.100	.190	.117	.280	.340	.215	.355	.260	.350	.235	.315	.295	.365	.320
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**

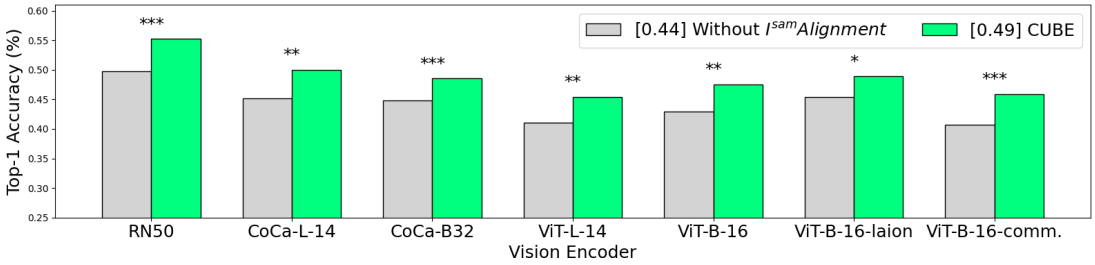


Figure 4: Evaluating the impact of CUBE on seven vision encoders. Object decoding performance on the THINGS EEG dataset (Gifford et al., 2022) across 200 object categories. All vision encoders are pretrained from OpenCLIP (Cherti et al., 2023). Asterisks indicate significant differences between models trained with and without I^{sam}.

Table 2: Object decoding performance of CUBE on the THINGS MEG dataset (Hebart et al., 2023) across 200 object categories. 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-1					Top-5				
Method	S01	S02	S03	S04	**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, with core technology dating back a century (Berger, 1929), is remarkably noisy with a low spatial resolution, recording non-invasively over the scalp a signal that reflects the high temporal resolution of the combined electrical activity of billions of neurons (Azevedo et al., 2009; Goriely, 2025) as tiny differences in ionic potentials. Despite these limits, EEG has been shown to remarkably carry meaningful information. Speech decoding from three seconds of EEG reaches the remarkable 41% accuracy among 1000 choices (Défossez et al., 2023). Similarly, we can decode objects with an accuracy of 57%—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 show here for the first time that we can now predict the perceived colours in natural images with high accuracy (F-score = 0.5). Importantly, the EEG data we analaysed here were collected without any explicit cues about colour, reflecting participants' natural viewing. It is striking that such noisy signals can carry such rich information (Robinson et al., 2023)—it is, in a sense, even beautifully colourful!

5.1 THE INTERACTION BETWEEN COLOUR AND OBJECT

Colour information plays an important role in object recognition (Bramão et al., 2011; Rosenthal et al., 2018), and, conversely, object and scene semantics influence perceived colours (Bloj et al., 1999; Hansen et al., 2006; Akbarinia, 2025a). Nevertheless, the interaction between colour and object remains surprisingly little understood (Teichmann et al., 2020; Taylor & Xu, 2021; Gegenfurtner, 2025). Our results from colour and object decoding strengthens this bidirectional relationship: colour decoding peaks when object representations are aligned, and object decoding improves when colour features are aligned.

A direct comparison between colour and object decoding is not straightforward. First, the evaluation metrics differ: F-score is used for multi-class colour decoding, whereas accuracy is used for single-class object decoding. Second, the ground truths differ: object labels are objective ("this is a snail"), whereas colour annotations are subjective averages. Third, colour and object are inherently intertwined, introducing potential confounds. For instance, colour-diagnostic objects can enhance colour decoding (e.g., a banana is yellow), while natural colour statistics can bias object recognition (Tanaka & Presnell, 1999; Therriault et al., 2009). For example, a spherical orange may be decoded as an orange, but a striped one as a volleyball. Fourth, material properties add complexity (Schmidt et al., 2025), as some materials, such as wood, have characteristic colour–texture associations.

Nevertheless, within our framework, colour decoding performs relatively better when normalised to chance and noise ceilings: the colour decoding F-score reaches 0.70 on a scale from zero to one, exceeding the object decoding accuracy of 0.57. To examine temporal dynamics, we trained networks on 100 ms EEG segments from different intervals, e.g., $[0, 100)$, $[100, 200)$, and $[900, 1000)$. Shorter windows (under 100 ms) were also tested from stimulus onset up to time t, using the same configuration as before. These analyses are illustrated in Figure 5. Although individual differences exist, across participants we find significant decodable information for both colour and object signals between roughly 75 ms and 500 ms, consistent with previous findings for simpler stimuli (Teichmann et al., 2020). In contrast to earlier work, however, colour decoding above chance emerges earlier—often immediately after stimulus onset—suggesting that colour information may precede object information in natural image perception.

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 cross-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

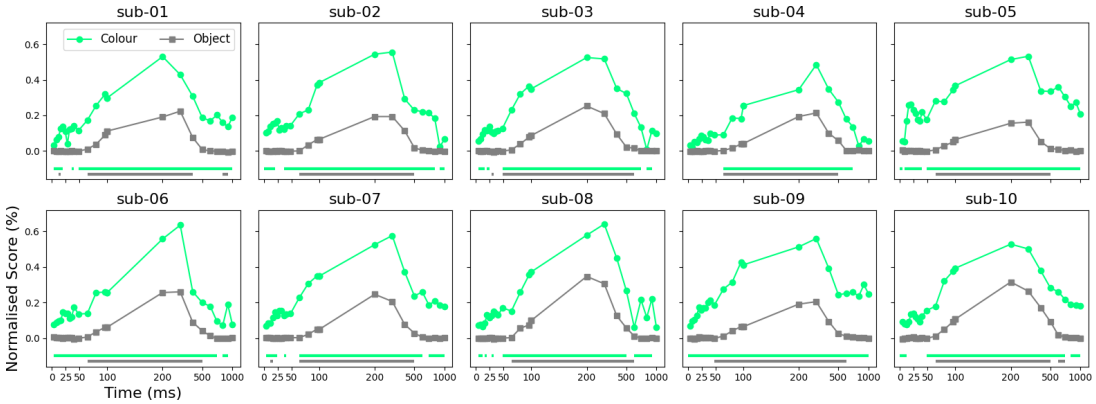


Figure 5: CUBE decoding of colour and object across temporal epochs. The x-axis (0 ms) marks stimulus onset; the y-axis shows normalised F-scores (colour) and top-1 accuracy (object), scaled by chance level and noise ceiling. Data points after 100 ms use EEG intervals $[t-100, t)$, and points before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

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 (Huang et al., 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** (**C**olo**U**r and o**B**j**E**ct 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, with theoretical implications for understanding how individual colour representations emerge in the brain under naturalistic conditions, as well as applied potential for brain–computer interfaces.

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A QUALITATIVE EXAMPLES

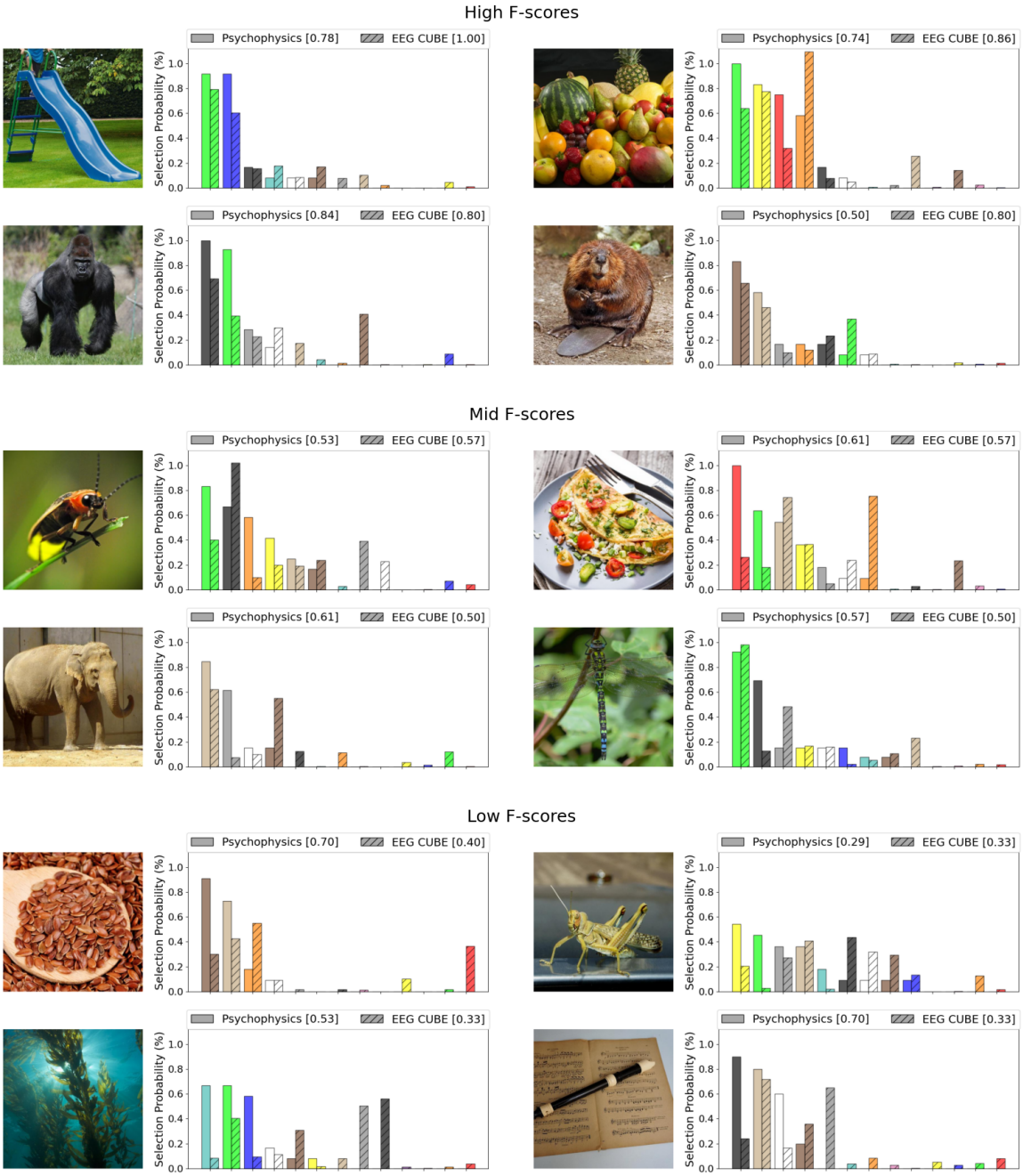

Figure S1: Examples of test images alongside the corresponding colour selections made by human participants in a psychophysical experiment and the colours decoded by CUBE from EEG signals. The reported F-score for the psychophysical data reflects the average inter-participant agreement computed using a leave-one-out strategy, whereas the EEG CUBE F-score represents the agreement between the model's predictions and the average human selections.