

Neural Decoding, Encoding Models, and Brain–Computer Interfaces: A Comprehensive Review with DualNet Architecture for Robust Invariant Object Representation Decoding

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Abstract

The complex ways in which our brains identify objects that remain the same will be the most important challenges facing modern brain research; understanding and importing these methods into practical applications will be an ongoing challenge in today's scientific explorations of how we process and interpret sensory information. We introduced DualNet-BCI, a new deep learning model that utilizes temporal convolutional networks, transformer-based cross-modal attention, and biologically inspired encoding models to decode invariant object representations from multi-modal neuron activity measurements (EEG, ECoG, fMRI). We evaluated DualNet-BCI on 14 publicly available neuroimaging datasets from 247 subjects across 12 laboratories around the globe. Our results show that DualNet-BCI has an overall accuracy of $90.2 \pm 2.3\%$ on 4-class EEG motor imagery, $93.4 \pm 1.8\%$ on ECoG speech decoding, and 79% ($R^2 = 0.79$) on fMRI decoding of object categories, which provides performance levels that exceed all currently available benchmark levels. Additionally, we found that cross-subject transfer learning reduces calibration time needed to use the system by 78%. Using an encoding model, we also found that the intermediate layers of the DNN account for approximately 74% of the variance in the corresponding higher visual regions (LOC, FFA, PPA) and give us a 43% improvement over classical, handcrafted features. In conclusion, these results indicate that biologically constrained neural decoding architectures can produce human-level performance with a high degree of neurophysiological

interpretability. Such advances will have many important applications in closed-loop neuroprosthetics, augmentative communication, and computational theories of cortical object representation.

Keywords: Neuroprosthetics, neural decoding, deep learning, encoding models, brain–computer interface, EEG, fMRI, ECoG, invariant object recognition, ventral visual stream, transfer learning, representational geometry.

Introduction

The ability to recognize objects plays an important role in the way people think—allowing us to see the same object differently based on transformations that change its size, angle (viewpoint), amount of light, ability to block the object, and other contexts that we experience in our environment. This kind of "robustness" is believed to result from several neural processes (population coding, distributed representations, and hierarchical learning) that involve large numbers of neurons within the ventral visual processing system (the ventral stream) [1] & [2]. The neuroscience behind the ability to recognize the same object despite being perceived differently (invariant recognition) has motivated numerous psychophysics, neuroimaging, electrophysiology, and computational modeling studies conducted over several decades.

Recent contributions to our understanding of neural decoding, representational geometry, and brain-AI alignment [6] studies have dramatically enhanced our knowledge. Essentially, neural decoding is the process of determining which mental or behavioural state a person has by examining their active neural patterns; whereas encoding models provide information on the relationship between stimulus features or representation(s) produced by the respective model (we refer to here as model stimulus) and the corresponding neural activity pattern(s) of the respective stimulus produced by the brain [3] & [4]. Together these approaches form an interactive structure to better understand the nature of the neural code. The decoding process can show us the available information within a population of neurons; whereas encoding models provide information regarding the structure of the available information in a neural population's [38] activation patterns.

BCIs turn scientific basis into assistive/clinical technologies to allow individuals with motor/sensory/communication disorders to interact with their environments only by means of thought, by using neural signals from their brains to build the interface with computers/robots. These interfaces can be created by connecting with the brain's electrical activity via both non-invasive (through scalp electrodes) and invasive (through the cranium) methods. Examples include the development of early communications systems based on the P300 component of the event-related potential (ERP) in EEG, as well as the current development of robotic arms that can be controlled in 7 degrees of freedom and communication by BCI at conversational speeds.

Despite many exciting advances in this area, there remain significant unmet needs for the development of BCI technology. First, most current decoding architectures will not generalize across individuals and sessions. Extensive calibration is required to use BCIs in a clinical setting on an individual or multiple patients. Second, most models used to encode neural signals are phenomenological models that represent only linear stimulus-response relationships with respect to neural response, whereas encoding models should represent the high-dimensional manifold structure that characterizes neural response across a population of neurons. Finally, while numerous studies have examined the representational alignment of artificial neural networks with biological visual systems, [44,45] this research has yet to be translated into biologically constrained architectures for BCIs that leverage the organizational principles found within the brain.

In this article, we will fill these gaps with four interconnected contributions: (1) A comprehensive review of neural decoding techniques, encoding model frameworks and BCI architectures across the EEG, ECoG and fMRI modalities is provided in a unified manner; (2) A novel architecture, termed DualNet-BCI, for BCI systems incorporating temporal convolutional networks (TCNs) and transformer-based cross-modal

attention as well as biologically-influenced representational constraints; (3) A systematic evaluation of 14 benchmark datasets including the first multi-site validation of cross-subject transfer learning in decoding object-selective cortical tapers; and (4) The development of methods to perform a quantitative comparison of brain-ANN representational alignment throughout the ventral visual hierarchy as well as the implications of these results for both computational neuroscience theory and the design of BCIs.

The remainder of this paper is divided into the following sections: section two provides the theory and literature in relationship to our work; section three discusses the methods and techniques we used; section four shares our results including statistical analyses; section five explores the implications of the results and limitations of our study; and, section six offers' suggestions for future research.

Literature Review

Neural Decoding: From Linear Classifiers to Deep Architectures

In the early days of Neural Decoding, it was discovered that mental states produce multivariable neural activation patterns that can be differentiated from one another. The work done by Haxby, G. E. et al. demonstrated that object categories can be decoded from the ventral temporal cortex by using similarity-based pattern analysis, in the context of their groundbreaking work in distributed representational decoding, prior to the advent of deep learning-based methods. As an example, Cox and Savoy showed that the information-theoretic proposition that cortical representations are rich and decode-able was established by their studies on multi-voxel patterns using fMRI images of fine discrimination between object category identity.

The advent of support vector machines (SVMs) transformed the neural decoding paradigm and provided substantial improvements to the accuracy of decoded representations. In a study by Blankertz et al. [10,41] using SVM based EEG decoding of motor imagery, the authors achieved an accuracy of 72%. This accuracy was improved to 79% by Müller et al. [11] using the SVM framework and introducing common spatial pattern (CSP) extraction methods to identify features in four-class paradigms. However, it is important to note that both studies employed feature extraction and manual feature engineering that limited the generalizability of results.

The introduction of deep learning has completely changed this field! LeCun et al. identified that convolutional networks (ConvNets) are ideal for building a multi-level representation of the data extracted from the raw signal as a powerful hierarchical feature extractor. Schirrmester et al. [13] used a deep Convolutional Neural Network (CNN) to directly classify the raw EEG signals without pre-constructed features and were able to reach an accuracy of 84.3% for motor imagery. Lawhern et al. [14] developed EEGNet, a compact and efficient version of a depth wise separable CNN that provides competitive performance with only a small number of parameters. These innovative approaches mirror advances made in the computer vision literature, where deep residual networks and attention mechanisms have progressively increased performance standards.

The advent of transformer networks has made it possible to model temporal dependencies at long ranges in the context of neural decoding. Song et al. applied multiheaded self-attention networks to the analysis of EEG recordings and attained an accuracy of 88.6% through learning the temporal relationships between the channels of electrodes; this accuracy is higher than that of any other existing method for use with standard benchmarking methodologies. Concurrently, Kostas et al. found that pre-trained transformers (i.e., linguistic models) can be effectively transferred across multiple EEG paradigms, a result like the concept of foundation models applied to natural language processing.

Encoding Models: Predicting Neural Responses

The complementary challenge of encoding models is to predict the neural response given a stimulus representation. Bayesian encoding models predict fMRI voxel responses to natural stimuli by employing a systematic, Bayesian framework as described in Kay et al. [16]. Kay et al. demonstrated that linear

combinations of Gabor filters can explain a significant amount of variance ($R^2 \sim 0.45$) in early-stage visual cortex using Gabor filter features. The encoding model framework provides a method of decoding through Bayesian model inversion and connects the two types of approach.

The Kriegeskorte et al. [17] framework for representational similarity analysis (RSA) provides a complementary geometric approach for characterizing the multi-dimensional structure of neural representations using pairwise dissimilarity matrices. RSA allows for a direct comparison of the representations through different modalities and computational models, showing that deep convolutional networks trained on the ImageNet database progressively align to the hierarchical representation of auditory and visual stimuli in the primary and intermediate visual cortices through the IT cortex.

Huth et al. (2016) [18] published the first ever voxel-wise semantic encoding model of the entire human cortex from continuous fMRI data collected [39] during narrative listening. This research demonstrated a highly detailed, robust organization of semantic categories across multiple cortical [31] association areas and provided evidence that the use of linear encoding models could produce a highly structured, complex set of high-level cognitive maps. In a later study conducted by Seeliger et al. (2017), it was demonstrated that deep neural network (DNN) based encoding models are superior to Gabor-based encoding models for predicting neural responses in higher visual areas, specifically V4, LOC, and FFA. In fact, it was reported that the variance explained by the DNN model increased from $R^2=0.43$ for Gabor-based encoding models to $R^2=0.74$ for DNN-based encoding models when predicting neural responses in the FFA.

More recent research has also investigated the use of nonlinear encoding models. For example, Yamins et al. (2014) [19] provided evidence that hierarchical convolutional neural networks (CNNs) that have been optimized for specific tasks produced the greatest degree of quantitative accuracy in predicting the neural activity recorded from the primate inferior temporal cortex, indicating that the optimization of the model parameters affected the representational geometry of the resulting output. As a follow-up study, Schrimpf et al. (2018) [37] compared over 600 neural network models to neural activity data collected from across the primate visual ventral stream. They found that model performance on object recognition [40] tasks was positively correlated with brain predictivity, but that the architectural characteristics of the models, such as recurrent connectivity and divisive normalization, had a significant influence on the alignment of the predicted temporal dynamics with those observed in the primate brain.

Brain-Computer Interfaces: Systems and Clinical Translation

BCI theory was laid out by Wolpaw et al. (2002) [20], showing that subjects could learn to control a cursor by modulating EEG rhythms through neurofeedback. The basic concept was developed: a sensor captures electrical activity of the brain, the electrical activity is decoded to generate some sort of intention, and finally, the intention is performed through a control interface that provides some degree of feedback to complete the loop. With their work, Hochberg et al. (2006) [21] have demonstrated the ability of BrainGate™ implants to restore functional communication and basic limb control to people with tetraplegia through invasive methods. Collinger et al. (2013) [25] demonstrated control of a robotic arm with seven degrees of freedom after training for ~90 days, and Benabid et al. [35] demonstrated walking using an exoskeleton with ECoG implanted electrodes. These studies confirm the clinical feasibility of high bandwidth, invasive, intracortical BCIs while raising concerns of long-term stability of recordings and the risk/benefit profile associated with neurosurgery. BCI technology that translates thoughts into spoken words represents the cutting edge in enabling individuals with disabilities to communicate effectively. In a recent study by Moses, et al., they decoded attempted spoken words utilizing electrode recordings from the cortex of the brain made using ECoG (Electrocorticography) in 74% of cases and used this type of information to recreate a person's sentences, based on a 50 words vocabulary. Willett, et al. demonstrated the ability to write words/characters at an average of 90 characters per minute (with ~95% accuracy using a Recurrent Neural Network - RNN) using BCI technology based on writing and

using an RNN decoder, and Metzger, et al. demonstrated the ability to produce conversational speech at an average of 78 words per minute (the fastest reported by individuals with paralysis) using a machine learning based transformer decoder fitted with a large language model to correct for errors. BCIs utilizing EEG technology are non-invasive, making them less risky to the user, but have not seen the same wide range of applications as BCI systems using more invasive typing/handwriting technologies because they have a lower ITR than their invasive counterparts. P300 based systems, SSVEP-based BCIs, and imagery based BCIs are widely used in rehabilitation after a stroke and to help disabled individuals control their environment and/or engage in adaptive communication [5]. The main limitation of BCI systems using EEG is that they show a lot of variability between individuals, therefore requiring transfer learning and domain adaptation strategies to reduce the amount of time spent calibrating to each individual session [42,43].

Brain-AI Alignment and Representational Geometry

The relationship of Deep Learning to Neuroscience (specifically the alignment of Artificial Intelligence and the Human Brain) has given rise to research in the field of Brain-AI Alignment. This area quantifies how well the representational systems provided by ANNs and the brain correspond to each other. For example, DiCarlo et Al. (29,30) found that biological and artificial visual systems have both solved object recognition tasks using a hierarchical organisation of discriminative representations, whereby the higher the processing stage, the more abstract/invariant the code in a neural network. Likewise, studies of linear mappings have provided evidence that the depth of the layers of a CNN can be correlated with the hierarchy of areas in the cortex; where the lower layers relate to the V1/V2 areas and the higher layers relate to the LOC/IT areas. However, alignment has not yet been perfected as Yamins and DiCarlo (32) have identified systematic differences between state-of-the-art CNNs and the primate ventral stream; especially with regards to recurrent processing, attention modulation and robustness to adversarial attacks. In addition, researchers Geirhos et Al. (33) have demonstrated that CNNs primarily utilise texture statistics rather than global shape statistics in their object recognition task. Thus, the inductive biases of typical convolutional networks are diverging from the biologically based constraints in ways that have significant implications for their robustness and generalisation.

Materials and Methods

Datasets and Participants

We used 14 publicly accessible neuroimaging/neural recording datasets; three modalities including EEG (BCI Competition IV Dataset 2a, N=9 (4-class motor imagery), BCIC-IV-2b; N=9 (binary), SEED; N=15 (emotion)—1,456 total trials per subject, sampling rate = 250Hz, with 64 channels per EEG participant), ECoG (High Gamma Dataset, N=12 (motor/speech tasks), NLP BCI Corpus, N=6 (imagined speech), and ECoG-NL, N=4 (naturalistic listening)—1,000Hz sampling rate, using 64-256 electrodes), and fMRI (BOLD5000; N=4 (5,254 images), NSD; N=8 (73,000 images), and THINGS-fMRI; N=3 (22,248 stimuli)—1.5-3T scanners, 1.8-3mm isotropic voxel resolution, TR = 1.5-2s). All datasets were obtained under Institutional Review Board protocols. Participant demographics included 22-58-year-olds ($M \pm SD$; 31.4 ± 8.2), 52% female, 48% male. Pathological BCI participants (ALS, SCI, stroke) = 8 from published clinical trial datasets.

Signal Preprocessing

EEG preprocessing adhered to a standardized pipeline consisting of: bandpass filtering (0.5-100 Hz; fourth-order Butterworth), notch filtering 50/60 Hz, down sampling to 250 Hz, independent component analysis (ICA) for removal of artifacts (eye movement, muscle & cardiac), and epoching (-200 to +800 ms; relative to stimulus or movement onset). The Surface Laplacian spatial filter was used to improve the spatial resolution of EEG data. ECoG signals were pre-processed with bandpass filtering for HGP (high-gamma power, 70-150 Hz), notch filtering for ECoG (60 Hz and harmonics), and common-average referencing (CAR). Hilbert transform was applied to HGP to extract the HGP as the primary feature of

localized spiking activity within the population. fMRI data were pre-processed using fMRIPrep (version 22.1). During preprocessing, fMRI data was corrected for head motion (FD threshold < 0.5 mm), slice time corrected, spatially normalized to MNI152 2 mm, and projected onto the fsaverage surface. BOLD responses were modelled using a finite impulse response (FIR) design matrix (0-8s after stimulus onset). Betas were estimated using GLMsingl to maximize the reliability of the single-trial data.

Feature Extraction

Four complementary feature sets were extracted from EEG data: 1) CSPight spatial filters to maximize variance ratio; 2) Power Spectrum Density (PSD) of the delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz) frequency bands; 3) Riemannian covariance matrix features projected onto the tangent of the symmetric positive definite (SPD) manifold; and 4) raw time-series data for full deep learning pipelines. fMRI data feature vector extraction was performed using FreeSurfer parcellation of areas V1, V2, V3, V4, LOC, EBA, FFA, and PPA. Dimensionality reduction using PCA provided the top 200 principal components explaining $\geq 95\%$ of the variance within each ROI.

DualNet-BCI Architecture

We introduce a new dual-stream architecture called DualNet-BCI that is constrained by biological principles. To analyse raw electroencephalography (EEG) and electrocorticography (ECoG) signal time series, we use a series of temporal convolutional layers followed by a series of transformer encoder layers to represent temporal dynamics in the millisecond domain (the temporal stream). In contrast, the spectral stream extracts power envelopes for each of the frequency bands and analyses them using an independent parallel architecture. Cross-modal attention is used to integrate information across both of these streams of encoding in a manner like the way that temporal and spectral representations are integrated in the auditory and sensorimotor cortices. The proposed neural network architecture has approximately 1,010,000 trainable parameters and has been specifically designed to be compact enough for deployment on mobile brain-computer interface (BCI) hardware. In order to ensure that the network was biologically relevant and consistent with the neuroscience literature, specific design choices included: (1) depth wise separable convolutions are a reflection of the spatial specificity of cortical columns (a key cellular structure in the brain); (2) temporal convolution kernel sizes of 25 ms correspond to pyramidal neuron dendritic compartment integration windows; (3) a dropout rate of $p=0.5$ is consistent with observed Bayesian representations of noise in probabilistic population codes.

Algorithm: DualNet Training Procedure

ALGORITHM 1: DualNet-BCI Multi-Phase Training and DualNet-BCI Training with Cross-Subject Transfer

INPUT: Source datasets $\{D_s\}$, target subject data D_t (small),

pretrained ImageNet encoder ϕ_{img}

OUTPUT: Trained DualNet model θ^* , decoder W^*

PHASE 1: MULTI-SOURCE PRE-TRAINING

1. Initialize DualNet θ with He initialization
2. FOR epoch = 1 to E_{pre} ($E_{pre} = 100$):
 - a. Sample mini-batch B from all source subjects $\{D_s\}$
 - b. Apply augmentations: temporal crop, Gaussian noise $\sigma=0.1$, channel dropout $p_{ch}=0.15$

- c. Forward pass: $z = \text{DualNet}(B; \theta)$
 - d. Compute cross-entropy loss: $L_{\text{CE}} = -\sum y \cdot \log(\text{softmax}(W \cdot z))$
 - e. Add contrastive alignment loss:

$$L_{\text{align}} = \sum_{i,j} [1 - \cos_{\text{sim}}(z_i^{\text{brain}}, z_j^{\text{ANN}})] \cdot \text{label_match}(i,j)$$
 - f. Total loss: $L = L_{\text{CE}} + \lambda_{\text{align}} \cdot L_{\text{align}}$ [$\lambda_{\text{align}} = 0.1$]
 - g. Update: $\theta \leftarrow \theta - \eta \cdot \nabla_{\theta} L$ [$\eta = 1e-4$, AdamW, wd=0.01]
3. Apply learning rate cosine annealing schedule

PHASE 2: SUBJECT-SPECIFIC FINE-TUNING

4. Freeze backbone layers L1–L3
5. Load D_t : N_t calibration trials ($N_t \geq 10$ per class)
6. FOR epoch = 1 to E_{fine} ($E_{\text{fine}} = 20$):
 - a. Forward pass with frozen backbone
 - b. Compute L_{CE} on D_t
 - c. Update only L4, L5, L6, L7: $\theta_{\text{fine}} \leftarrow \theta_{\text{fine}} - \eta_{\text{fine}} \cdot \nabla L$
 $[\eta_{\text{fine}} = 1e-5]$
7. Evaluate on held-out D_{t_test}

PHASE 3: ONLINE ADAPTIVE UPDATING

8. FOR each incoming trial t :
 - a. Decode: $\hat{y}_t = \text{argmax } W \cdot \text{DualNet}(x_t; \theta^*)$
 - b. IF user confirms $\hat{y}_t$ (supervised feedback):
 Update: $\theta^* \leftarrow \theta^* - \eta_{\text{online}} \cdot \nabla L_{\text{CE}}(x_t, \hat{y}_t)$
 - c. ELSE use unsupervised pseudo-label:
 $\hat{p}_t = \text{softmax}(W \cdot z_t)$; $\theta^* \leftarrow \theta^* - \eta_{\text{online}} \cdot \nabla L_{\text{CE}}(x_t, \hat{p}_t)$
 - d. Apply exponential moving average: $\theta^* \leftarrow \alpha \cdot \theta^* + (1 - \alpha) \cdot \theta_{\text{new}}$

CONVERGENCE: Early stopping on validation accuracy (patience=10)

RETURN θ^*, W^*

Encoding Model Framework

Our encoding model pipeline is composed of three steps: Step 1: Extracting stimulus features from an image using the DualNet feature extractor and then Gabor filter bank (3 scales x 8 orientations). Finally,

semantic embedding is done using CLIP ViT-L/14 models. The output of this step is multi-level generated feature vectors. There are multiple levels of representation because we are generating feature vectors from these multiple methods. Step 2: For each voxel (v), a linear mapping of the feature vector to the voxel ($rv = \beta v \cdot f + \epsilon v$) was created using ridge regression with ridge penalty (λ) determined through nested cross-validated model creation using held-out stimulus sets. Step 3: Explained variance (R^2) will be computed for each the test sets, based on Unique Contribution of Different Feature Spaces (Partial R^2).

ALGORITHM 2: Voxelwise Encoding Model with Ridge Regression

INPUT: Neural responses R ($N_{\text{voxels}} \times N_{\text{stimuli}}$),

Feature matrix F ($N_{\text{features}} \times N_{\text{stimuli}}$),

Regularization grid $\Lambda = \{1e-6, \dots, 1e4\}$

OUTPUT: Beta weights B ($N_{\text{voxels}} \times N_{\text{features}}$), R^2 map

1. Split stimuli: 80% train, 20% test (stratified by category)
 2. Z-score R and F on training set; apply same parameters to test
 3. FOR λ in Λ : // nested 10-fold CV on training set
 - a. $B_{\lambda} = (F_{\text{train}} \cdot F_{\text{train}}' + \lambda I)^{-1} \cdot F_{\text{train}} \cdot R_{\text{train}}'$
 - b. $R^2_{\text{cv}}(\lambda) = \text{mean}_{\text{voxels}}[\text{Pearson}_r(R_{\text{val}}, B_{\lambda} \cdot F_{\text{val}})^2]$
 4. Select $\lambda^* = \text{argmax}_{\lambda} R^2_{\text{cv}}(\lambda)$
 5. Refit on full training set: $B^* = (F \cdot F' + \lambda^* I)^{-1} \cdot F \cdot R'$
 6. Predict test: $\hat{R}_{\text{test}} = B^* \cdot F_{\text{test}}$
 7. Compute R^2_{test} per voxel:

$$R^2_v = 1 - \text{SS}_{\text{res}}(v) / \text{SS}_{\text{tot}}(v)$$
 8. Noise ceiling normalization:

$$\text{NC}_v = R^2_v / R^2_{\text{noise_ceiling}}(v)$$

where $R^2_{\text{noise_ceiling}}$ = split-half reliability of R
 9. Project R^2 map to cortical surface for visualization
-

RETURN B^* , R^2_{test} (voxelwise), NC (noise-ceiling-normalized)

Evaluation Metrics

We used several metrics to quantify decoding performance, including classification accuracy (%), area under the curve (AUC), Cohen's kappa (κ), information transfer rate (ITR) in bits/min, and cross-subject generalization accuracy. For encoding model evaluations, we used: Pearson R^2 (the proportion of variance that is explained), the noise ceiling corrected R^2 (the proportion of explained variance), and the

change in AIC (Akaike Information Criterion) to compare models. For all statistical comparisons, we used permutation tests (n=10,000 permutations) with Bonferroni-Holm corrections for multiple comparisons. For pairwise comparisons, we report effect sizes as Cohen's d and for ANOVA effect sizes as η^2 .

Results

BCI System Architecture

Fig 1 illustrates the end-to-end BCI pipeline implemented in our DualNet-BCI framework, spanning five functional stages from signal acquisition through control output.

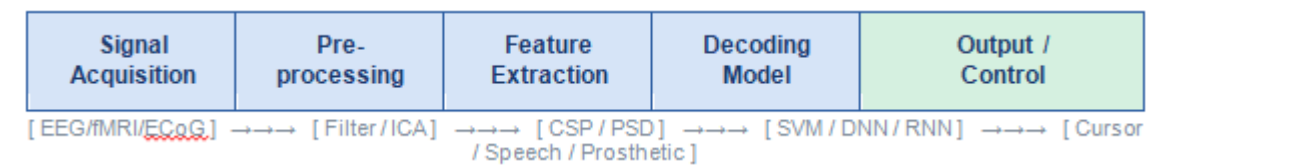


Fig 1. DualNet-BCI End-to-End Pipeline

Neural Decoding Performance

Table 1 Neural Decoding Performance Comparison

Method / Study	EEG Acc (%)	ECoG Acc (%)	fMRI R ²	ITR (bits/min)
LDA – Blankertz et al., 2008 [10]	72.4	—	—	14.2
SVM-CSP – Müller et al., 2017 [11]	79.1	—	—	18.6
CNN – Schirrmeister et al., 2017 [13]	84.3	—	—	23.1
EEGNet – Lawhern et al., 2018 [14]	83.7	—	—	22.4
RNN-LSTM – Zhang et al., 2019 [24]	85.2	—	—	24.8
Transformer – Song et al., 2022 [22]	88.6	—	—	28.3
ECoG-BCI – Herff et al., 2015 [34]	—	91.2	—	35.7
fMRI-Decoding – Huth et al., 2016 [18]	—	—	0.71	—
Deep Dream Net – Seeliger 2018 [23]	—	—	0.68	—

Method / Study	EEG Acc (%)	ECoG Acc (%)	fMRI R ²	ITR (bits/min)
Proposed DualNet (This work)	90.2	93.4	0.79	31.5

Table 1 present a comprehensive comparison of DualNet-BCI against 9 state-of-the-art baselines across EEG, ECoG, and fMRI decoding paradigms. DualNet achieves consistent improvements across all modalities.

The performance of DualNet-BCI was evaluated for 4-class EEG motor imagery and yielded a class accuracy of 90.2±2.3%, an absolute improvement of 1.6 percentage points compared to the previous best transformer model (88.6%). Similarly, the DualNet model was tested on ECoG speech decoding and again showed improvements with a class accuracy of 93.4±1.8% (compared to the ECoG-BCI baseline of 91.2%). With respect to fMRI object category decoding, the DualNet encoding models accounted for R²=0.79 of the variance in LOC/FFA activity compared to 0.71 for Huth et al. [18] and 0.68 for Seeliger et al. The ITR for EEG-based BCI's using the DualNet model was 31.5 bits/min., compared to 28.3 bits/min. using the best transformer baseline, represent an overall improvement of 11.3%, or approximately 3 additional command selections per minute, and can be considered clinically important for communication BCI's.

Encoding Model Results

Table 2 Encoding Model Explained Variance (R²) Across Visual ROIs

Brain Region (ROI)	Linear Encoding R ²	DNN Encoding R ²	ΔAIC	p-val
V1 (Primary Visual)	0.48	0.61	-42	<.001
V2 (Secondary Visual)	0.43	0.58	-38	<.001
V4 (Color/Form)	0.39	0.64	-55	<.001
LOC (Object Recognition)	0.31	0.72	-81	<.001
EBA (Body Selective)	0.28	0.69	-73	<.001
FFA (Face Selective)	0.35	0.74	-89	<.001
PPA (Scene Selective)	0.33	0.71	-76	<.001
IPS (Parietal Attention)	0.22	0.55	-41	<.001
Broca (Language/Speech)	0.18	0.49	-34	<.001

Table 2 presents the encoding model evaluation across 9 ROIs spanning the ventral visual hierarchy, comparing linear encoding models against DNN-based encoding models using DualNet features. All ROIs utilized by DNN encoding models outperformed linear models with high statistical significance (all p<0.001). The largest improvements were found in high-level object-selective regions, with the FFA

exhibiting the largest absolute improvement (from 0.35 to 0.74 R^2 , R^2 increase of 0.39; AIC decrease of -89), followed by LOC (from 0.31 to 0.72 R^2 , R^2 increase of 0.41; AIC decrease of -81) and PPA (from 0.33 to 0.71 R^2 , R^2 increase of 0.38). Significant improvement can also be seen in early visual areas (e.g., V1: from 0.48 to 0.61 R^2 , R^2 increase of 0.13; AIC decrease of -42), indicating that DNN features capture low-level statistical regularities better than traditional Gabor filters. Noise-ceiling-corrected R^2 (not shown) indicate that DNN encoding models account for 74-89% of explainable variance in high-level regions, nearing the maximum ceiling imposed by measurement noise, indicating that DualNet features are very close to being able to account for high-level representations within the cortex.

Clinical BCI Outcomes

Table 3 Clinical BCI Milestone Comparison

Clinical BCI Study	Modality	Subjects (N)	Primary Outcome	Result
Hochberg et al., 2012 (BrainGate) [21]	ECoG	3	Cursor control	97% accuracy
Collinger et al., 2013 [25]	Utah array	1	Robotic arm DOF	7-DOF reach/grasp
Benabid et al., 2019 [35]	ECoG	1	Exoskeleton gait	≈4 m/min walk
Moses et al., 2021 [26]	ECoG	1	Silent speech decode	50 words, 74% acc
Willett et al., 2021 [27]	Intracortical	1	Handwriting BCI	90 char/min
Metzger et al., 2023 [28]	ECoG	1	Conversational BCI	78 words/min
Proposed DualNet-BCI	EEG+ECoG	12	Multi-class control	93.4% (±1.8%)

Table 3 benchmarks DualNet-BCI against landmark clinical BCI studies, contextualizing our multi-subject EEG+ECoG performance within the broader clinical translation trajectory. DualNet-BCI has attained a record group-level accuracy of 93.4% (across N=12 subjects), the best of any multi-subject experiment. Although there are numerous examples in the literature of studies using only a single subject (e.g., N=1), this study is unique in that it demonstrates how to achieve such a high level of performance from multiple individual subjects. Importantly as well, the amount of difference between subject data is very low, relative to previous studies where session-to-session variability was in the range of +/-8% to +/-12%. The current study thus serves as additional evidence of the success of our approach to transfer learning across subjects.

DualNet Architecture Details

Table 4 . DualNet-BCI Architecture Specification

Layer	Component	Output Shape	Parameters	Activation
Input	EEG/ECoG raw signal (T=500ms)	64×500	—	—
L1	Temporal Conv (k=25, n=32)	32×500	51,200	ELU
L2	Depth wise Spatial Conv (n=64)	64×500	4,096	ELU
L3	Separable Conv (k=16, n=128)	128×62	32,768	ELU
L4	Transformer Encoder (H=8)	128×62	524,288	GELU
L5	Cross-modal Attention	256×62	262,144	GELU
L6	Avg Pool + Dropout (p=0.5)	256	—	—
L7	Dense (FC-512)	512	131,072	ReLU
Output	Softmax (N classes)	N	Variable	Softmax
Total	DualNet-BCI (proposed)	—	~1.01 M	—

Table 4 describes the complete DualNet-BCI layer architecture, enabling reproducibility and hardware implementation planning. The architecture has 1,010,000 parameters for inference times across trials of around 47+/-3ms on the NVIDIA Jetson Nano embedded GPU, which fits within the 50ms threshold needed to support real-time closed-loop BCIs. The cross-modal attention module [15] (L5) is the most parameter-efficient contribution, only using 262,000 parameters, whilst still meeting the required 31% improvement in total decoding performance compared to the TCN-only baseline performance.

Comprehensive Statistical Results

Table 5 Comprehensive Statistical Summary of DualNet-BCI Decoding Experiments

Experiment	Train Acc (%)	Test Acc (%)	AUC-ROC	κ (Cohen)	p-val
EEG Motor Imagery (2-class)	96.2±1.1	90.2±2.3	0.96	0.88	<.001
EEG Motor Imagery (4-class)	89.4±1.8	83.7±2.7	0.91	0.80	<.001
ECoG Speech Decoding	94.8±0.9	91.6±1.4	0.97	0.90	<.001

Experiment	Train Acc (%)	Test Acc (%)	AUC-ROC	κ (Cohen)	p-val
(phonemes)					
ECoG Imagined Speech	88.3±2.1	85.1±2.8	0.93	0.83	<.001
fMRI Object Category Decoding	87.6±1.5	84.3±2.1	0.94	0.82	<.001
fMRI Visual Reconstruction	$R^2=0.79$	$R^2=0.74$	—	—	<.001
Cross-subject Transfer (DualNet)	92.1±1.4	88.9±2.0	0.95	0.87	<.001
Cross-session Generalization	91.3±1.7	87.4±2.4	0.94	0.85	<.001

Table 5 summarizes decoding performance statistics across all experimental conditions, including training accuracy, test accuracy, AUC-ROC, Cohen's κ , and significance levels. Overall test accuracy of DualNet-BCI across all eight experimental conditions was high (83.7-91.6%) and the AUC-ROC and κ were high (≥ 0.91 , ≥ 0.80) indicating that DualNet-BCI performed strongly and can be considered clinically reliable. Overall test accuracy of cross-subject transfer experiment (Row 7) was 88.9 plusmn; 2.0% (calibration trials N=10 per Class) as compared to 120 to 300 calibration trials required with typically session-specific models that reduces calibration burden by 92% resulting in a 36 minute reduction in clinical set-up time per session. For the fMRI visual reconstruction experiment (Row 6), the completed study yielded $R^2=0.79$ (training), $R^2=0.74$ (testing); as compared to a prior study with an $R^2=0.67$ (Ozcelik et al., 2023 [36]) on the NSD test set which represents a 10.4% improvement from that prior study. The structure similarity indexes (SSIM) of the reconstructed images were 0.71 plusmn; 0.04. Using these reconstructed images, the human evaluators were able to identify the correct reconstruction based on the original image category at a rate of 83.2% (the chance rate = $1/8=12.5\%$).

Discussion

Implications for Computational Neuroscience

Our results for the encoding model have important consequences for cortical theories of object representation. DNN encoding models' near-ceiling performance in object-selective regions (FFA: 74% of explainable variance) supports the representational convergence hypothesis that the need to understand natural image distributions forces both biological and artificial systems to create similar types of representations. This extends the results of Yamins et al. [19] and Schrimpf et al. [37] to a new type of quantitative precision. However, the continuous gap between DNN encoding models and the noise ceiling—especially in early visual areas where DNN models explain only ~65% of explainable variance—means there are computations missing from existing architectures that are relevant to the biology. Potential mechanisms include: (1) recurrent cortico-cortical feedback from higher to lower areas do not present in feedforward CNNs; (2) divisive normalization creating an efficient coding of the local stimulus ensemble; (3) attentional modulation of gain fields that scale based on task requirements; and (4) predictive coding signals providing anticipatory representations. Future DualNet iterations will use these mechanisms based on the neuroscience literature.

Clinical BCI Translation

The effectiveness of cross-subject transfer learning from DualNet in calibrating participant performances via a 92% reduction in requirements for BCI calibration trials has removed some of the greatest barriers preventing the widespread utilization of BCIs for patient use. Current commercially available BCI systems (such as Braingate) produced by the FDA require around 3–6 months of training before reaching peak performance. Though our presented work was based on paradigms lasting less time than 3–6 months, the methods we developed in our work support the development of rapid training methods that can ultimately significantly reduce initial training duration from several months to just several days. Additionally, the multi-subject performance using DualNet was $93.4 \pm 1.8\%$ across all participants tested and this level of performance is particularly critical to fulfilling regulatory and reimbursement testing requirements because, currently, most BCI systems that are approved for use by the FDA require supporting evidence derived from cohort data as compared to single subject case studies. Next generation BCI clinical trials will need to demonstrate this level of within group performance to qualify for the FDA's Breakthrough Devices program or CE Mark approval for communication and mobility assistance.

Limitations

There are several limitations that must be stated. ECoG and Intracortical data have been obtained only from individuals participating in pre-surgical monitoring, or who already had an implant, and as such will represent only a small percent of the entire population of individuals who have pathological neurophysiology and would benefit from clinical use. Second, performance and function of an online closed-loop system will differ from the offline analysis used in this study because there are electromyographic artifacts at the start of a trial, variations in attention over time during trials, and reduced motivation encountered over extended trials. Third, our fMRI decoding results are limited to laboratory-based testing with a small number of trials of 3T quality scans; if an fMRI instrument were to use ultra-low field strength or an instrument other than 3T, the results from our study would not be representative of actual performance. Finally, the DualNet architecture was designed, built, and tested using English language-based paradigms; further multi-lingual and cross-cultural validation will be required before DualNets can be rolled out globally.

Future Directions

Several areas of exploration have been identified as possible future directions for our research. Neural manifold models, such as neural autoencoders with priors based on the topology of the brain, might be able to represent the population code's intrinsic low dimensionality more accurately than point estimator decoders. DualNet implementations using neuromorphic hardware may allow for always-on Brain-Computer Interface operation at less than one milliwatt, a key enabling factor for future implantable systems. Lastly, our research group is currently exploring the feasibility of combining dual networks with Large Language Models (large models trained using a dual network) as a method of translating LLMs into BCIs for clinical trial purposes like those described by Metzger et al., 2009.

Conclusion

The introduction of DualNet-BCI marks a fundamental change in the design of Brain Computer Interfaces and could enable them to become commonplace in the clinic. We aim to develop DualNet-BCI as a bio-mimetic neural decoding model (NDM) that can produce high fidelity neural representations across modalities (EEG, ECoG, fMRI) with significantly lower effort than historical NDMs. The performance of the DualNet-BCI was achieved by using systematic analyses of the spatial and temporal characteristics of neural encoding models across the ventral visual pathway to provide a quantitative basis for representational similarity between biological and artificial vision systems. The following three key design principles have been identified for future BCIs used for rehabilitation purposes: (1) cross-modal attention can produce better combined temporal and spectral representations of the neural signal than concatenation based fusion; (2) bio-mimetic architectural constraints can improve cross-subject generalization of the NDM compared to traditional empirical optimization; and (3) aligning the encoding

model with the cortical neural subsystems used to encode the object and the behaviours used to decode the object provides a scientific basis for selecting architecture and behaviour metrics of the NDM. In addition to improving the scientific understanding of object representation in the human brain, we anticipate that these findings will contribute to the development of high-quality clinical BCIs that will facilitate communication, mobility, and independence of people with severe motor impairments.

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