

Object classification from randomized EEG trials

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Deep Learning Human Mind for Automated Visual Classification

C. Spampinato, S. Palazzo, I. Kavasidis, D. Giordano

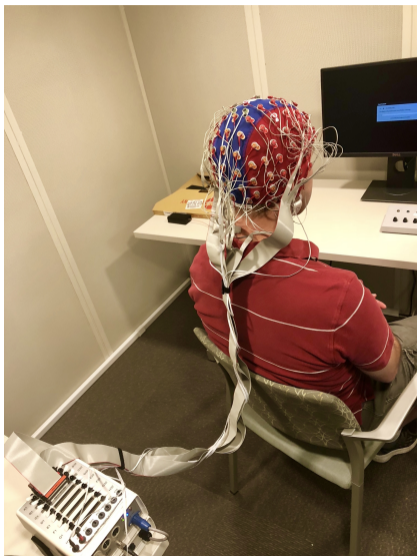
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- ▶ 6 subjects
- ▶ 2,000 ImageNet images/subject
- ▶ 40 classes, 50 images/class
- ▶ block design
- ▶ 84.0% accuracy

Bozal, A.	(B.S. thesis 2017)	89.03%
Du, C., <i>et al.</i>	(ICMM 2019)	81.24%
Du, C., <i>et al.</i>	(IF 2021)	
Du, C., <i>et al.</i>	(KDD 2018)	
Fares, A., <i>et al.</i>	(ICBB 2018)	97.1 %
Fares, A., <i>et al.</i>	(BMC MIDM 2019)	97.3 %
Fares, A., <i>et al.</i>	(ICMM 2020)	89.06%
Hwang, S., <i>et al.</i>	(IWCBCI 2019)	95.89%
Jiang, J., <i>et al.</i>	(THMS 2019)	94.1 %
Jiao, Z., <i>et al.</i>	(IJCAI 2019)	92.99%
Kavasidis, I., <i>et al.</i>	(ICMM 2017)	
Li, D., <i>et al.</i>	(Pattern Recognition 2020)	
Mukherjee, P., <i>et al.</i>	(ICIP 2019)	89.6 %
Palazzo, S., <i>et al.</i>	(ECCV 2018)	
Palazzo, S., <i>et al.</i>	(FG 2020)	42.6 %
Palazzo, S., <i>et al.</i>	(TPAMI 2020)	48.1 %
Palazzo, S., <i>et al.</i>	(ICCV 2017)	83.9 %
Palazzo, S., <i>et al.</i>	(arXiv 2018)	90.4 %
Zhang, W. & Liu, Q.	(ICAICI 2018)	99.6 %
Zheng, X. & Chen, W.	(BSPC 2021)	99.50%
Zheng, X., <i>et al.</i>	(BSPC 2020)	94.4 %
Zheng, X., <i>et al.</i>	(Pattern Recognition 2020)	97.13%
Zhong, S., <i>et al.</i>	(ICSESS 2018)	96.2 %
Zhong, S., <i>et al.</i>	(ICAICA 2019)	98.24%
Zhong, S., <i>et al.</i>	(ICMM 2019)	98.4 %
Zhou, Q., <i>et al.</i>	(JOPCS 2019)	80.9 %

The Perils and Pitfalls of Block Design for EEG Classification Experiments

Ren Li¹, Jared S. Johansen¹, Hamad Ahmed¹, Thomas V. Ilyevsky¹, Ronnie B. Wilbur¹,
Hari M. Bharadwaj¹, and Jeffrey Mark Siskind¹, *Senior Member, IEEE*

Abstract—A recent paper [1] claims to classify brain processing evoked in subjects watching ImageNet stimuli as measured with EEG and to employ a representation derived from this processing to construct a novel object classifier. That paper, together with a series of subsequent papers [2], [3], [4], [5], [6], [7], [8], claims to achieve successful results on a wide variety of computer-vision tasks, including object classification, transfer learning, and generation of images depicting human perception and thought using brain-derived representations measured through EEG. Our novel experiments and analyses demonstrate that their results crucially depend on the block design that they employ, where all stimuli of a given class are presented together, and fail with a rapid-event design, where stimuli of different classes are randomly intermixed. The block design leads to classification of arbitrary brain states based on block-level temporal correlations that are known to exist in all EEG data, rather than stimulus-related activity. Because every trial in their test sets comes from the same block as many trials in the corresponding training sets, their block design thus leads to classifying arbitrary temporal artifacts of the data instead of stimulus-related activity. This invalidates all subsequent analyses performed on this data in multiple published papers and calls into question all of the reported results. We further show that a novel object classifier constructed with a random codebook performs as well as or better than a novel object classifier constructed with the representation extracted from EEG data, suggesting that the performance of their classifier constructed with a representation extracted from EEG data does not benefit from the brain-derived representation. Together, our results illustrate the far-reaching implications of the temporal autocorrelations that exist in all neuroimaging data for classification experiments. Further, our results calibrate the underlying difficulty of the tasks involved and caution against overly optimistic, but incorrect, claims to the contrary.

Index Terms—Object classification, EEG, neuroimaging

Randomized Design

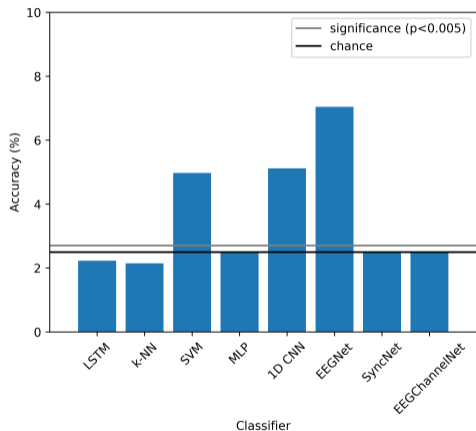
7 Questions

- 1 Is this task even possible?
- 2 How many classes?
- 3 How much training data is needed?
- 4 Which classification architectures work?
- 5 Do recording artifacts (eye blinks) hurt? (addressed in poster and paper)
- 6 Does frequency-domain analysis help? (addressed in poster and paper)
- 7 Can one decode across subjects?

New Dataset

- ▶ 1 subject
- ▶ 40,000 ImageNet images/subject
- ▶ 40 classes, 1,000 images/class
- ▶ randomized design
- ▶ 10 sessions, six hours each

Is this task even possible?



● Is this task even possible?

YES, but only barely

● How many classes?

● How much training data is needed?

● Which classification architectures work?

● Do recording artifacts (eye blinks) hurt?

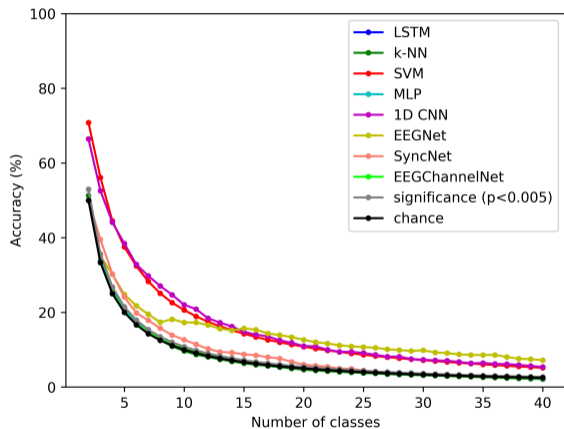
(addressed in poster and paper)

● Does frequency-domain analysis help?

(addressed in poster and paper)

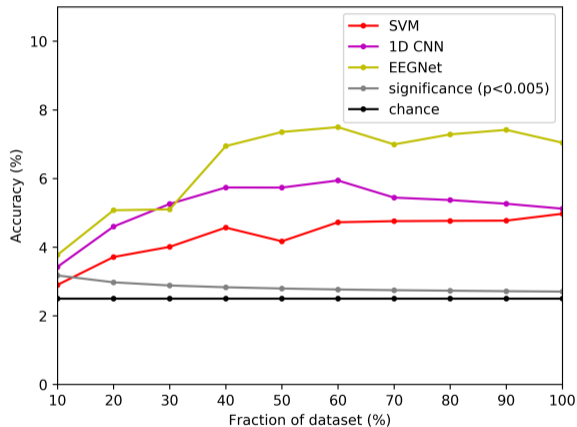
● Can one decode across subjects?

How many classes?



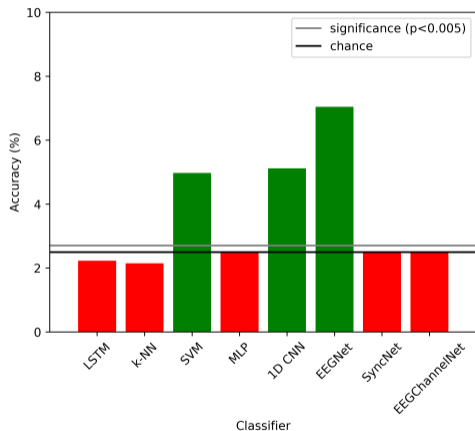
- Is this task even possible? YES, but only barely
- How many classes? 40 is about the limit
- How much training data is needed?
- Which classification architectures work?
- Do recording artifacts (eye blinks) hurt? (addressed in poster and paper)
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How much training data is needed?



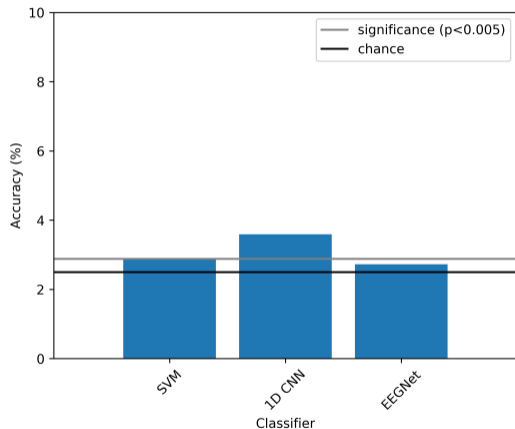
- Is this task even possible? YES, but only barely
- How many classes? 40 is about the limit
- How much training data is needed? only about 60% of our dataset
- Which classification architectures work?
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- How many classes? 40 is about the limit
- How much training data is needed? only about 60% of our dataset
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Can one decode across subjects?



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- How many classes? 40 is about the limit
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- Which classification architectures work? only SVM, 1D CNN, and EEGNet
- Do recording artifacts (eye blinks) hurt? (addressed in poster and paper)
- Does frequency-domain analysis help? (addressed in poster and paper)
- Can one decode across subjects? **not yet**

Take-Home Messages

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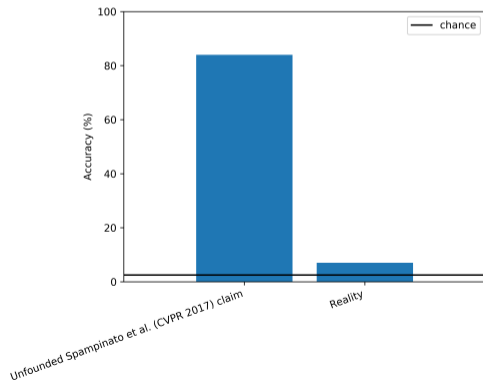
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- ▶ It took collecting the **largest EEG dataset** ever collected from a single subject, at the bounds of feasibility.

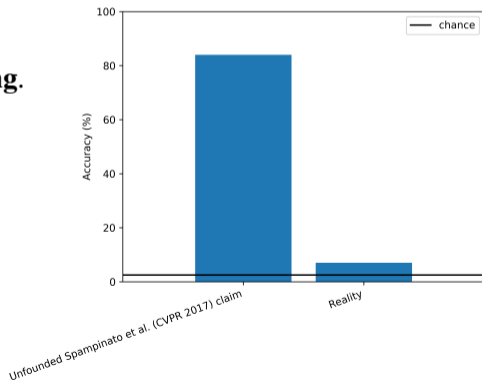
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- ▶ Don't believe everything you read in CVPR.



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- ▶ Don't believe everything you read in CVPR.
- ▶ The problem is **hard, unsolved**, and thus **interesting**.





<https://dx.doi.org/10.21227/bc7e-6j47>

<https://dx.doi.org/10.21227/x2gf-5324>