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Modeling psychopathology through stacked deep neural networks of executive function

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Abstract

It remains a substantial challenge to model psychopathology using neuroimaging data. High rates of comorbidity and heterogeneity between and within psychiatric disorders make predictive modeling especially challenging. To address this challenge, we model psychopathology using the well-established P-factor. Furthermore, psychiatric disorders do not, themselves, reflect singular neurobiological processes. Therefore, we attempt to improve our ability to predict psychopathology by transferring knowledge from individual models trained to predict elements of executive function, cognitive processes associated with psychopathology, including working-memory, set-shifting, and inhibitory control.

These analyses included 6037 children aged 9 and 10 from the Adolescent Brain and Cognitive Development Study that possessed adequate resting-state fMRI, T1 MRI, and relevant assessment data. The P-factor was generated using a well-established factor structure from the literature. Neural networks were trained to predict working-memory, set-shifting, inhibitory control, and the P-factor itself. The latter model was compared to a model in which the individual networks of executive function were stacked and re-trained to predict the P-factor. The data was partitioned into ten unique sets of train, test, and validation (ratio 4:1:1). Neural networks performed significantly better than traditional supervised machine learning algorithms (Lasso and Partial Least Squares Regression) in predicting components of executive function (p's < .001). Each of these models was also evaluated individually for significance by evaluating against 1000 permuted models (all p's < .001). Furthermore, the model trained via transfer learning to predict psychopathology performed significantly better (p < .001) than that of the model trained to predict the p-factor directly.

The given analyses suggest that utilizing strategies like transfer learning may improve the potential utility of neuroimaging data, in combination with other known risk factors, for clinical prediction of risk for psychopathology.