Vanicek *et al.: Intrinsic Activity*, 2019; **7**(Suppl.1):A3.49
doi:10.25006/IA.7.S1-A3.49
published online: 11 September 2019

INTRINSIC ACTIVITY

Joint Meeting of the Austrian Neuroscience Association (16th ANA Meeting) and the Austrian Pharmacological Society (25th Scientific Symposium of APHAR)

Innsbruck, 25–27 September 2019

MEETING ABSTRACT

A3.49

Classification in major depressive disorder using randomForest and various cortical and subcortical gray matter measures

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Background: In clinical practice diagnostical categories as major depressive disorder (MDD) remain less definable, which potentially leads to inappropriate treatment and hence to insufficient treatment response. Machine learning algorithms based on structural MRI has been applied fairly successfully for classification purposes. In a meta-analytical report sensitivity and specificity rates where 70% and 71%, respectively, in order to discriminate patients with MDD from healthy subjects [1]. Morphological segmentation pipelines entail a new degree of resolution of complex structures as the neocortex as well as subcortical brain regions. Structural MRI generates estimations of parameters as cortical thickness and surface area along cortical volume [2] as well as on subfields of the hippocampus and nuclei of the amygdala and thalamus [3,4]. Nevertheless, there is a lack of a neurobiological biomarker and of established methods to classify diagnostical entities. Therefore, we aim to discriminate patients with MDD from healthy subjects based on various cortical gray matter parameters (cortical thickness, area and volume) as well as on subcortical regions and subunits of the hippocampus, amygdala and thalamus.

Methods: We analysed cross-sectional 3-Tesla MRI data (sequence: MPRAGE) of 24 patients with MDD and 39 healthy study subjects. To estimate mean cortical thickness, area and volume we utilized the FreeSurfer software (version 6.0). Thirtyfour regions where extracted on defined regions by the Desikan-Killiany atlas [5]. In addition, comprehensive segmentation of the hippocampus, amygdala and thalamus into specific sub-compartments was executed. Predictive analytics was performed by using the statistical software "R" and "randomForest" (RF). Next to the mean accuracy, sensitivity and specificity, RF selected the most informative sets of predictors based on cortical and subcortical gray matter parameters.

Results: When performing a separate RF model for each of the structural MRI measures (cortical thickness, surface area, cortical volume, subcortical brain regions, subfileds of the hippocampus or amygdala or thalamic nuclei), a maximum accuracy over 0.67 for the validation sets across repeats was attained. In a combined RF model, using all structural MRI measures, we achieved a mean accuracy for the validation sets across repeats over 0.74, with an excellent sensitivity and poor specificity (0.90 and 0.47, respectively). Feature selection emphasized cortical gray matter regions or subcortical structures across all measures.

Discussion: Machine learning and randomForest revealed highest accuracy (0.74; sensitivity of 0.90 and specificity of 0.47) to discriminate MDD from healthy subjects when sMRI measures of all regions and subdivisions where utilized in the model. These interesting findings need further confirmation on an external study sample. We are currently in the process of allocating a viable cooperating working group that could provide an external validation data set and are optimistic with regards of verifying our findings in the near future.

Keywords: machine learning – randomForest software – structural MRI – FreeSurfer software – major depressive disorder – classification

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