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One sentence summary: This is the first study to show altered functional connectivity in pediatric NDPH.

Background: New daily persistent headache (NDPH) begins abruptly and continues daily for at least 3 months. Although rare, NDPH is one of the most treatment-refractory and probably the least understood primary headache disorders. The present study is the first to explore brain functional connectivity in pediatric patients with NDPH. In addition, we aimed at evaluating the clinical indices of NDPH severity (i.e., disease duration, pain intensity, pain sensitivity, and functional disability).

Methods: In this cross-sectional study, resting-state functional scans were collected for 13 patients with NDPH and 13 pain-free, healthy controls using magnetic resonance imaging (20 females, 12.6–18.1 years old, mean age = 16.1, *SD* ±1.6). In patients, brain alterations were correlated with indices of NDPH severity.

Results: The results demonstrated that NDPH patients, compared to controls, showed altered functional connectivity between brain regions mainly involved in the affective, cognitive, and sensory functions of pain, including the amygdala, insula, middle frontal regions, somatosensory cortex, and cerebellar subregions (corrected for multiple comparison using cluster-wise *p*FDR < 0.05). No correlation was detected between functional connectivity patterns and the measures of disease severity.

Conclusion: These alterations in functional connectivity seem to represent a disrupted pain modulatory system comprising multiple brain networks in this pediatric patient group. Elucidating the underlying mechanisms of NDPH in the developing brain is an important step in the pathogenesis of NDPH and could contribute to the development of more effective treatments.

CATEGORY: OTHER

OR-18 | Migraine classification using deep learning on structural brain MRI data

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One sentence summary: We use a data-driven deep learning approach on T1-weighted structural brain MRI data to automatically classify migraine (Mig) and identify brain regions that differentiate individuals with migraine from healthy controls (HC).

Background: Migraine is a common neurovascular disorder and since it has multiple possible causes, its accurate diagnosis remains difficult using traditional methods. Deep learning (DL) methods, recent state-of-the-art, have shown promising results for the diagnosis and early detection by discovering diverse patterns in imaging data automatically. In this study, we utilize the power of DL using a data-driven approach on T1-weighted structural brain MRI data to automatically classify migraine (Mig) and identify brain regions that differentiate individuals with migraine from healthy controls (HC).

Methods: As DL requires large datasets for robust prediction, datasets from our studies were merged with a public dataset—Information eXtraction from Images (IXI), resulting in 67 Mig and 507 HC (see Table 1). We randomly split this combined dataset into three: the first set (55 Mig and 495 HC) was used to train the DL model; the second set (6 Mig and 6 HC) was used for validation, to identify the best DL model; the third set (6 Mig and 6 HC) was an unseen dataset that was used for blinded testing. Since our training dataset was highly imbalanced, we oversampled the Mig cohort during training, using a traditional machine learning approach for imbalanced learning. As a preprocessing step, we registered all images to the MNI_152 1mm template and then parcellated the template using FreeSufer's labels for cortical and subcortical structures. We used a 3D ResNet-18 as the DL classifier network and utilized the Grad-CAM method (a well-adopted method in computer vision research) on the trained ResNet-18 to extract brain regions that contributed to migraine classification according to the DL model. The training process is visualized in Figure 1.

Results: Average age (Mig 40.5 ± 12 years, HC 41.7 ± 12.8 years, $p = 0.4$) did not differ between groups. However, there were significantly more females in the migraine group (Mig 51/67 or 76% female) than in the healthy control group (HC 274/507 or 54% female, $p = 0.0002$). Patients with migraine averaged 18.3 ± 5.7 headache days/28. Of these patients, 14 had episodic migraine and 53 had chronic migraine, and on average, they had migraine for 23 ± 13.2 years. Our method achieved 75.00% and 66.67% accuracy overall on validation and unseen testing data, respectively. Specifically, for validation, our method achieved 83.33% sensitivity and 66.67% specificity. For the blind testing, our method achieved 83.33% sensitivity and 50.00% specificity. The brain regions that most contributed to migraine classification included: insula (white matter and gray matter), precentral (white matter and gray matter), postcentral white matter, caudal middle frontal white matter, rostral middle frontal white matter, superior frontal gray matter, and parsopercularis white matter.

Conclusion: Results indicate that deep learning has good utility for classifying migraine using structural brain MRI data. In addition, deep learning shows potential for discovering brain regions that contribute to migraine classification.

P-104 | Classification of post-traumatic headache (PTH) using deep learning on structural brain MRI data

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