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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 pFDR < 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

Rahman Siddiquee, M.[1]; Shah, J.[1]; Schwedt, T.J.[2]; Chong, C.D.[3]; Nikolova, S.[4]; Dumkrieger, G.[5]; Ross, K.B.[6]; Berisha, V.[1]; Li, J.[7]; Wu, T.[8]

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One sentence summary: We use a deep learning approach on structural brain MRI data to automatically classify post-traumatic headache (PTH) and identify brain regions that most contribute to differentiating individuals with PTH from healthy controls (HC).

Background: Post-traumatic headache (PTH) is the most common symptom following mTBI. Although some PTHs resolve within the first few days, a large proportion of individuals with PTH do not have headache resolution during the acute phase and have PTH persistence. In this study, we utilize the automatic feature extraction power of the deep learning method on structural brain MRI data to automatically classify post-traumatic headache (PTH) and identify brain regions that most contribute to differentiating individuals with PTH from healthy controls (HC).

Methods: T1-weighted images collected from PTH and HC research participants at the Mayo Clinic were combined with HC data from a public dataset—Information eXtraction from Images (IXI), resulting in 48 PTH and 507 HC (see Table 1). This dataset was randomly split into three: the first set (36 PTH and 495 HC) was used to train the DL model; the second set (6 PTH and 6 HC) was used for validation, to identify the best DL model; the third set (6 PTH and 6 HC) was an unseen dataset that was used for blinded testing. Since the training dataset was highly imbalanced, during training the PTH cohort was oversampled using a traditional machine learning approach for imbalanced learning. All images were registered to the MNI_152 1mm template and overlayed with FreeSufer's labels for cortical and subcortical structures. A 3D ResNet-18 was used as the DL classifier network using the Grad-CAM method on the trained ResNet-18 to identify brain regions that contributed to PTH classification. The training process is visualized in Figure 1.

Results: Age (PTH 41.5 ± 13.3 years, HC 41.7 ± 12.8 years, p = 0.9) and sex (PTH 29/48 female, HC 274/507 female, p = 0.4) did not differ between groups. The classification model achieved 83.33% accuracy on validation (100 sensitivity, 83.33% specificity) and 75% accuracy on unseen testing data (66.67% sensitivity, 91.67% specificity). The brain regions that most contributed to PTH classification included: lingual (white matter and gray matter), pericalcarine (white matter and gray matter), middle temporal (white matter and gray matter), cerebellum, and inferior and superior temporal (white matter and gray matter).

Conclusion: A deep learning-based classification model of brain MRI structural data accurately classifies PTH and identifies brain regions that differentiate PTH from HC.

Dataset summary

TABLE 1 Summary of the datasets from different sources (total: 48 PTH, 507 HC)

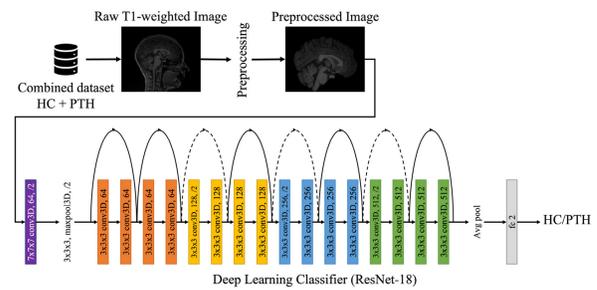| Dataset	Subject #	Age (mean ± std)	Sex
Dataset 1	10 PTH	37.3±12.7	3 M, 7 F
Dataset 2	38 PTH	42.7±13.3	16 M, 22 F
	41 HC	38.4±12.5	16 M, 25 F
Dataset 3	38 HC	38.2±9.6	21 M, 17 F
Dataset 4 (IXI)	428 HC	42.4±13.0	196 M, 232 F

Proposed pipeline

FIGURE Overview of the proposed pipeline. We removed the skull from the T1-weighted images and co-registered them to the MNI 152 template. We used a 3D ResNet-18 for image classification.

P-105 | Clinical significance of osmophobia and its effect on quality of life in people with migraine

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One sentence summary: Both 24-hour and 3-month quality of life of people with migraine with osmophobia were more affected than those without osmophobia.

Background: In this study, we aimed to evaluate the clinical significance of osmophobia and its effect on quality of life in people with migraine.

Methods: A total of 145 people with migraine were included in this cross-sectional study. Patients were evaluated with the migraine data form, the Migraine 24-Hour Quality of Life Questionnaire (24-HrMQoLQ), the Migraine Disability Assessment Scale (MIDAS), the Patient Health Questionnaire-9 (PHQ-9), the Insomnia Severity Index (ISI), the Generalized Anxiety Disorder-7 (GAD-7), the Allodynia Symptom Checklist (ASC), and the Fatigue Severity Scale (FSS). To evaluate the presence of osmophobia retrospectively, a semi-structured interview was conducted with the patients by the neurologist.

Results: There was no significant difference between migraine patients with and without osmophobia in terms of age, gender, education level, income status, body mass index, attack severity, attack duration, number of attacks per month, and disease duration (p > 0.05).

The mean 24-Hr-MQoLQ of patients with osmophobia was significantly lower than those without osmophobia. The decrease in the 24-Hr-MQoLQ was statistically significant in the areas of feeling and concerns and social functionality. The mean of the MIDAS scale was higher significantly in patients with osmophobia than those without osmophobia. In addition; the mean ISI, PHQ-9, FSS and ASC scores of patients with osmophobia were statistically significantly higher than those without osmophobia.

Conclusion: Both 24-hour and 3-month quality of life of people with migraine with osmophobia were more affected than those without osmophobia. At the same manner, insomnia, depression, fatigue and allodynia were observed at higher rates in people with migraine with osmophobia than in migraine without osmophobia. Osmophobia, which is one of the