Interpretable Automatic Detection of Incomplete Hippocampal Inversions Using Anatomical Criteria

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Abstract

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Incomplete Hippocampal Inversion (IHI) is an atypical anatomical pattern of the hippocampus that has been associated with several brain disorders (epilepsy, schizophrenia) [1–5]. IHI can be visually detected on coronal T1 weighted MRI images. IHI can be absent, partial or complete (no IHI, partial IHI, IHI). However, visual evaluation can be long and tedious, justifying the need for an automatic method. In this paper, we propose, to the best of our knowledge, the first automatic IHI detection method from T1-weighted MRI. The originality of our approach is that, instead of directly detecting IHI, we propose to predict several anatomical criteria, which each characterize a particular anatomical feature of IHI, and that can ultimately be combined for IHI detection [6].

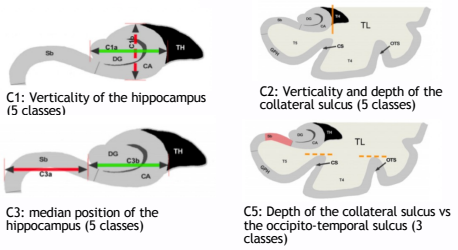


Figure 1. Schematic of criteria 1-5 extrated from 6.

Such individual criteria have the advantage of providing interpretable anatomical information regarding the morphological aspect of a given hippocampus. We relied on a large population of 2,008 participants from the IMAGEN study. The approach is general and can be used with different machine learning models. In this paper, we explored two different backbone models for the prediction: a linear method (ridge regression) and a deep convolutional neural network. We demonstrated that the interpretable, anatomical based prediction was at least as good as when predicting directly the presence of IHI, while providing interpretable information to the clinician or neuroscientist. This approach may be applied to other diagnostic tasks which can be characterized radiologically by several anatomical features

Methods

IMAGEN dataset

- 2006 images split into 75/25% train/test set with best similarity in distribution
- Average age of 14 yo.
- 50/50 M/F

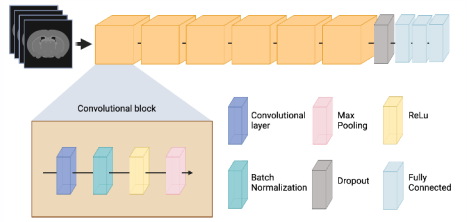
Pre-processing

Models

Ridge Regression :

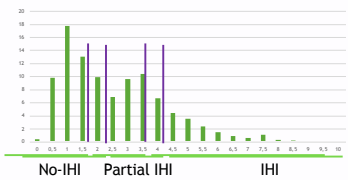
$$\min_{\beta} E(\alpha,\beta) = \sum_{i=1}^{n}(y_i - X_i\beta)^2 + \alpha \parallel \beta \parallel^2$$

Conv5-FC3 implemented in ClinicaDL [7]:



Conversion to C0

Iteratively used 2 thresholds to separate composite scores (SC) of training set into no-IHI (score of 0), partial IHI (0.5) and IHI (1) and compute balanced accuracy (BA). The thresholds with the best BA was used for the conversion: 2.25 and 4.25)



Results

	C1_L	C1_R	C2_L	C2_R	C3_L	C3_R	C5_L	C5_R	Sci_L_add	Sci_R_add	SCi_L	Sci_R
	Weighted Kappa						Kappa		ICC			
Ridge Regression	0.558 ± 0.027	0.256 ± 0.037	0.675 ± 0.024	0.599 ± 0.019	0.717 ± 0.019	0.627 ± 0.031	0.268 ± 0.031	0.187 ± 0.034	0.684 ± 0.023	0.576 ± 0.031	0.708 ± 0.021	0.633 ± 0.024
Conv5-FC3	0.717 ± 0.022	0.501 ± 0.033	0.749 ± 0.021	0.644 ± 0.028	0.769 ± 0.018	0.694 ± 0.028	0.502 ± 0.031	0.331 ± 0.047	0.811 ± 0.015	0.678 ± 0.032	0.788 ± 0.015	0.703 ± 0.027

Table 1. Performances for the prediction of individual criteria C1, C2, C3, C5 and for the direct prediction of the IHI score (either using the sum of the predictions of individual criteria, denoted as "SC_{L,R} add", or using direct prediction of SC, denoted as "SC_{L,R}"). The table shows the mean ± the standard error computed using bootstrap on the test set. Criteria 1 to 5 are evaluated using a weighted kappa score to make up for their linearity. C5 is evaluated using an unweighted kappa score and the composite scores were evaluated using Inter-Class Correlations. Overall, the deep network outperformed the ridge regression on all tasks.

	C0_L	C0_R	SCi_L_add	Sci_R_add	SCi_L	SCi_R
Ridge Regression	0.546 ± 0.031	0.500 ± 0.047	0.640 ± 0.027	0.563 ± 0.037	0.628 ± 0.029	0.601 ± 0.033
Conv5-FC3	0.763 ± 0.023	0.668 ± 0.045	0.739 ± 0.023	0.647 ± 0.037	0.740 ± 0.023	0.610 ± 0.043

Table 2. Kappa scores for prediction of C0, either directly, or through thresholding the sum of the predictions of the individual criteria ("SC_{L,R} add"), or through thresholding the direct prediction of the IHI score ("SC_{L,R}"). Mean ± standard error (of each metric), computed using bootstrap on the test set. The models performed better when using individual criteria and composite scores.

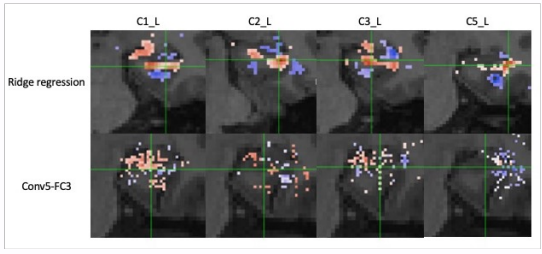


Figure 2. Weight maps extracted from ridge regression and saliency maps from the Conv5 FC3 for C1, C2, C3, C5 in the left hemisphere on T1 weighted MRI image. Criteria C1 and C3 which asses the position of the hippocampus highlight its surroundings in both cases and criteria C2 and C5 which deal with sulci positions highlight the latter as expected.

Conclusion

We have proposed to automatically detect IHI by predicting anatomically interpretable individual criteria. We showed that this approach does not decrease predictive performance compared to directly predicting the presence of IHI. Predicting individual criteria provides much more information about the specific anatomical characteristics underlying the IHI of a given participant, thereby providing more interpretable information to the clinician or neuroscientist. This training strategy has the potential to be applied to other diagnosis tasks which can be characterized by individual interpretable criteria.

References

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