AGE2HIE: TRANSFER LEARNING FROM BRAIN AGE TO PREDICTING NEUROCOGNITIVE OUTCOME FOR INFANT BRAIN INJURY



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AGE2HIE: transfer learning

across task, modality, age, health condition



INTRODRUCTION

Methodology

- Hypoxic-Ischemic Encephalopathy (HIE) affects 1-5 /1,000 newborns, with 30% to 50% of cases resulting in adverse neurocognitive outcomes. However, these outcomes can only be reliably assessed as early as age 2.
- Early and accurate prediction of HIE-related neurocognitive outcomes using deep learning models is critical for improving clinical decision-making, guiding treatment decisions and assessing novel therapies.
- A major challenge in developing deep learning models for this purpose is the scarcity of large, annotated HIE datasets.

Results

- AGE2HIE with transfer learning improves accuracy.
- AGE2HIE with transfer learning enhances generality.
- Existing studies primarily rely on private datasets with limited sample sizes. Our results from a twosite dataset (N=156) demonstrated a sensitivity of

- We have assembled the first and largest public dataset, however it contains only 156 cases with 2-year neurocognitive outcomes.
- We have collected 8,859 normal brain MRIs with 0-97 years of age that are available for brain age estimation using deep learning models.

Table 1. Accuracy without (\times) vs with (\checkmark) transferring age-pretrained model to HIE outcome prediction.

within the same site	Setting	Transfer	Accuracy (%)	Sensitivity (%)	Specificity (%)
	Training on MGH (N=72)	×	72.28±17.92	$70.00{\pm}29.15$	71.21 ± 18.26
	Testing on MGH	\checkmark	74.85±9.21	74.76 ± 21.27	$75.50{\pm}17.51$
	Training on BCH (N=84)	×	51.24±8.47	$58.29{\pm}18.35$	$41.33{\pm}18.73$
	Testing on BCH	\checkmark	54.38±12.19	$66.92{\pm}23.46$	$46.05 {\pm} 20.07$
	Training on MGH+BCH (N=156)	×	68.66±8.5	78.82±12.95	66.52±16.27
	Testing on MGH+BCH	\checkmark	70.45±9.1	$77.35{\pm}14.28$	66.83±15.16

Table 2. Generality without (\times) vs with (\checkmark) transferring age-pretrained model to HIE outcome prediction.

Train/Test cross-site	Setting	Transfer	Accuracy (%)	Sensitivity(%)	Specificity(%)
	Training in MGH (N=72)	×	$57.14{\pm}18.99$	90.00±20.00	$49.36{\pm}19.78$
	Testing in BCH (N=84)	\checkmark	62.57±9.79	84.29±13.93	52.21±17.56
	Training in BCH (N=84)	×	$72.50{\pm}11.27$	60.00±13.33	$75.88{\pm}18.69$
	Testing in MGH (N=72)	\checkmark	77.21 ± 8.55	64.43 ± 11.27	82.57 ± 14.92

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