Can Artificial Intelligence Effectively Predict Delayed Cerebral Ischemia After Cerebral Aneurysm Rupture?

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Background

- Aneurysmal subarachnoid hemorrhage (aSAH) results in significant mortality and disability.[1]
- Delayed Cerebral Ischemia (DCI) is the leading cause of poor outcome after aSAH among those who survive the initial hemorrhage event.[1]
- Significant effort is expended to identify patients at risk of DCI, but existing tests, such as trans-cranial Doppler, suffer from relatively poor sensitivity.[2]
- Tests to identify patients with DCI **prospectively** are of high interest.

Objective

1. To create a machine learning (ML) system based on clinical variables to predict DCI in aSAH patients.
2. To determine which variables have the most impact on DCI prediction.

Methods

Study Design

- A retrospective cohort study of all aSAH patients at Stanford University neurovascular referral center from January 2006 to September 2014.
- Inclusion criteria were: presence of clinical variables for modeling, DCI development recorded, baseline non-contrast CT and CTA available
- The SHAP (SHapley Additive exPlanations) method was used to determine which variables were the strongest predictors of DCI

Machine Learning Algorithm Selection and Training:

- Prediction outcome of the ML algorithm was DCI development (DCI+).
- The ML algorithm was trained based upon age, sex, HTN, diabetes, hyperlipidemia, CHF, CAD, smoking history, family history of aneurysm, modified Fisher Grade, Hunt and Hess score, and external ventricular drain (EVD) placement.
- A 5-fold cross validation was used to select the ML algorithm and Random Forest yielded the best results.
- 276 cases (222 DCI- and 54 DCI+) were used for training and 93 cases (77 DCI- and 16 DCI+) were used for testing the algorithm.

Results

- 500 aSAH patients were identified and 369 met inclusion criteria: 70 patients developed DCI (DCI+) and 299 did not (DCI-).
- The Random Forest ML algorithm predicted DCI:
  - Accuracy: 81.7%
  - Sensitivity: 12.5%
  - Specificity: 96.1%
  - PPV: 40%
  - NPV: 84.1%.
- SHAP value demonstrated Age, EVD placement, Fisher Grade, and Hunt and Hess score, and HTN had the highest predictive values for DCI.
- Younger age, absence of hypertension, higher Hunt and Hess score, higher modified Fisher Grade, and EVD placement increased risk of DCI.

	DCI + (n=70)	DCI – (n=299)	P-Value
Gender(F, %)	54 (77.14%)	199 (66.56%)	0.11
Age (Years)	50±10.35	52±12.89	0.24
HTN	33 (47.14%)	163 (54.51%)	0.91
HL	14 (20%)	55 (18.39%)	0.89
DM	3 (4.29%)	32 (10.70%)	0.15
CAD	1 (1.43%)	8 (2.68)	0.85
Smoking	33 (47.14%)	83 (27.76)	0.003**
Family Hx of Aneur	5 (7.14%)	30 (10.03%)	0.61
Hunt and Hess	2.77±0.76	2.37±0.84	0.0003***
Fisher Grade	3.29±0.54	3±0.80	0.0045**
EVD Placement	50 (71.43%)	142 (47.5%)	0.0062**

Table 1. Summary of clinical variables of DCI+ vs. DCI- Patients
Numbers within parenthesis are percentages of total patients within each group. The remaining numbers are means plus or minus the standard deviation. P-value calculation: two tailed t-test for continuous variables and chi-square for binary variables.

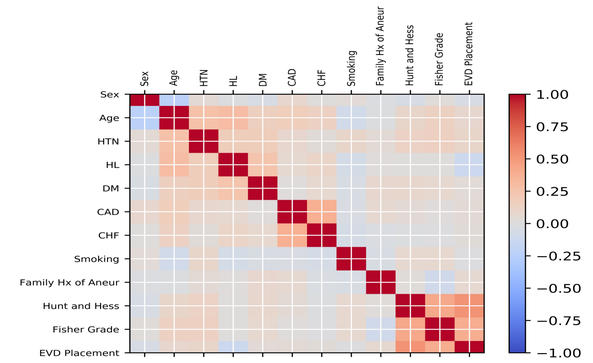

Figure 1. Correlation of aSAH patient characteristics
Darker red signifies positive correlation while darker blue signifies negative correlation among all aSAH patients.

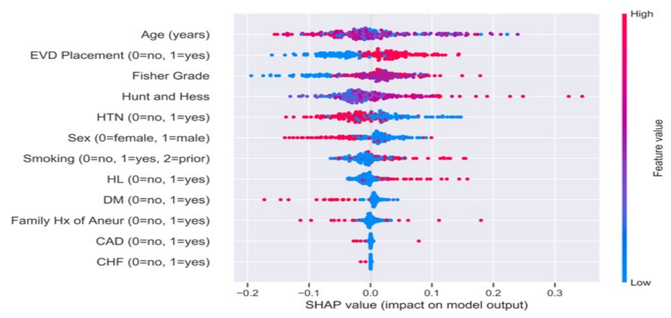

Figure 2. Clinical variables that predict DCI+
Age, EVD placement, modified Fisher Grade, and Hunt and Hess scale were the strongest predictors of DCI+.

Conclusions & Future Directions

1. ML models based upon clinical variable predict DCI with high specificity and good accuracy.
2. Addition of baseline imaging data may improve the model's performance and sensitivity

References

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2. Lysakowski C, et al. (2001). *Stroke* 32: 2292-2298
3. Vergouwen MD, et al. (2010). *Stroke* 41: 22391-2395