Fine-grained prediction of Huntington's disease progression using a stacked ensemble approach

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We applied a stacked ensemble based approach for predictive-classification of 184 HD gene positive subjects from TRACK-HD dataset. Our model sets a new benchmark for fine-grained classification of HD, & thus sets the ground for clinically useful future work such as prediction of onset

- Classification of individual disease state in Huntington's disease (HD) is key for stratification of patients in clinical trials
- However, there has been no coordinated effort to assess benefits of using Machine learning (ML) based Stacking ensemble driven predictions of disease state in HD



- Stacked ensemble model achieved an accuracy of 96.5%±3.6 in binaryclassification task
- It also performed better than base-models & comparative ensemble models albeit nonsignificantly



Maitrei Kohli¹, Dorian Pustina³, John Warner³, Rachael I. Scahill², Sarah J. Tabrizi², Daniel C. Alexander¹, Peter A.

- Stacked model achieved an accuracy of 85.2% ±8.0 in fine-grained classification task
- It also performed significantly (>9%) better than base-models & comparative ensemble models

Our Stacked ensemble approach sets a new benchmark for fine-grained classification task

3. Methods

ML framework comprises of:

(a) Tier 1 (Base models): array of 6* standard ML models; trained & fit on actual training-data using repeated 10-fold cross-validation (b) Tier 2 (meta-model): trained on predictions made by Tier 1 models; learns how to best combine these predictions to reduce variance & generalisation error

Data +: baseline cross-sectional data from 184 HD gene-positive participants from the TRACK-HD dataset, which includes clinical, imaging & genetic data

Imaging → Caudate; Pallidum; Putamen;

Genetic \rightarrow CAG Repeat Length

Clinical \rightarrow SDMT; SWRT; TMS; TFC

General → Age; Sex

Figure 1: Input Features used for classification

5. Conclusion

 Our stacked model achieved best predictive-classification fine-grained classification tasks

These encouraging results indicate that the Stacked ensemble approach might potentially be a powerful tool for making clinically useful predictions such as timeto-onset \rightarrow Future work



Bayes

*Full forms of clinical input Features used: SDMT \rightarrow symbol digit modality test; SWRT \rightarrow stroop word reading test; TMS \rightarrow total motor score; TFC \rightarrow total functional capacity

**Tabrizi, Sarah J., et al. "Predictors of phenotypic progression and disease onset in premanifest and earlystage Huntington's disease in the TRACK-HD study: analysis of 36-month observational data." The Lancet Neurology 12.7 (2013): 637-649.





Subjects: Details about how subjects were grouped in various classes can be found at -Tabrizi et al., 2013** No. of subjects in each group



Figure 2: No. of subjects in each class/group

*ML models used

Base-models \rightarrow Ir = logistic regression; knn = k nearest neighbour; cart = decision trees; svm = support vector machine; bayes = Gaussian Naïve Bayes; MLP = multi-layer perceptron Meta-model (Stacking) → Gaussian Naïve

Comparative ensemble methods \rightarrow ; AdaB = adaboost; XGB = extreme gradient boosting; RF = random forest

***Data: Full list of Imaging input Features used:**

(1.) Caudate; (2.) Pallidum; (3.) Putamen; (4.) Accumbens area; (5.) Lateral vents; (6.) Thalamus proper; (7.) Temporal; (8.) Frontal; (9.) Occipital; (10.) Parietal; (11.) Sensory Motor; (12.) Insula; (13.) Cingulate; (14.) Insula white matter

