Machine learning methods for age prediction using cortical thickness and cerebral blood flow

M. Ethan MacDonald [1-3], Deepthi Rajashekar [1,3], Rebecca J. Williams [1-3], Hongfu Sun [1,3], Cheryl R McCreary [1-3], Richard Frayne[1,2], Nils D. Forkert [1,3], G. Bruce Pike [1-3]

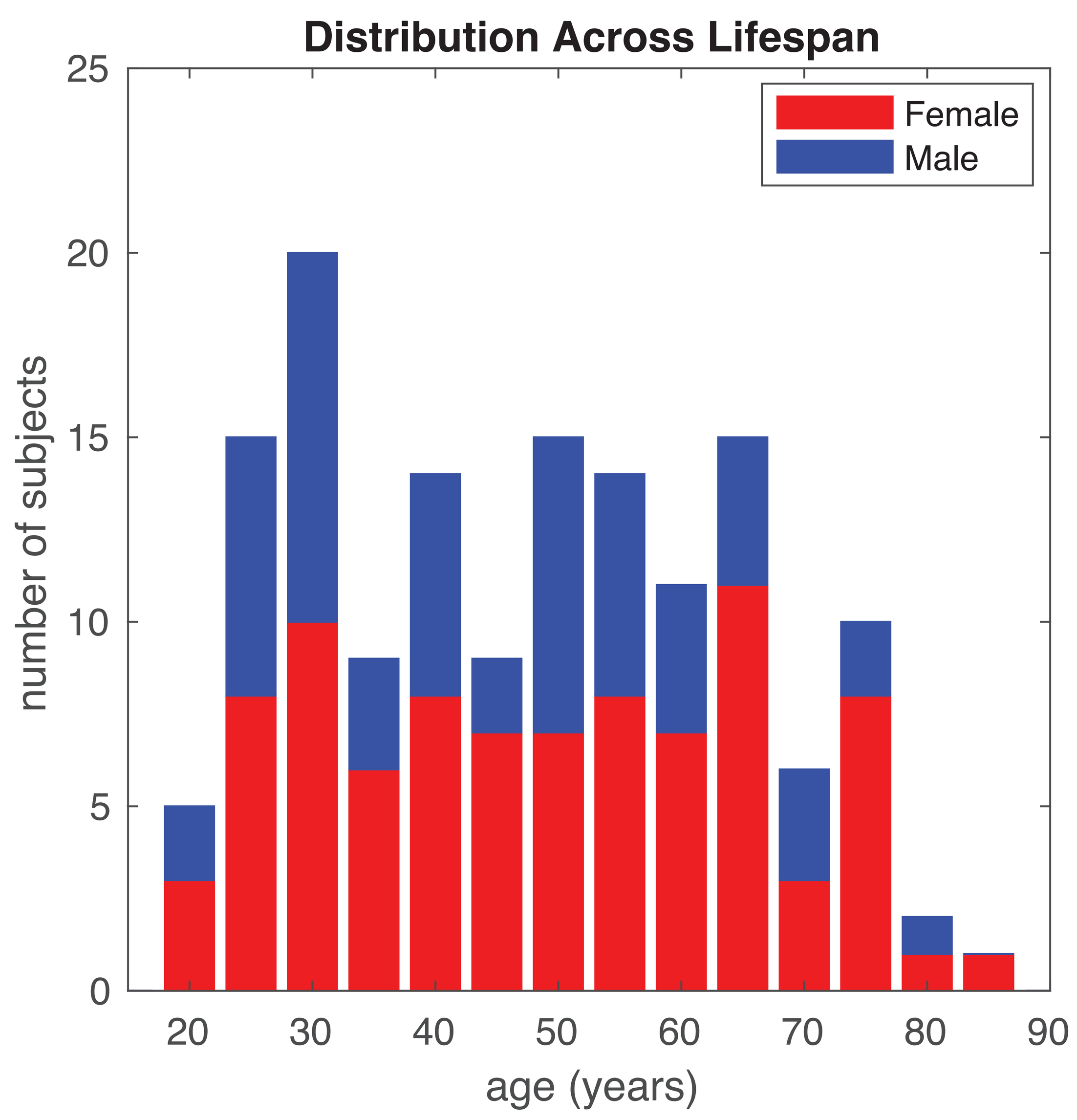
1. Radiology & Clinical Neurosciences, University of Calgary, Calgary, AB, Canada
2. Seaman Family MR Research Centre, Foothills Medical Centre, Calgary AB, Canada
3. Healthy Brain Aging Lab, University of Calgary, AB, Canada

INTRODUCTION

- Chronological age prediction has been performed in many studies using brain morphology features including cortical thickness [1-4]
- Incorporating additional data, such as cerebral blood flow (CBF), has been shown to improve age prediction using multiple linear regression and feature selection [5]
- The relationship between cortical thickness and CBF is, however, complex and multiple linear regression is likely not the optimal algorithm for taking advantage of multimodal data
- The aim of this work was to evaluate sixteen different machine learning algorithms for estimating chronological age from regional cortical thickness and CBF data using the coefficient of determination (R^2) as the performance metric

METHODS

- A total of 146 subjects (58-M, 88-F; 18 to 87 years) were collected at a single centre (see Figure below)
- Subjects were imaged with a 3T MR scanner (Discovery 750, GE Healthcare) with a 12 channel neurovascular head coil
- All subjects included in this analysis were screened with the Montreal Cognitive Assessment and had scores >25
- 3D T1-weighted (T1w) and arterial spin labelling (ASL) images were acquired and used for this analysis
- The reconstructed image resolutions were 1 mm isotropic and 1.9 x 1.9 x 5 mm^3 for T1w and ASL, respectively
- CBF was calculated from the ASL images
- T1w images were processed using standard FreeSurfer (version 5.3.0) pipelines and the Desikan-Killiany atlas to measure the mean cortical thickness for each hemisphere and 34 cortical regions per hemisphere.
- The mean CBF was also calculated for each of the 70 cortical ROIS in each subject
- Sixteen machine learning algorithms were applied to the following feature sets: 1) cortical thickness only, 2) CBF only, and 3) both cortical thickness and CBF



- To test for the effects of feature selection with recursive ReliefF [6] was used to optimize features of each machine learning algorithm
- Performance was evaluated with and without feature selection
- Models were built and trained using R [7] and processing was performed on a parallel computing cluster
- The regression model types used for age prediction were:

  1) multiple linear regression (MLR),
  2) partial least squares (PLS),
  3) ridge regression (RR),
  4) elastic net (ENET),
  5) neural network (NN),
  6) multivariate adaptive regression splines (MARS),
  7-9) linear, radial basis function, and polynomial support vector machine (lSVM, rSVM, pSVM),
  10) k-nearest neighbors (KNN),
  11) simple classification and regression tree (CART),
  12) M5 tree, 13) bagged trees, 14) random forest, 15) boosted trees, and 16) cubist [8]

RESULTS

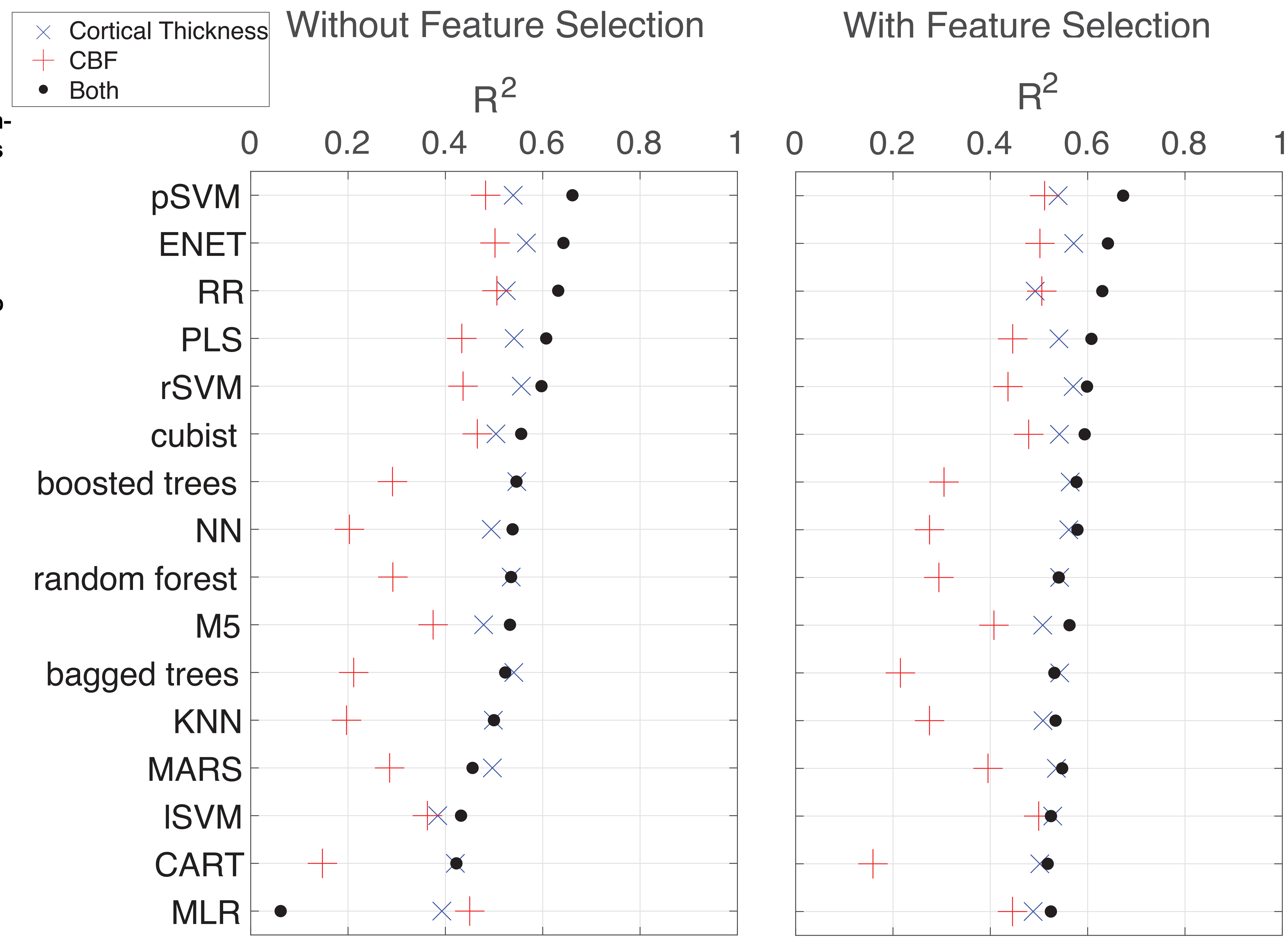
- The Figure below shows R^2 results for all the machine learning algorithms sorted by performance
- There are two sets of results, one without feature selection (left) and one with the optimized feature selection (right)
- The pSVM performed best with R^2 or 0.66 and 0.67, with and without feature selection
- In general feature selection improved performance, but the largest improvement was seen for MLR, where R^2 increased from 0.06 to 0.52
- The other machine learning algorithms did not improve as much with feature selection
- The strongest prediction of chronological age was achieved with pSVD using both cortical thickness and CBF features

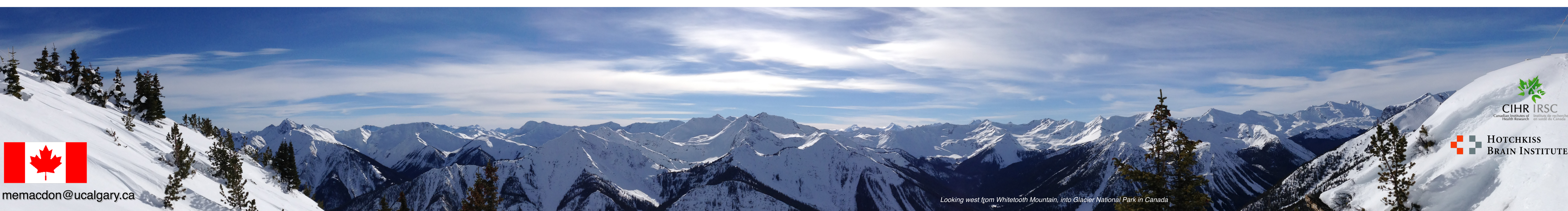
DISCUSSION

- The main finding of the study, is that several machine learning algorithms can perform better with CBF included with cortical thickness features
- MLS, PLS, NN, MARS, lSVM, rSVM, KNN, CART, M5, bagged trees, random forest, boosted trees, and cubist performed equally well with cortical thickness features alone or combined cortical thickness and CBF features
- Our findings indicate that adding CBF features to cortical thickness features improves chronological age prediction with more advanced machine learning models, like pSVD, ENET, and RR, are used

REFERENCES

[1] Franke K, et al., Neuroimage 2015;115:1-6.
[2] Gaser C, et al., PLoS ONE 2013;8:e67346.
[3] Franke K, et al., Frontiers in Aging Neuroscience 2013;5:90.
[4] Franke K, et al., Neuroimage 2012;63:1305-12.
[5] MacDonald ME, et al. , 26th ISMRM 2018:0188.
[6] Robnik-Šikonja M, Machine Learning 2003;53:23-69.
[7] R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
[8] Kuhn M, Johnson K. Applied predictive modeling: Springer; 2013.





memacdon@ucalgary.ca