Identification of most sensitive hemodynamic parameters to predict asymptomatic unilateral internal carotid artery stenosis by random forest ensemble classifier

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Background

- Internal carotid artery stenosis (ICAS) causes up to 15% of all strokes [1,2]
- Often these strokes are located at the edges of vascular territories, i.e., in individual watershed areas (iWSAs)[3]
- Best hemodynamic MRI parameter to predict disease severity and increased discriminative ability of hemodynamic changes within iWSA are currently unclear[4]
- Identifying most sensitive parameters and volumes of interest (VOIs) can increase clinical applicability and provide deeper understanding of the pathology
- An RFC was chosen as those can deal with high-dimensional data sets and are reported to be robust to overfitting[5,6]

Methods

- 24 asymptomatic unilateral ICAS-patients (70.6±6.4y) and 24 healthy controls (HC) (70.4±4.6y) underwent multi-modal MRI (Philips 3T Ingenia) (Fig. 1)[7]
- 8 perfusion, oxygenation and microvascular parameters were included (see Fig.2).
- Feature vectors were generated from mean parameter values inside and outside iWSA[3] in grey matter (GM) and white matter (WM) for each hemisphere and for interhemispheric side differences
- An RFC (MathWorks MATLAB 9.8) was trained for feature ranking using 96 features (12 VOIs x 8 parameters)[8]
- Importance scores and out-of-bag accuracies were calculated[5]

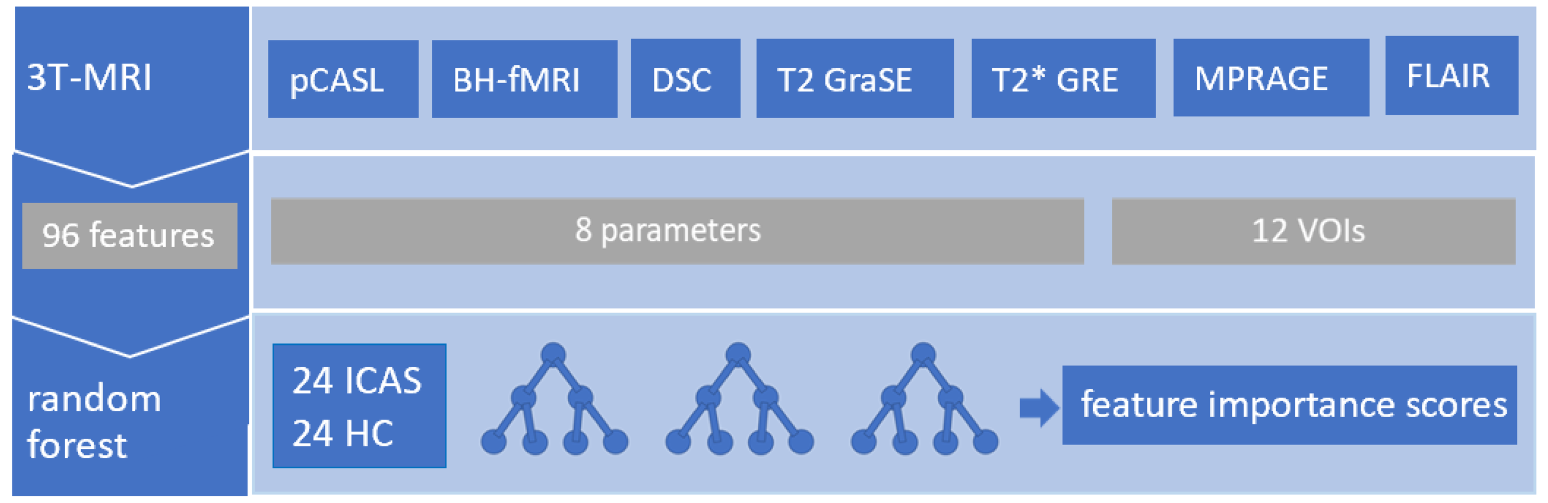

Figure 1: Overview of major processing steps. pCASL: pseudo-continuous arterial spin labelling; BH-fMRI: breath-hold functional MRI; DSC: dynamic susceptibility contrast MRI

Aims

We aim to **identify most sensitive** parameters and volumes of interest (VOIs) to predict ICAS by applying a random forest classifier (RFC)[5] to an extensive set of **eight multi-modal MRI parameters**. We hypothesized an **increased accuracy considering iWSA-VOIs**.[6]

Conclusion

RFCs can identify most sensitive features, i.e. **TTP, CBF and CVR inside iWSAs**, to predict ICAS and may reveal most relevant hemodynamic parameters for **diagnostics and further research** in cerebrovascular diseases

Figures

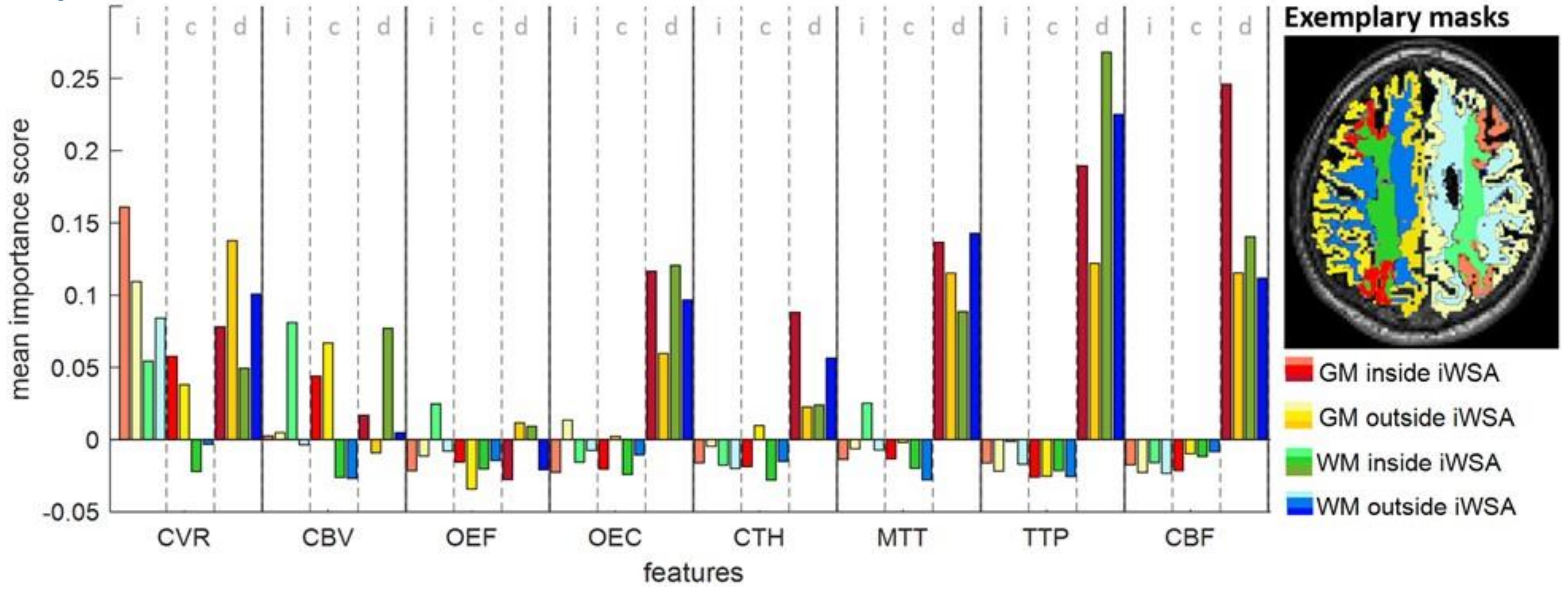

Figure 2: Feature importance scores of an RFC trained with 96 features. Scores were averaged 1000 times. Features were extracted from eight MRI parameter maps (cerebrovascular reactivity (CVR), cerebral blood flow (CBF), cerebral blood volume (CBV), oxygen extraction fraction (OEF), oxygen extraction capacity (OEC), capillary transit time heterogeneity(CTH), mean transit time (MTT) and time to peak (TTP), each sampled from 12 different VOIs. For each parameter, the first, second and third group of four bars refer to ipsilateral (i) and contralateral (c) mean values, and interhemispheric differences (d) between mean values, respectively. For each group, the colour scheme is similar for GM inside iWSAs (red), GM outside iWSAs (yellow), WM inside iWSAs (green) and WM outside iWSAs (blue). The colour intensity increases from group one to three.

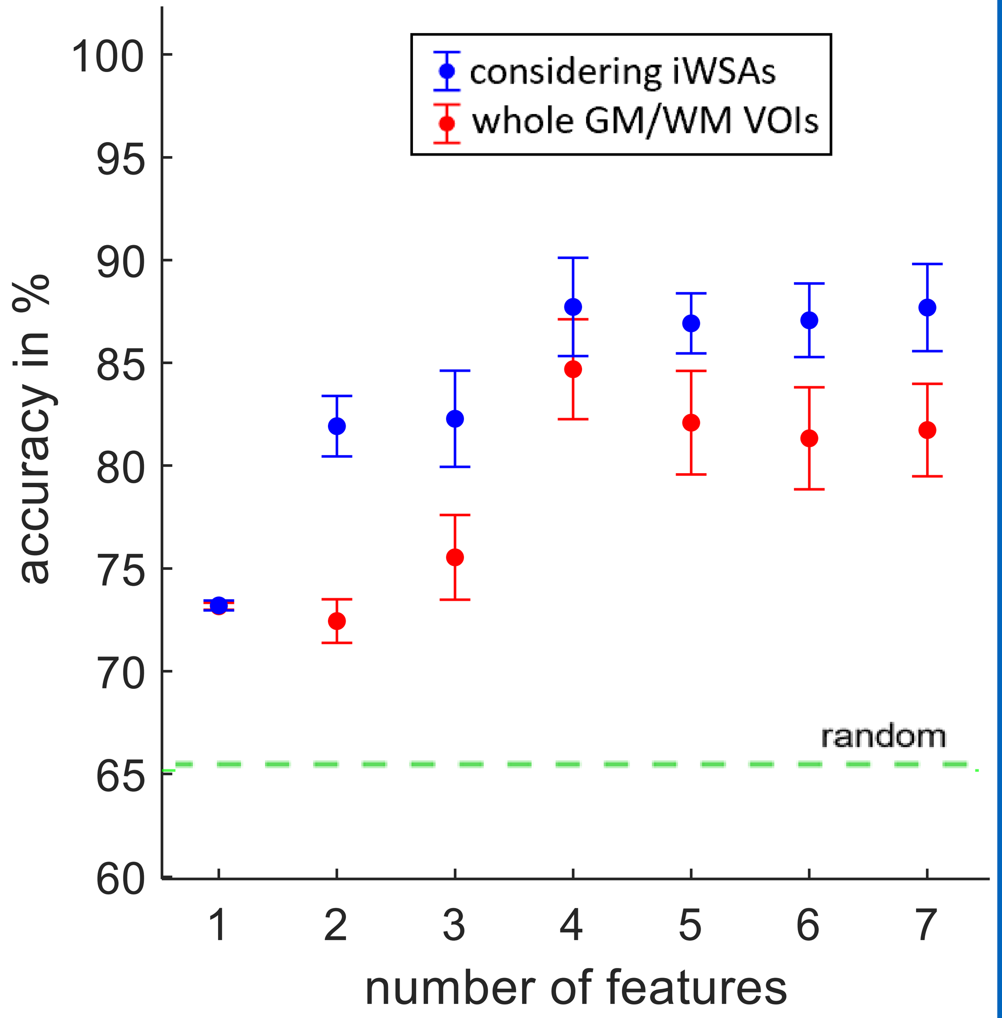

Figure 4: Accuracies of an RFC trained with increasing number of features. Features were added in order of decreasing importance scores (rank in Fig. 2). Accuracies were averaged 200 times. Mean values and standard deviations are shown for the model trained with features considering VOIs inside and outside iWSAs (blue) and whole GM and WM VOIs (red). Considering iWSAs improved accuracies significantly. The green line represents mean accuracy of a model trained on randomly labelled data to consider feature selection bias.[10]

rank	parameter	hemisphere	matter	iWSA	mean importance score (± standard deviation)
1	TTP	difference	WM	inside	0.60
2	CBF	difference	GM	inside	0.53
3	CVR	ipsilateral	GM	inside	0.38
4	CVR	difference	GM	outside	0.31
5	MTT	difference	WM	outside	0.26
6	OEC	difference	WM	inside	0.22
7	CTH	difference	GM	inside	0.18

0 0.1 0.2 0.3 0.4 0.5 0.6

Figure 3: Feature importance scores of an RFC trained with 7 highest ranked features. Scores were averaged 200 times. For each feature, corresponding parameters, VOI characteristics, mean importance scores and standard deviations are shown.

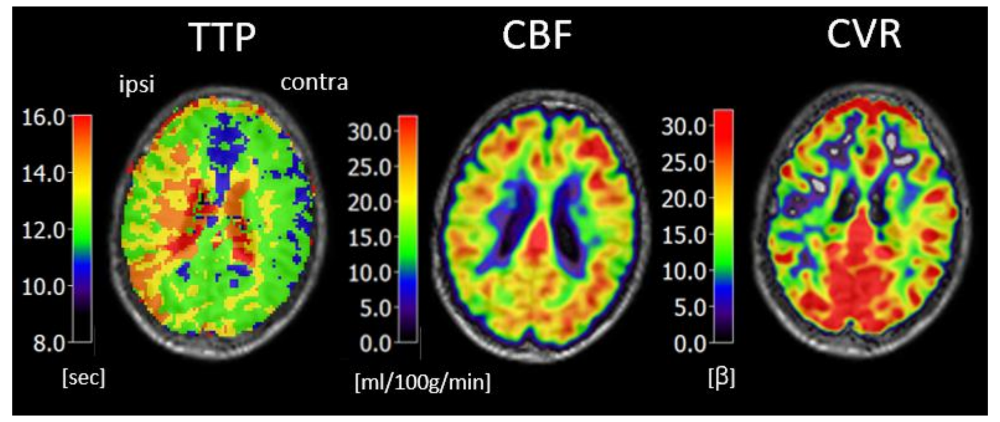

Figure 5: Exemplary maps of highest ranked parameters

Results

- Bootstrapped importance scores of an RFC trained with 96 features (Fig. 2)
- Excluding correlated features, highest ranked features are interhemispheric differences of TTP in WM, CBF in GM and ipsilateral CVR in GM, all inside iWSAs (Fig. 3&5)
- Using an increasing number of the highest ranked features as input, the accuracy rises from 82.3±2.8% to 87.7±2.1% (42 of 48 subjects correctly classified, area under the curve 0.88) for the three and seven most important features, respectively (Fig. 3&4)
- More than four features do not provide significant improvement
- Whole hemisphere GM and WM VOIs, neglecting iWSA information, yielded a significantly lower accuracy (81.7±2.3% for seven features, t-test, p < 0.001)

Discussion

- We successfully applied an RFC to determine most relevant parameters and VOIs to predict ICAS
- Ranking order and increased accuracy of hemodynamic parameters within iWSAs are in line with[3,7]
- Few sensitive features, i.e., difference of TTP, CBF and ipsilateral CVR allow to detect ICAS patients

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