Automated Semantic Segmentation of Volumetric Cardiovascular Features and Disease Assessment

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INTRODUCTION

- Cardiac remodeling includes changes in ventricular size, mass, geometry and regional wall motion. Cardiovascular MRI is clinically used to assess and monitor the progressive course of heart failure.
- The benefits of comprehensive quantitative measurements remain untapped due to costs and interpretation variability.
- We introduce a novel deep learning method that quantifies volumetric cardiac dynamics to inform classifier training for remodeling pathology.

Fig 1: Cardio myocyte is the primary remodeling cell. For example, myocardial necrosis and disproportionate thinning of the heart typically follows myocardial infarction.

PURPOSE

Develop a cardiovascular pathology system capable of classifying MRI images based on volumetric dynamics associated with remodeling.

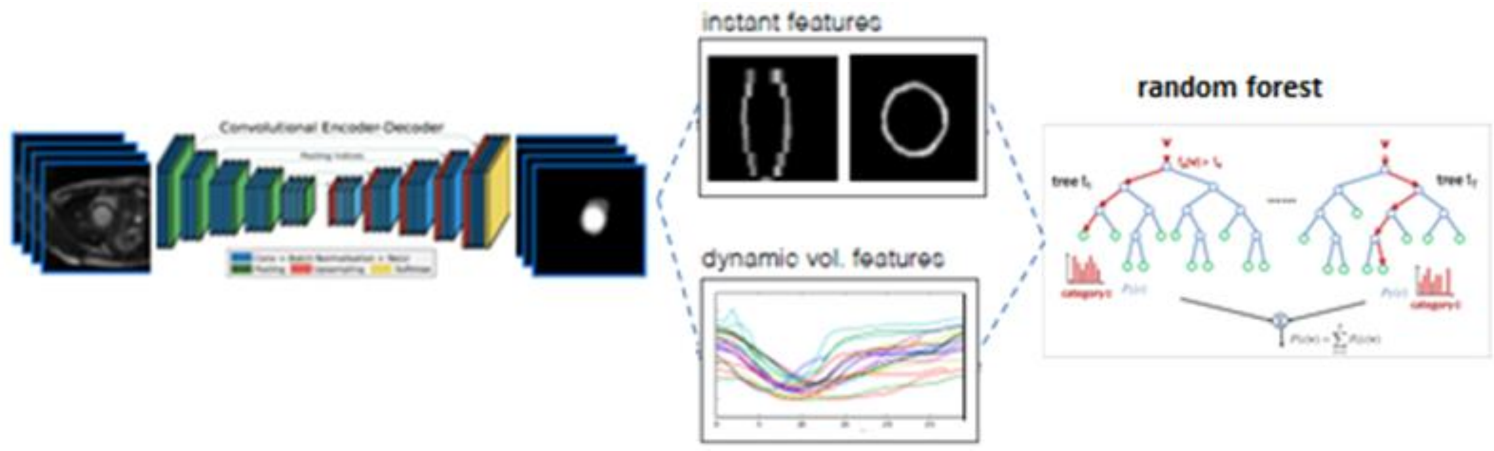

Fig 2: Automatic Cardiac Pathology Classification Pipeline

MODEL

Data Preprocessing, Feature Selection, Error Analysis

- Filtered images with defective pixel color distributions.
- Pair-wise correlated attributes exceeding threshold of 0.9 eliminated and remaining features z-score normalized.
- Feature selection determined maximally varying subset of predictors. Error analysis was applied to each pipeline processing element.

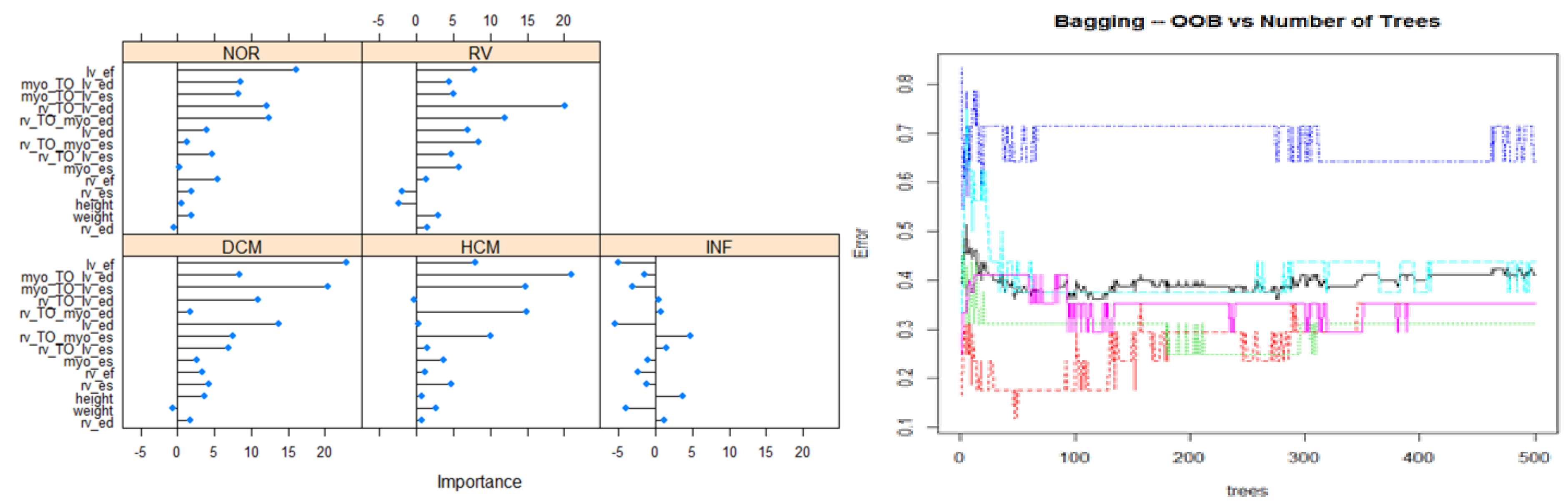

Fig 3: *Random Forest Classifier* **Left:** Selected features based on Gini impurity decrease ranking. **Right:** Computed out-of-bag error performance metric over 500 trees. Blue line is prediction accuracy.

CNN Training

- Dataset Partition: Train (65%), Hold out (15%), Test (20%).
- Pretrained GoogLeNet model with SGD optimizer chosen as baseline. Test set 95% CI (0.50, 0.65) with transfer learning.
- Dilated autoencoder implemented as ResNet-101 was trained on mini-batch of images and associated GT masks.
- Semantic Segmentation Evaluation Metrics

	RVC	LVM	LVC
ED	0.935	0.862	0.932
ES	0.890	0.840	0.887
Average	0.913	0.851	0.910

Table 1: Dice scores for the 3D voxel-wise label map prediction using semantic segmentation SGD optimizer with momentum..

DATASET

MICCAI Challenge 2017

- 150 patients, approximately 4000 images with 28 - 40 3D volumes/slice covers cardiac cycle.
- Two MRI scanners of magnetic strengths 1.5 T and 3.0 T acquired images over 6 year period.
- Parasternal short axis slices from apex to base.
- Random real-time data augmentation – rolling, rotation, shear, zoom, flip and zero padding.
- Mix of anonymized clinical public and private data with physician graded images.

CONCLUSIONS

- A fully automatic processing system for cardiac pathology classification on cine-MRI outperformed a robust pre-trained CNN with transfer learning.
- Our image pipeline includes semantic segmentation with dilated convolutions, volumetric feature extraction and random forest model classification.
- 5-ary classifier test set performance: Accuracy 85.0%, Sens 86.6%, PPV 87.7%, Spec 96.1%, NPV 96.4%.
- Error analysis revealed learning rate, optimizer type and feature selection were greatest contributors to improved model performance.

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