

The background features several abstract, rounded geometric shapes in shades of teal and dark blue. A large, light teal shape is in the top left, and a smaller, darker teal shape is in the top right. In the bottom right corner, there are overlapping teal and dark blue shapes.

Predicting Age with MRI data

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INTRODUCTION





 **HEALTHY CONTROLS**

 **MILD COGNITIVE
IMPAIRMENT**

 **ALZHEIMER'S DISEASE**

Kirova et al. (2015);
Davis et al. (2018)

BIOMARKERS OF MCI AND AD

1

Hippocampal atrophy

2

Ventricular enlargement
rates

Leung et al. (2013);
Moon et al. (2018)

WHY PREDICT AGE AND DIAGNOSIS?

DISEASE DEVELOPMENT

Provides insights into disease
progression over time

BIOMARKER DEVELOPMENT

Enhancing diagnostic accuracy and potentially
enabling the identification of individuals at higher
risk of disease conversion

AIMS & OBJECTIVES

I plan to investigate different models to find what best predicts age based on MRI features



RANDOM FOREST CLASSIFIER/ REGRESSOR

- Constructs multiple decision trees on subsets of the data and aggregates their predictions to make final classifications
- Handles non-linearity and complex relationships
- Can handle data with large amounts of features

SUPPORT VECTOR CLASSIFIER

- Finds the hyperplane that separates classes in the feature space while maximizing the margin between the classes, for effective classification of data points.
- Can capture complex relationships
- Can accommodate feature interactions

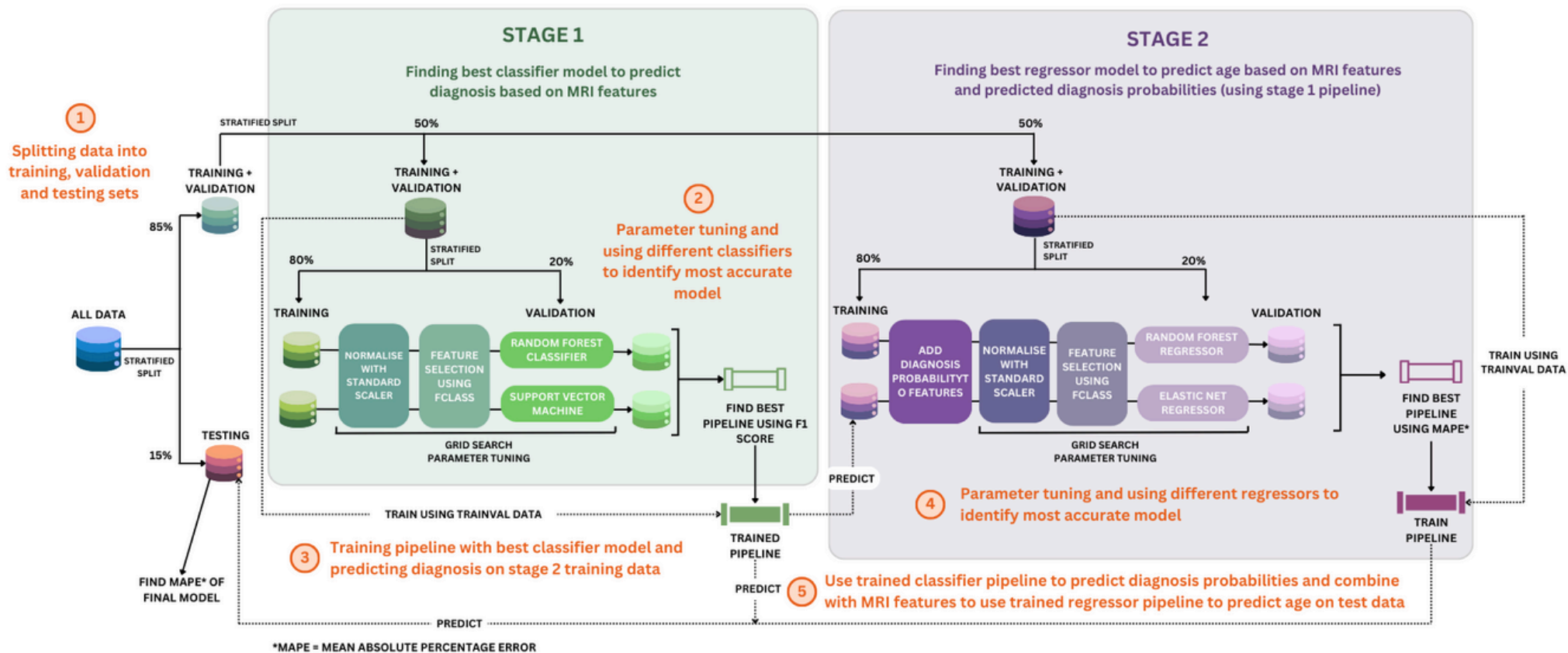
ELASTIC NET REGRESSION

- Takes into account both l_1 and l_2 penalties, similar to a combined linear and lasso regression
- Robust model to outliers, which may be useful as we have lots of features to predict from
- Obtain sparse models with a reduced number of predictors, making it easier to interpret the model's coefficients and understand the relationships between predictors and the target variable.

METHODS



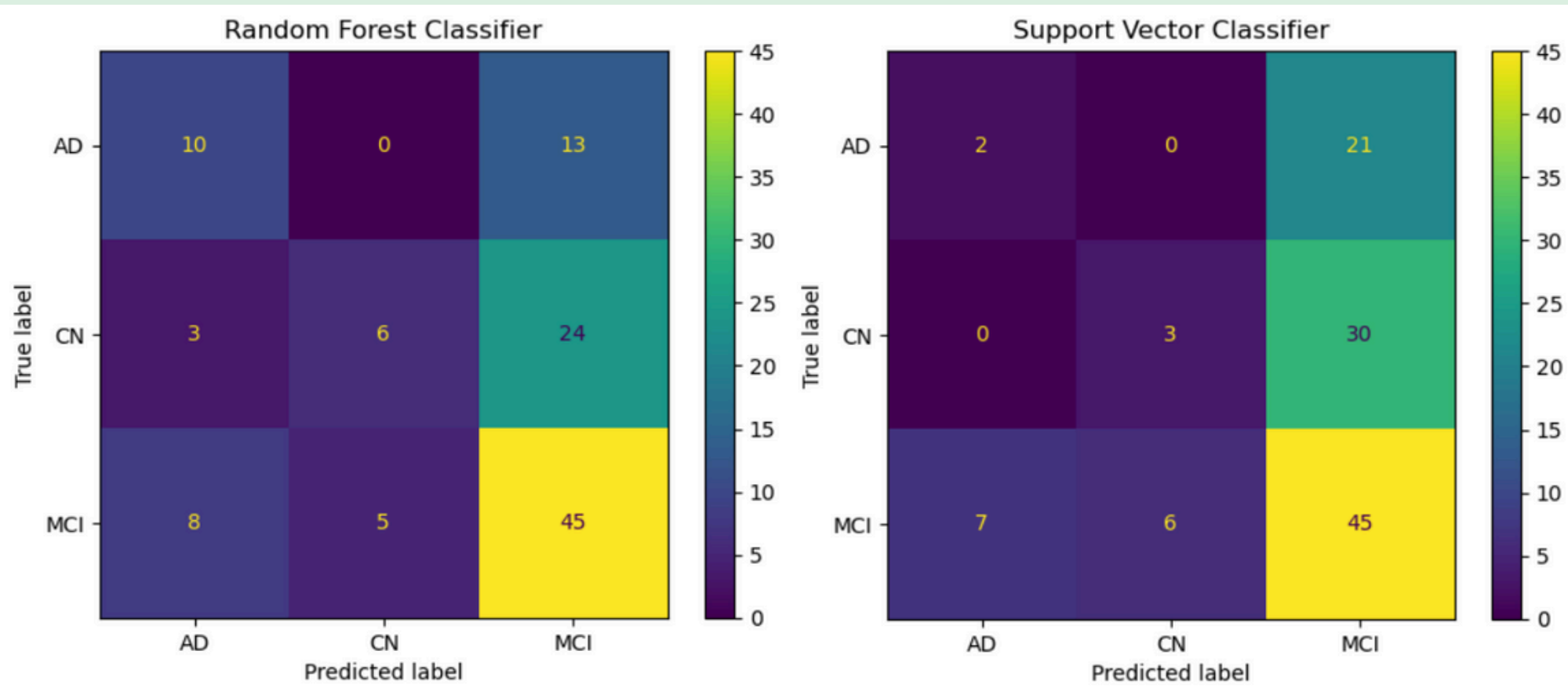
Methods Graphic



RESULTS



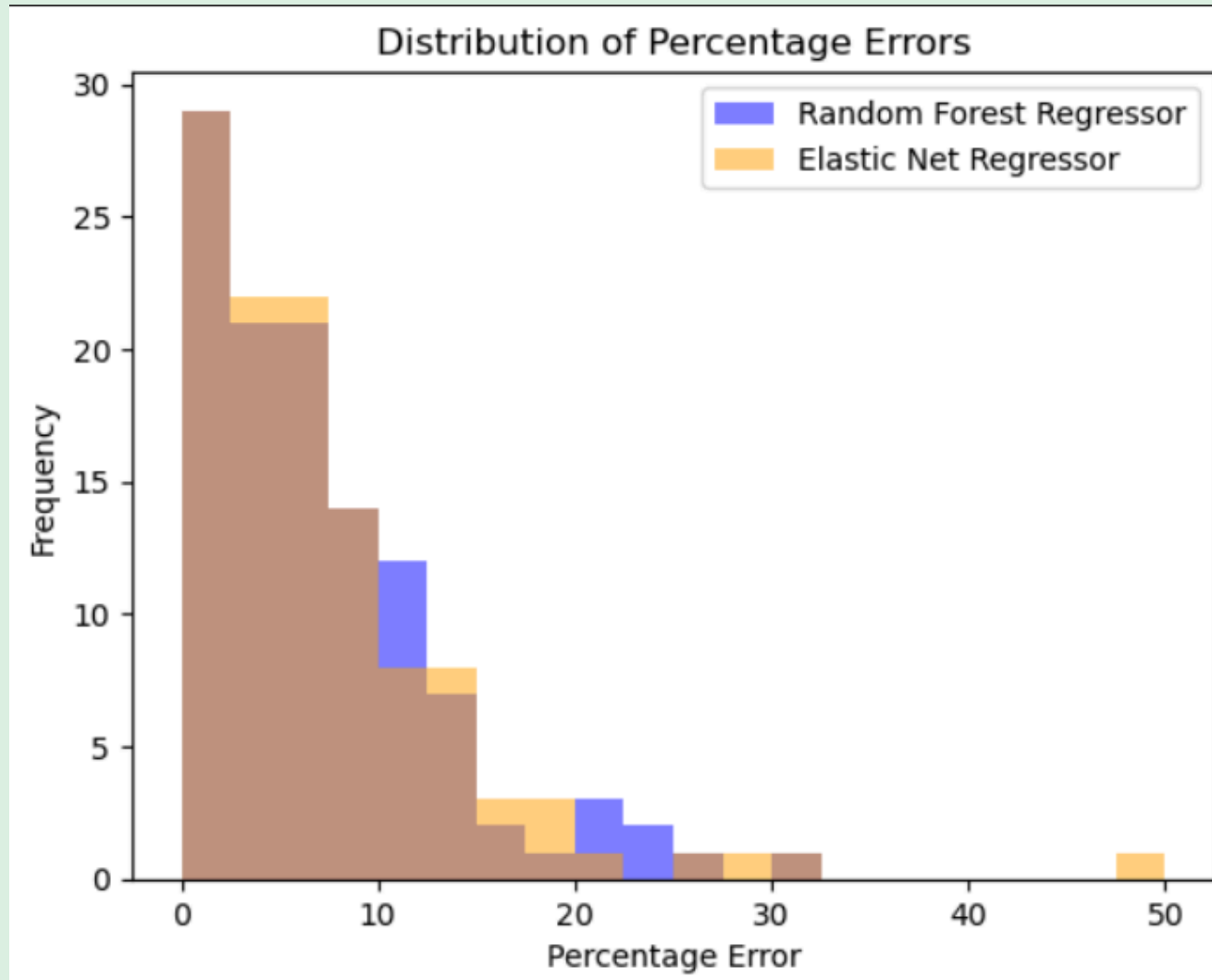
RESULTS: CLASSIFIERS



RFC accuracy = 54%

SVC accuracy = 44%

RESULTS: REGRESSORS



BEST MODELS

RANDOM FOREST CLASSIFIER

compared to SVC f1 score = 0.36

F1 SCORE
0.50

RANDOM FOREST REGRESSOR

compared to elastic net MSE = 7.3%

MEAN ABSOLUTE
PERCENTAGE ERROR
7.1%

OVERALL PIPELINE PERFORMANCE

MEAN ABSOLUTE
PERCENTAGE ERROR

6.8%

DISCUSSION



BEST MODELS: WHY?

RANDOM FOREST CLASSIFIER

Possibly more robust to noisy data and overfitting, which is important in medical diagnosis where data might be noisy or incomplete.

RANDOM FOREST REGRESSOR

Ensemble of trees in this model may have been able to handle complex interactions between feature and age that ElasticNet could not

BIOMARKERS OF MCI AND AD

1

Hippocampus

2

Ventricles

3

Amygdala

Leung et al. (2013);
Moon et al. (2018)



EVALUATION

SMALL DATASETS

REFERENCES

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THANK YOU

