

Lung Capacity Prediction in Patients with Pulmonary Fibrosis

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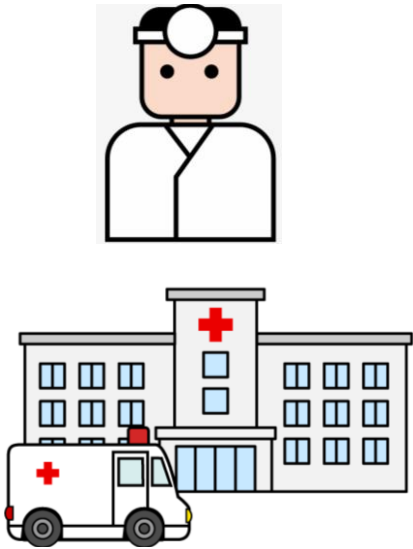
Capstone Project, November 2020

The Problem

- Respiratory failure is the 4th leading cause of death world-wide
- Pulmonary fibrosis is a chronic progressive disease with unpredictable prognosis.
- **Proposed solution:**
Deep learning-based algorithm that, based on patient general information and chest CT images predicts the future patient's lung capacity.

Who Might Care?

Hospitals & physicians



Insurance Companies



The patient



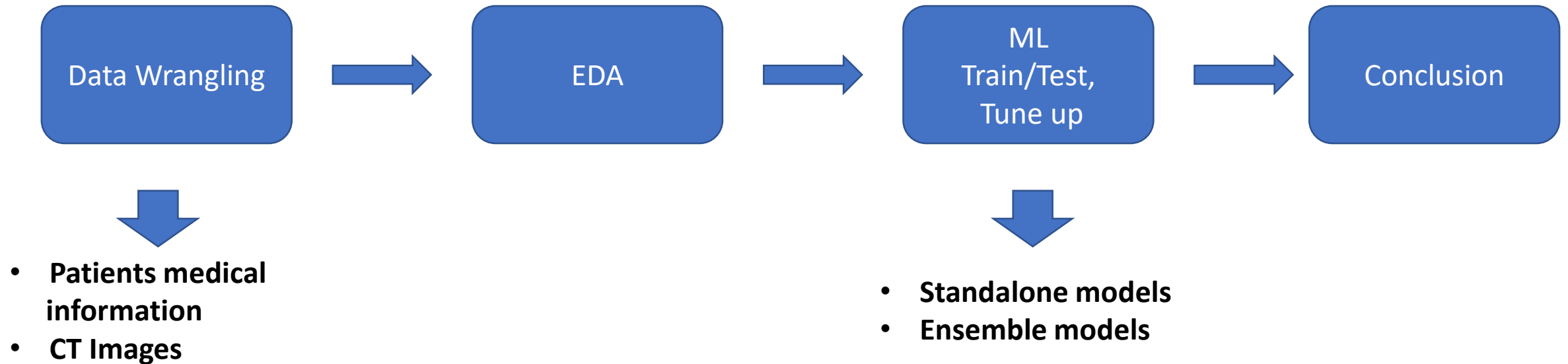
The patient's Family



The Data

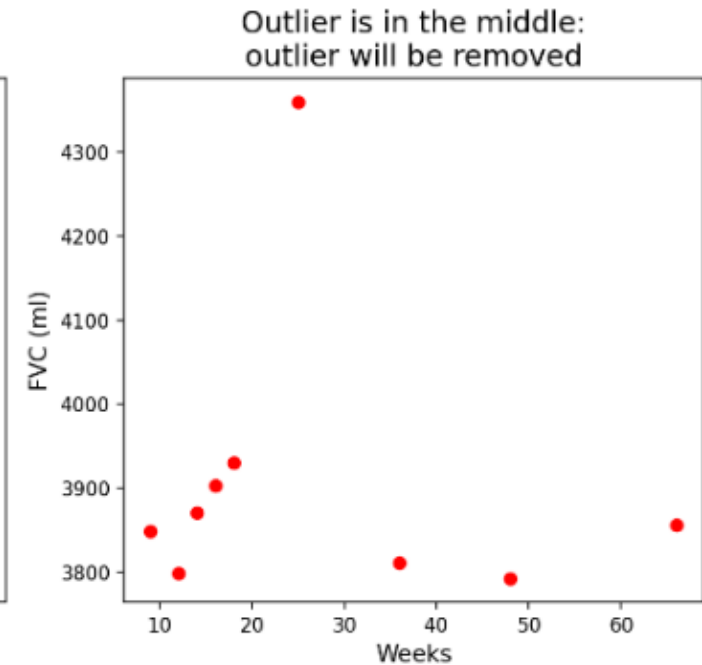
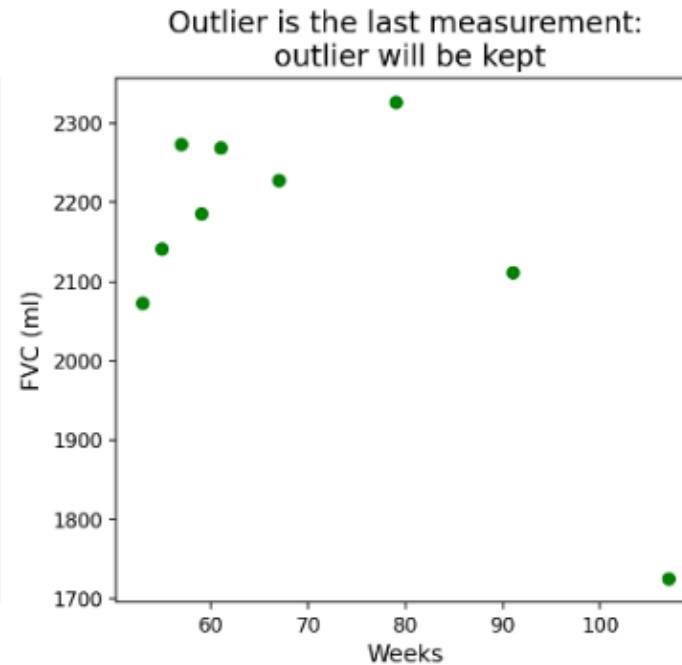
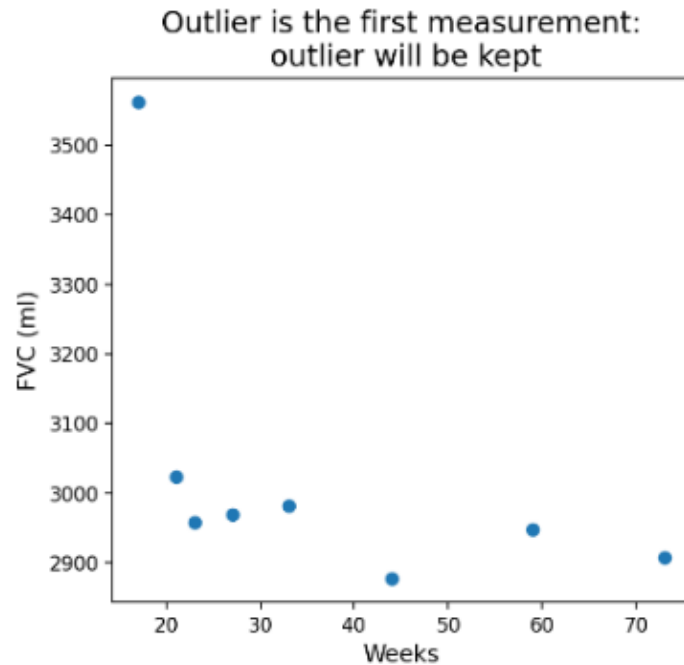
- Data Source :
 - Kaggle: 176 patients gathered from different public and private hospitals
- Data composition:
 - Age, Sex, Smoking status
 - Lung capacity measurements and their timeline: FVC (forced vital capacity) vs weeks.
 - CT images (dcm format)

How the problem was tackled

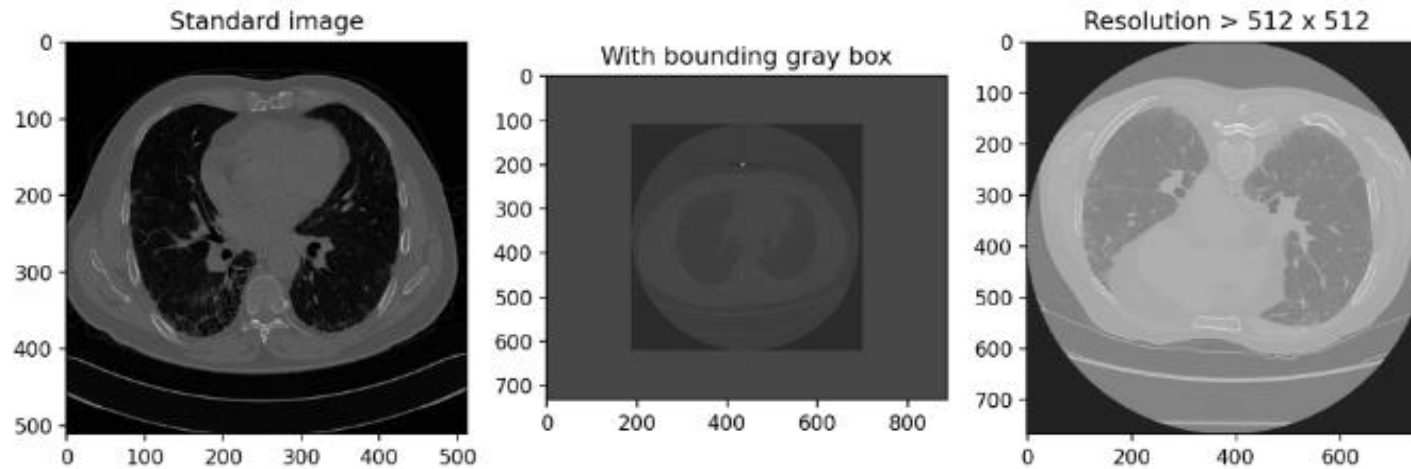


Data Wrangling – Sex, Age, Smoking status, FVC values

- No missing values
- Outliers in the FVC measurements:

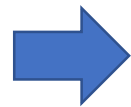
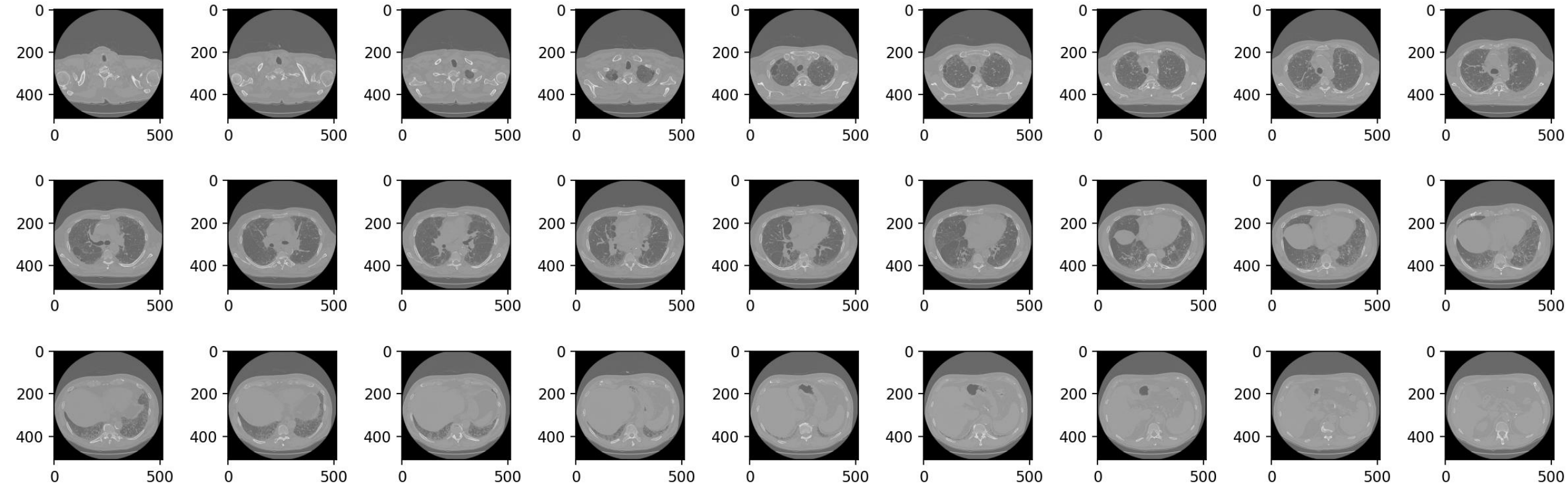


Data Wrangling - CT images (a)



- ➡ Normalize Resolution
- ➡ Remove bounding box
- ➡ Change contrast

Data Wrangling - CT images (b)

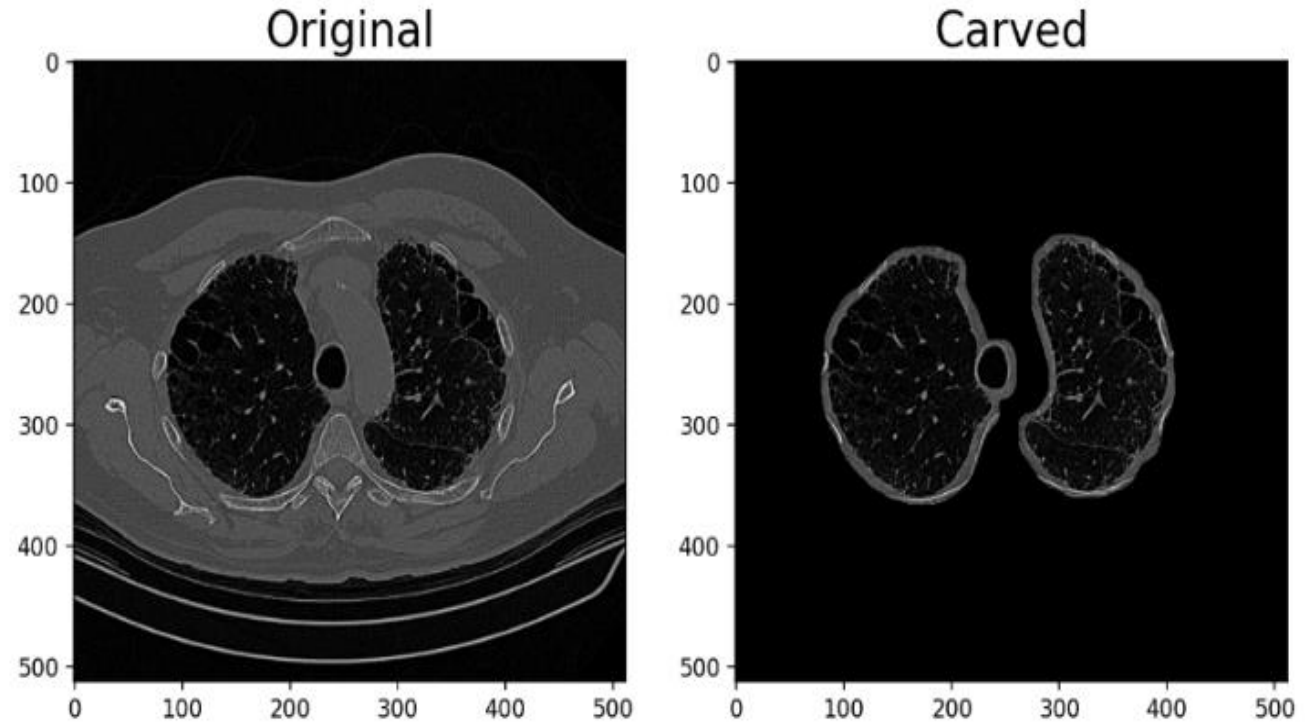


Mark the top and bottom images displaying the lung

Data Wrangling - CT images (c)

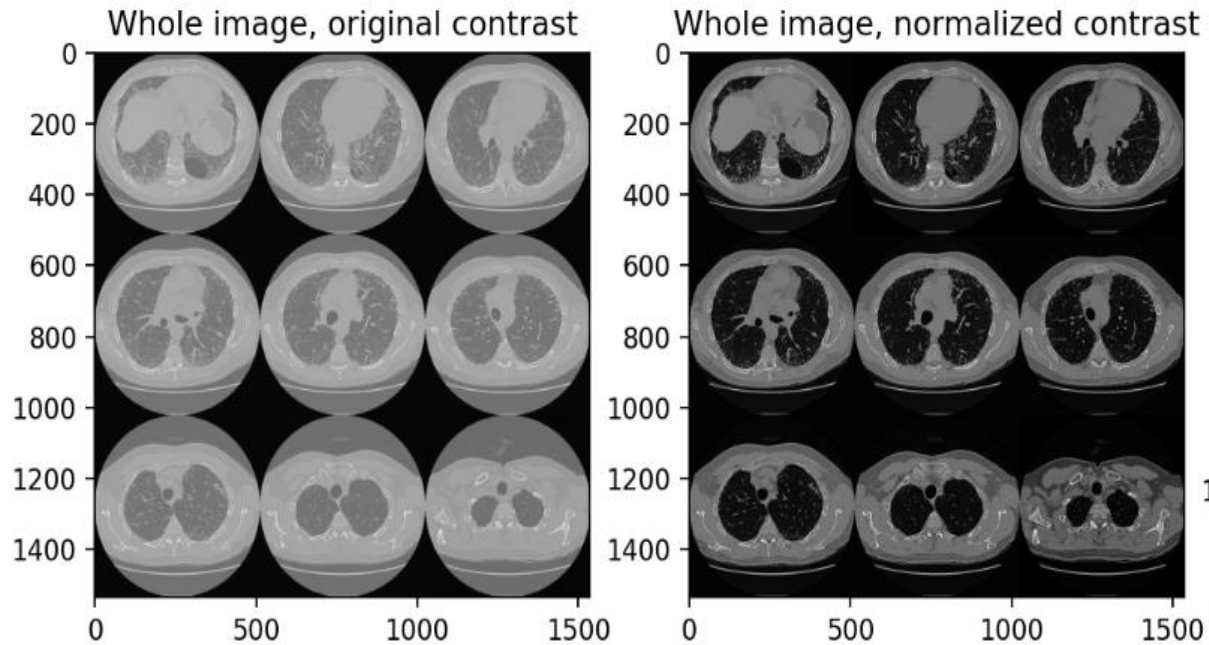
Hypotheses:

- More accurate predictions
- Faster training/testing

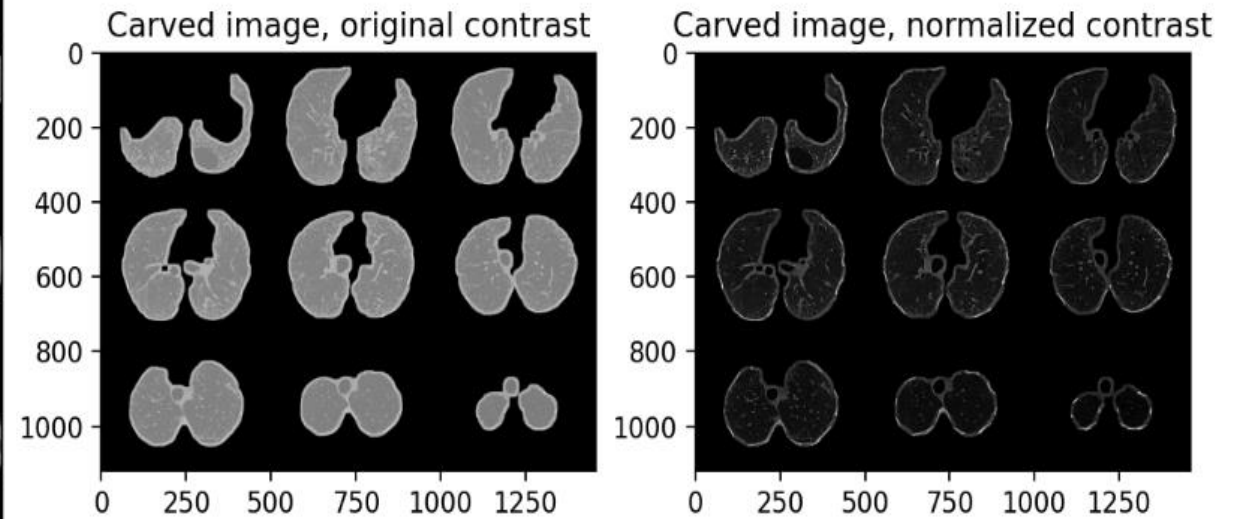


Data Wrangling - CT images (d)

Preparing 3x3 images grids:

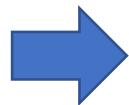
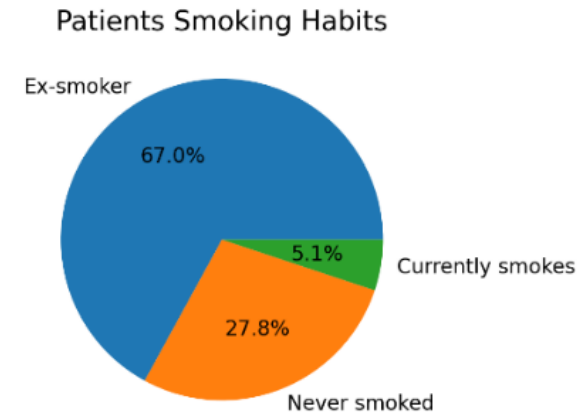
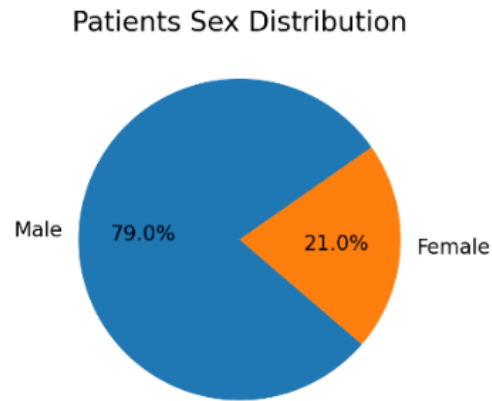
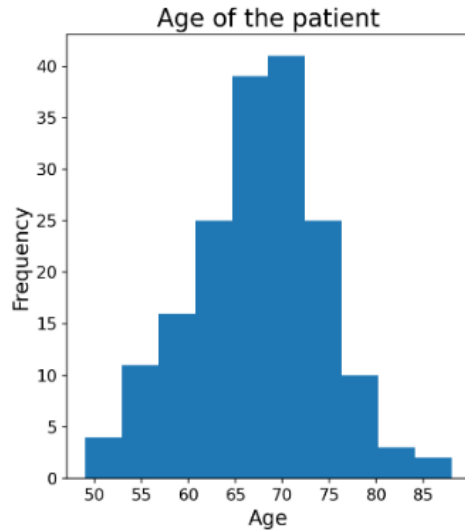


3x3 whole images



3x3 carved images

EDA – Age, Sex, Smoking Status

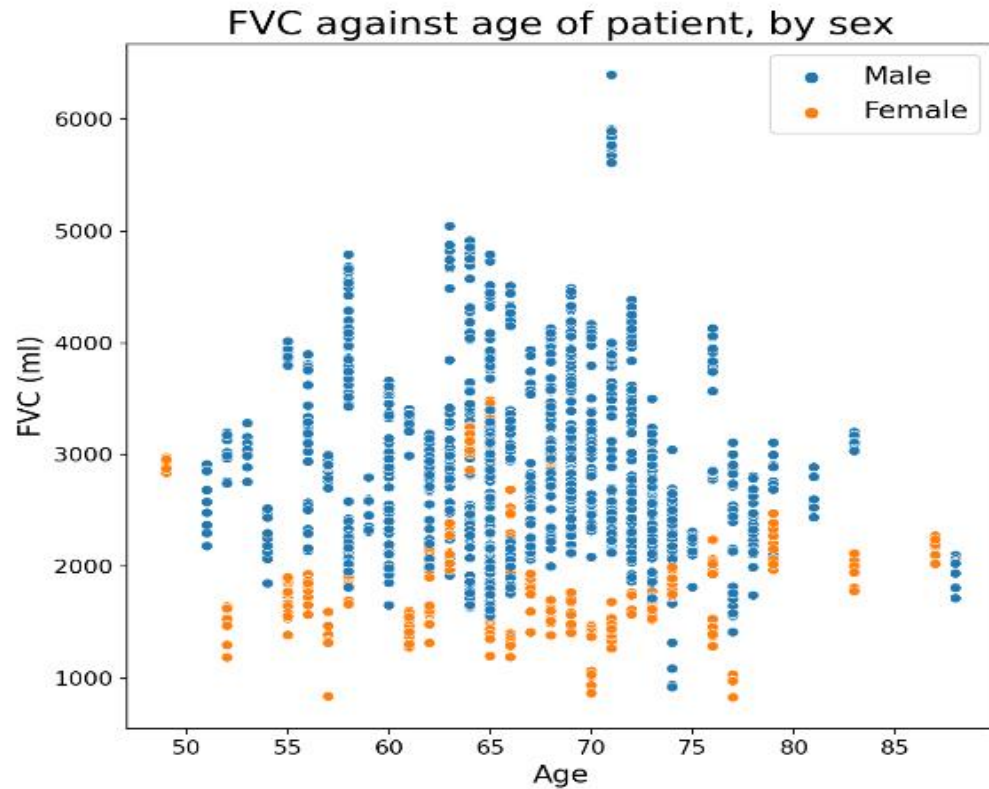


Age normally distributed (mean 67.3 years)



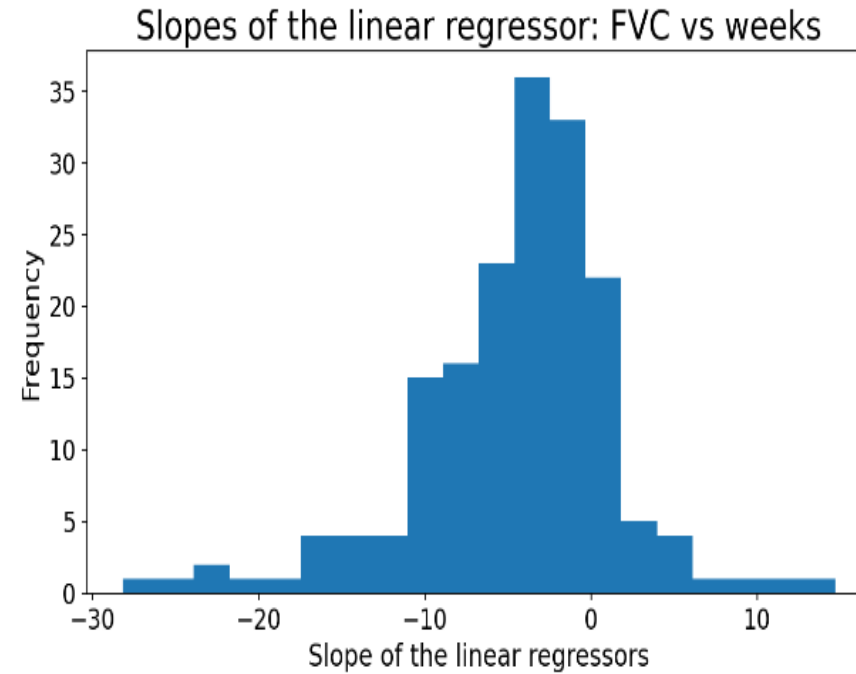
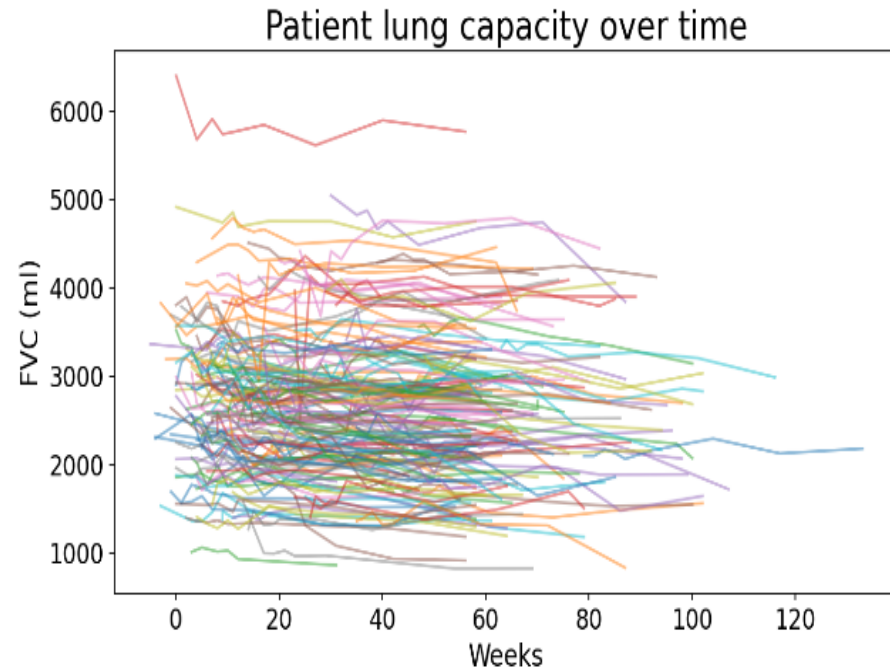
Majority of patients are **men, ex-smokers**

EDA – FVC



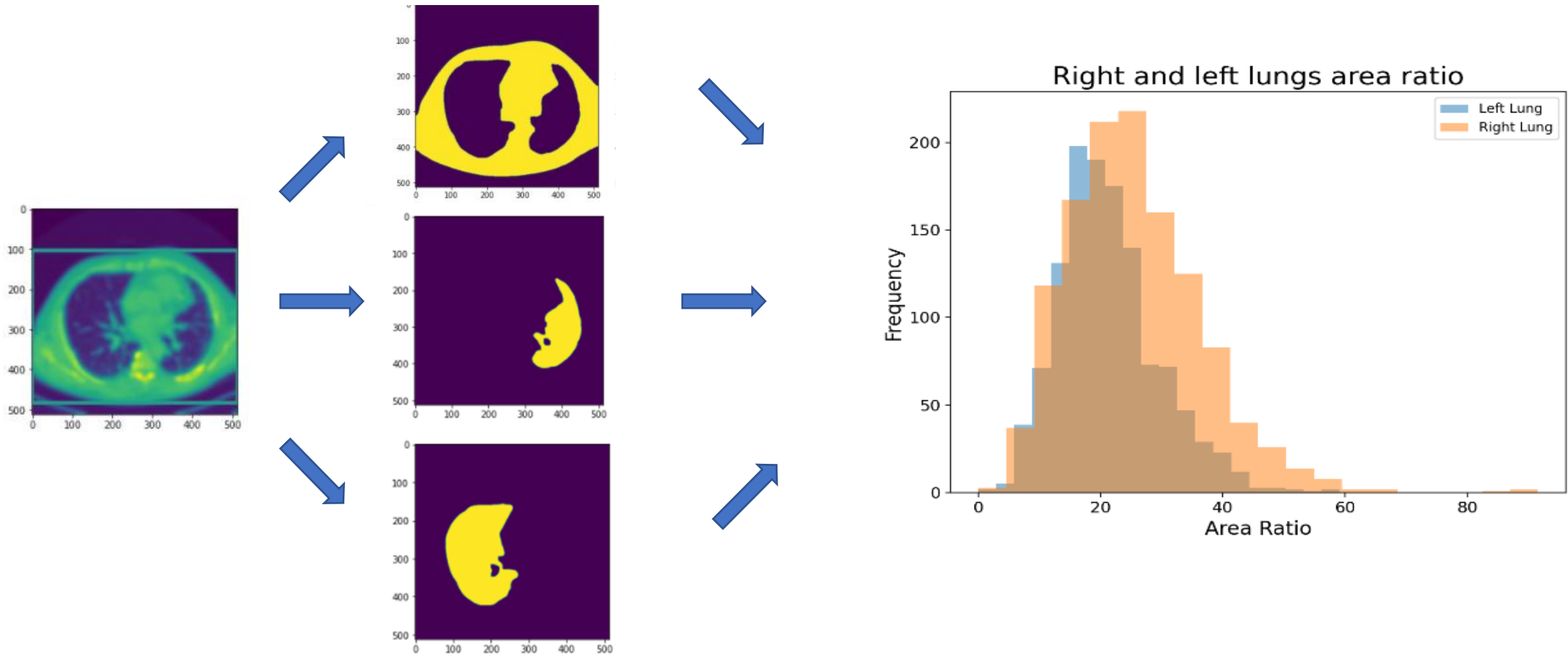
Males have higher lung capacity (bigger chest)

EDA – FVC decay



The lung capacity dropped for most of the patients

EDA – Area of right and left lungs



Modeling – Strategy

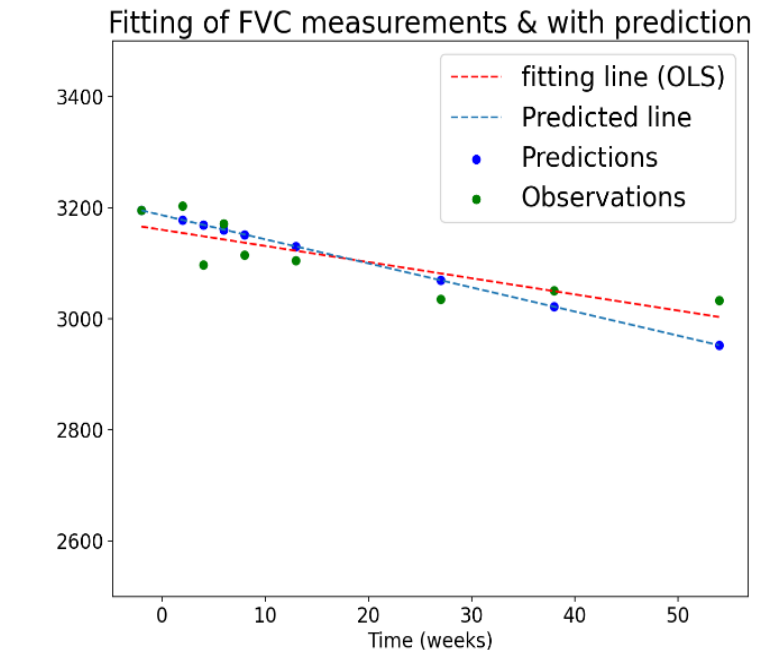
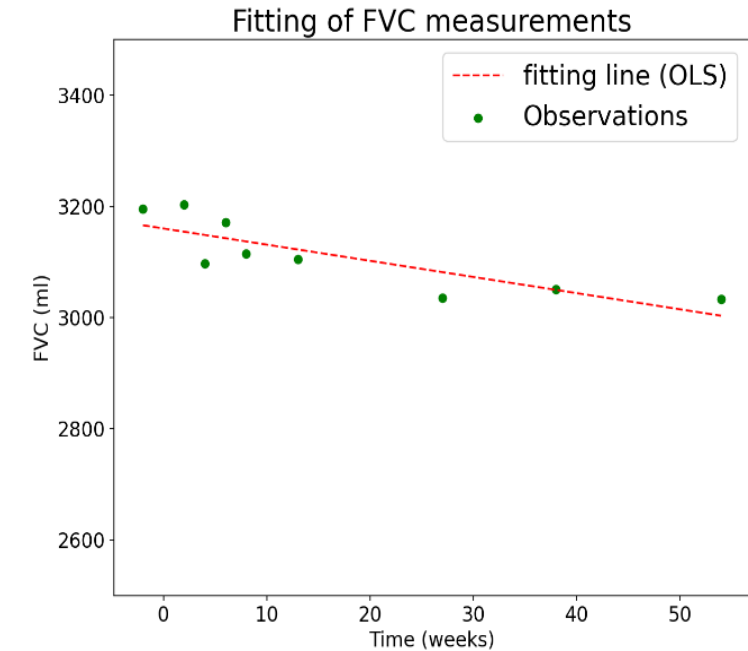
STEP 1: Fit observed FVC measurements with an OLS regressor

STEP 2: Extrapolate the slope of the best fit line

STEP 3: Train deep learning model to predict the slope, based on images and/or patients' information

STEP 4: Use the baseline FVC values (1st measurement) to estimate the intercept of the fitting line

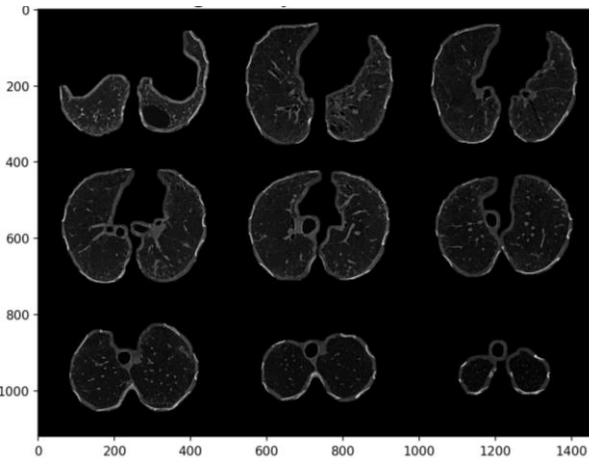
STEP 5: Calculate the future FVC values



Modeling – Slope Models

INPUT

Patient Medical
Information



STANDALONE MODELS

FCN

CNN

AUTOENCODER
+ CNN

TRANSFER LEARNING
+ CNN

+ Patient Medical
Information

+ Patient Medical
Information

+ Patient Medical
Information

ENSEMBLE MODELS

FCN

FCN

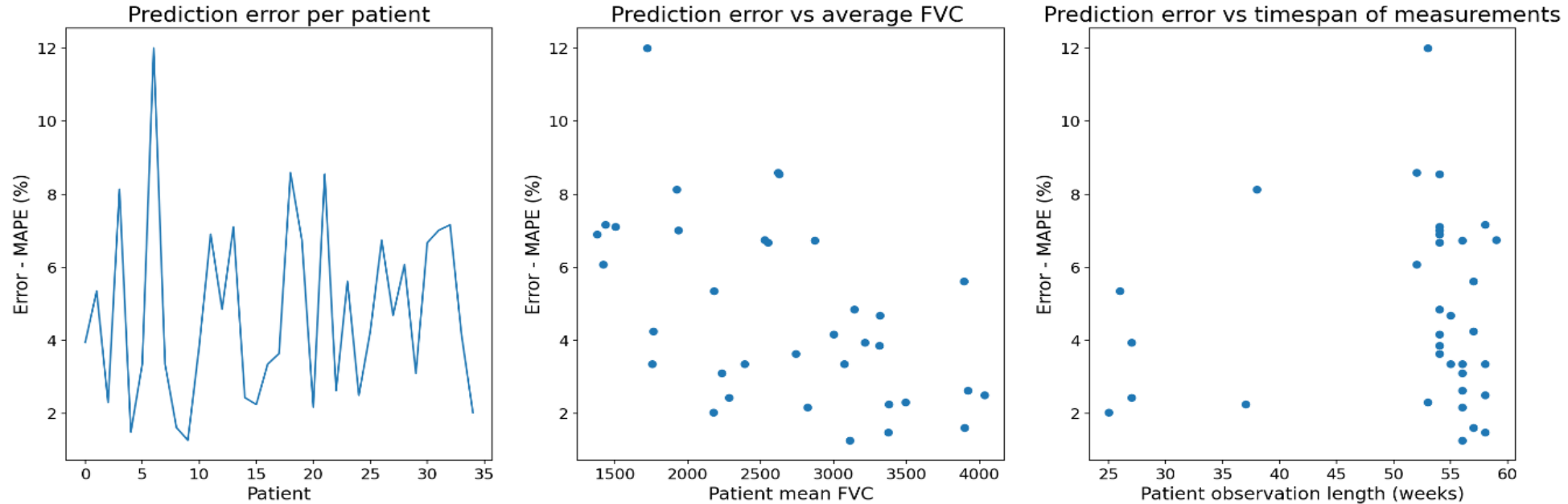
FCN

Modeling – Summary

| Model | Input | STANDALONE MODELS FVC prediction error (MAPE) | ENSEMBLE MODELS FVC prediction error (MAPE) |
|----------------------------|--|--|--|
| NN | Numerical and categorical medical data | 7.19% | N/A |
| CNN-1a | 3x3 whole images, 1536x1536 pixels | Original contrast: 7.40% Normalized contrast: 7.17% | Original contrast: 4.97% Normalized contrast: 4.90% |
| CNN-1b | 3x3 carved images, 1120x1460 pixels | Original contrast: 7.26% Normalized contrast: 7.46% | Original contrast: 4.87% Normalized contrast: 5.00% |
| CNN-2 Encoder | 3x3 whole images, 1536x1536 pixels | Enc 48x48, Norm. contrast: 7.33% Enc 96x96, Norm. contrast: 7.32% Enc 192x192, Norm. contrast: 7.47% Enc 384x384, Norm. contrast: 7.28% | Enc 48x48: 5.82% Enc 96x96: 5.00% Enc 192x192: 5.10% Enc 384x384: 5.76% |
| CNN-3 Transfer Learning | 3x3 whole RGB images 1024x1024 pixels | Normalized contrast: 7.09% | Normalized contrast: 4.76%** |

- Both patient medical data and chest CT images **contain key insights** for the prediction of the patient's lung capacity.
- Carving the images **does not consistently improve** the model performance.
- Normalizing the contrast on the images **improve the model predictive power only** when whole images are utilized.
- Transfer learning is the **winning strategy**.

Modeling – Best Model Prediction Analysis (a)

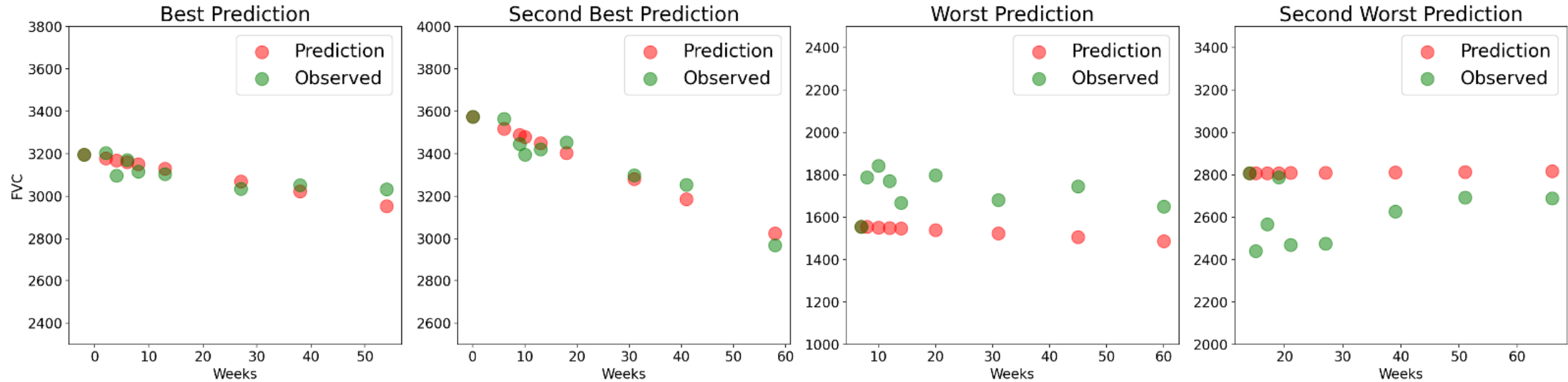


The error of the model seems to be inversely correlated to the mean of the FVC measurements



The longer the patient is observed, the higher the error of the model

Modeling – Best Model Prediction Analysis (b)

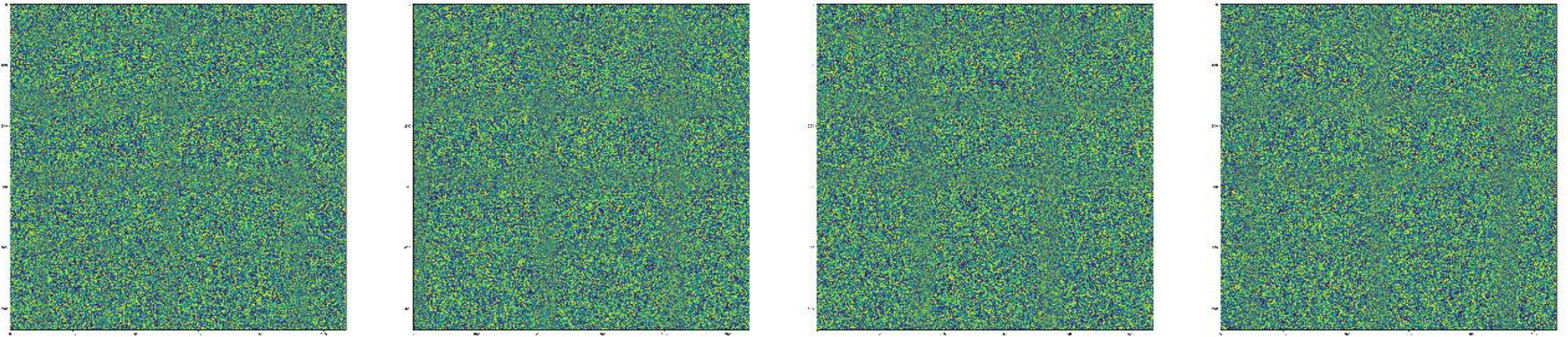


When the lung capacity of the patient changes linearly overtime, the model performs well.

When lung capacity changes drastically, predictions are less accurate.


Modeling – Feature maps of CNN1a

What does the model “see”?



String-like patterns  shape of the scar tissue

Conclusion

- Both the **patient medical information** and **chest CT images** contain key insights for the prediction of the future patient's lung capacity.
- **Transfer learning** produced the best predictive models: MAPE **7.09%** (standalone) to **4.76%** (ensemble)
- The model performs well when lung capacity decays linearly but **underperforms otherwise**.
 Utilize the last FVC measurement (or the average of last n measurements) as baseline value for the future predictions.
- **How to obtain better predictions:**
 - Information on the patients' pharmacological treatment (and when it was initiated),
 - Presence of comorbidities (such as diabetes, cardiovascular disease, other chronic diseases)
 - Other general information (blood pressure, weight, body mass index).
 - Increase the number of pictures
 - Increase the number of patients