Lung Capacity Prediction in Patients with Pulmonary Fibrosis

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The Problem

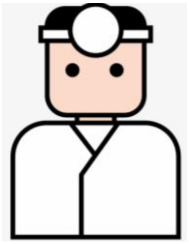
- Respiratory failure is the 4th leading cause of death world-wide
- Pulmonary fibrosis is a chronic progressive disease with unpredictable prognosis.

- **Proposed solution:**

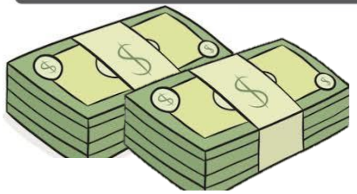
  Deep learning-based algorithm that, based on patient general information and chest CT images predicts the future patient's lung capacity.

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)

https://www.kaggle.com/c/osic-pulmonary-fibrosis-progression

How the problem was tacked

Data Wrangling → EDA → ML Train/Test, Tune up → Conclusion

Data Wrangling:

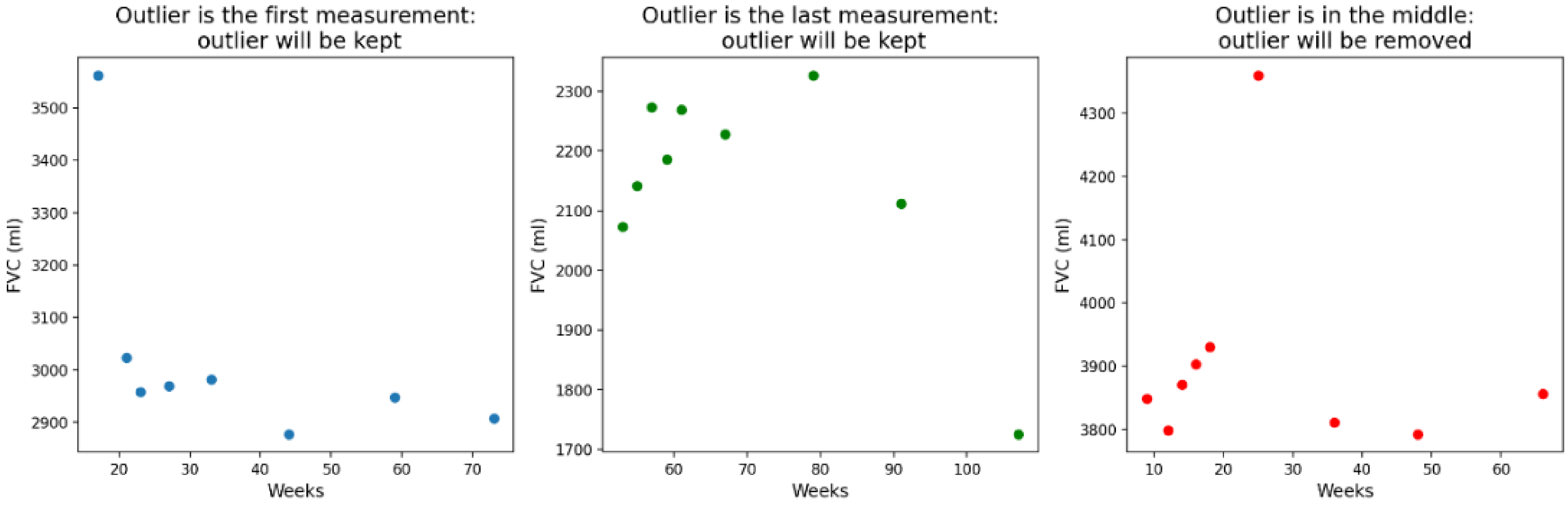
- **Patients medical information**
- **CT Images**

ML Train/Test, Tune up:

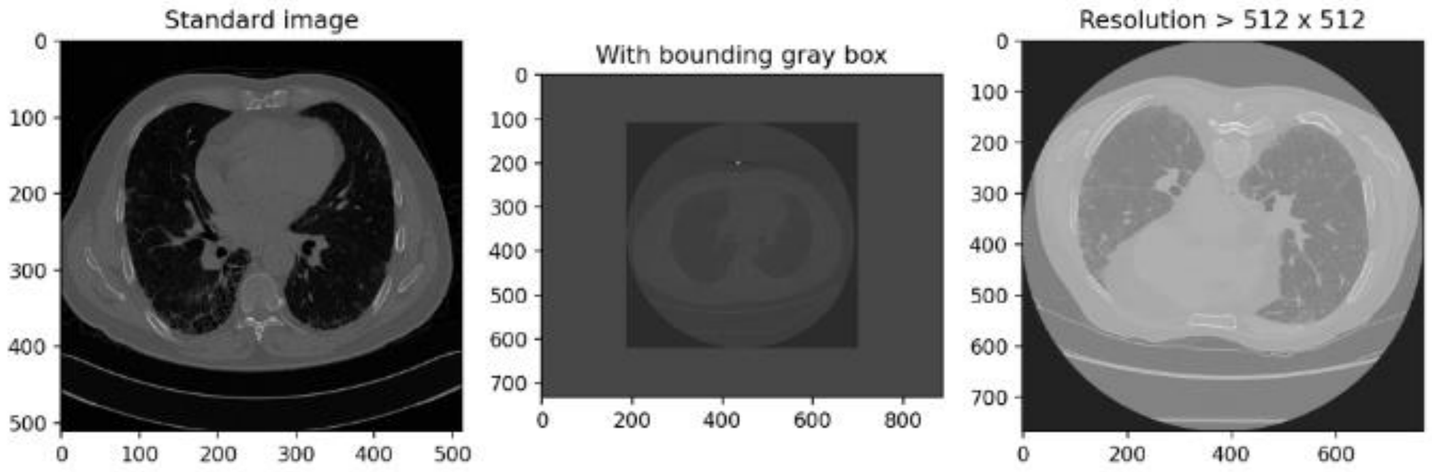
- **Standalone models**
- **Ensemble models**

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

- **No missing values**
- **Outliers in the FVC measurements:**



Data Wrangling - CT images (a)

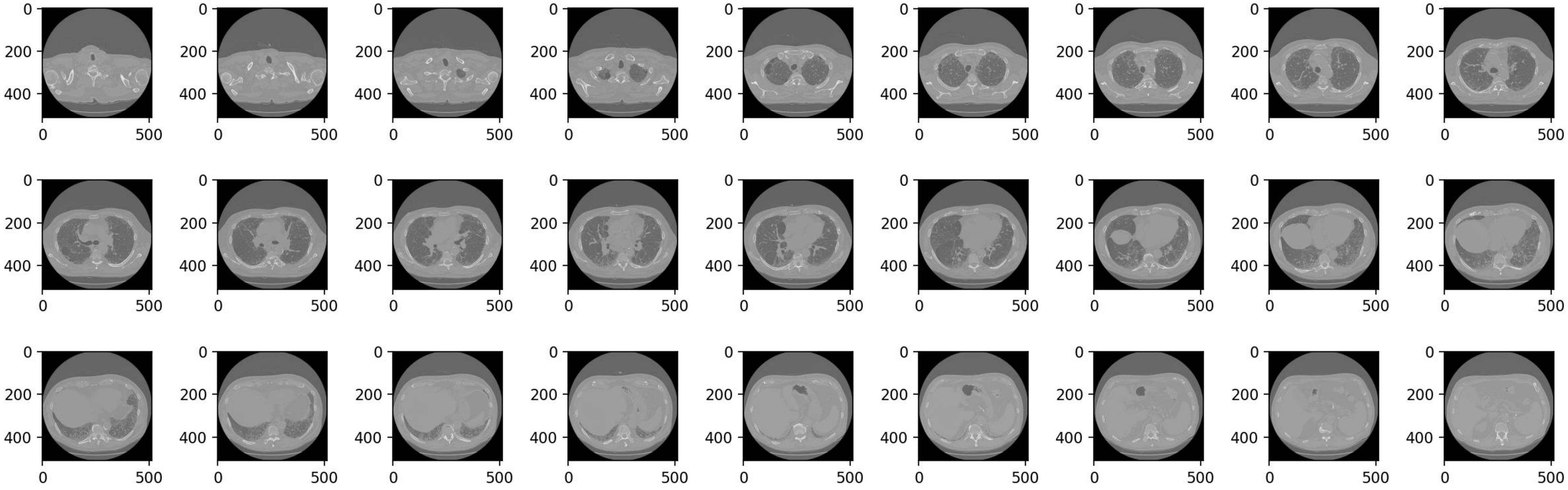


Normalize Resolution

Remove bounding box

Change contrast

Data Wrangling - CT images (b)

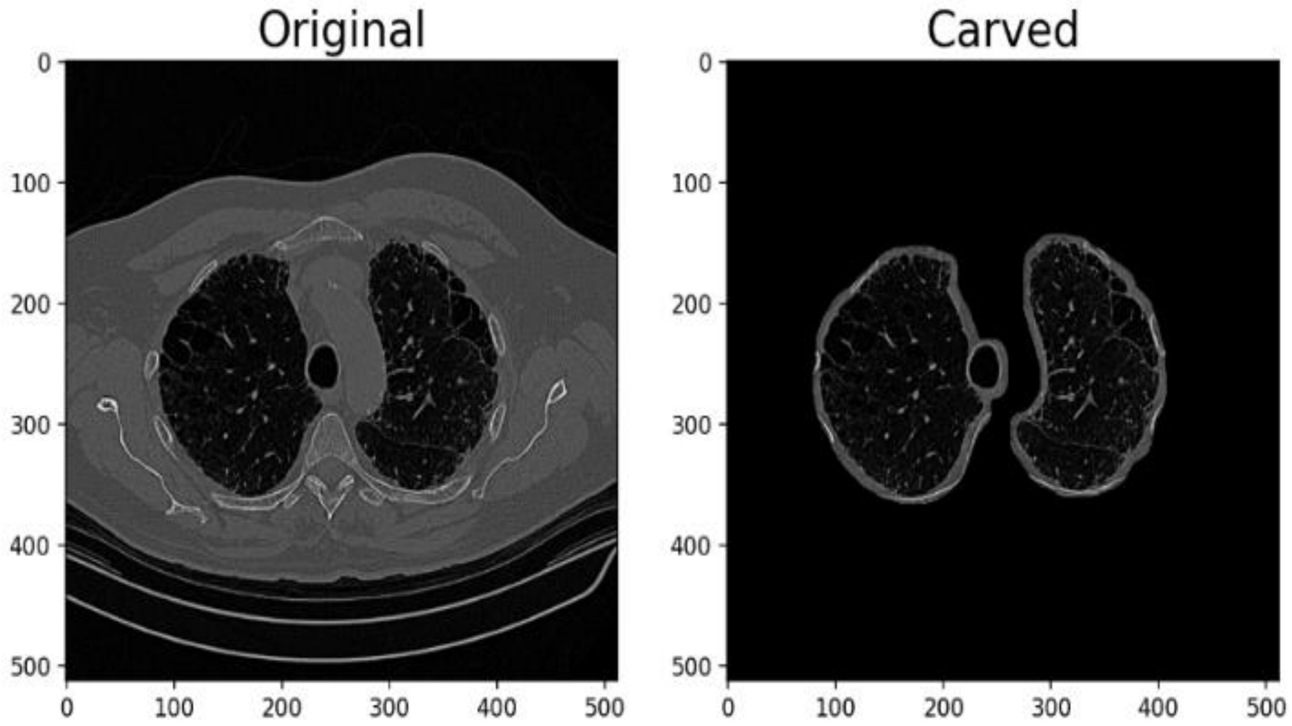


Mark the top and bottom images displaying the lung

Data Wrangling - CT images (c)

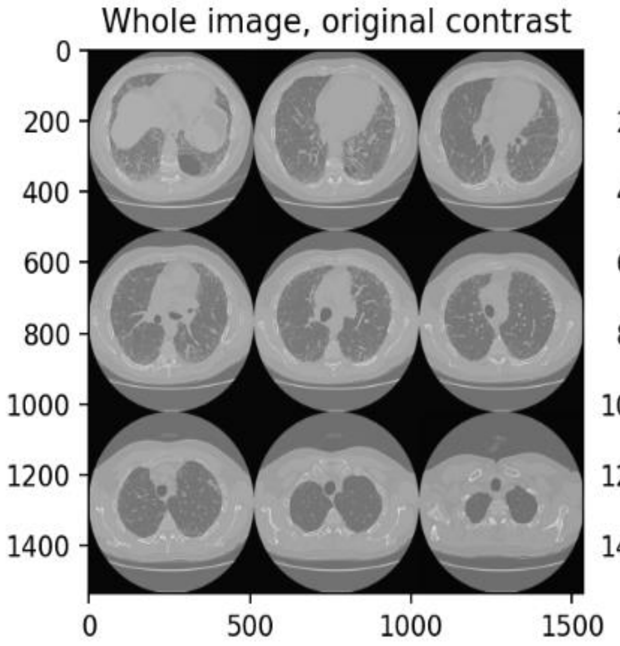
Hypotheses:

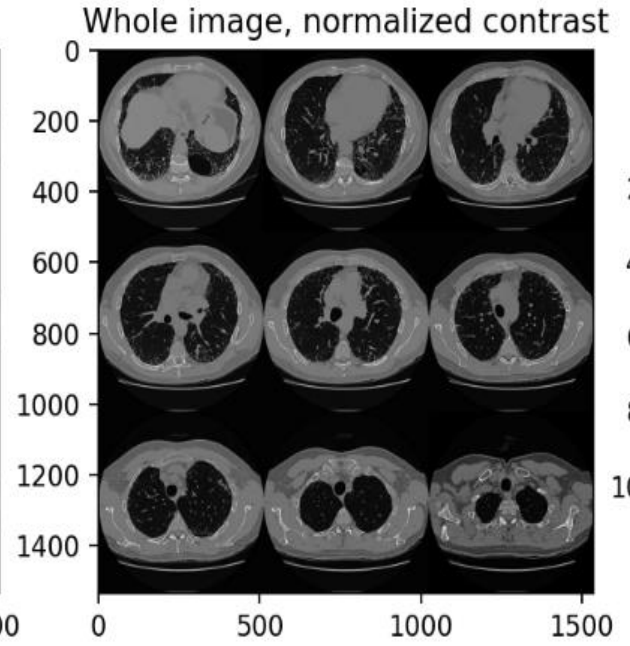
- More accurate predictions
- Faster training/testing

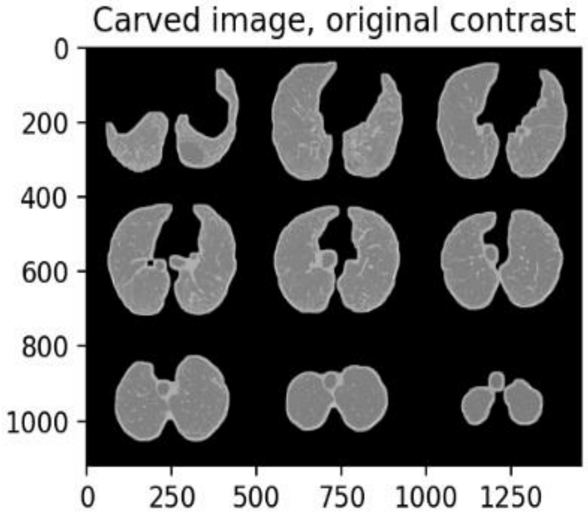


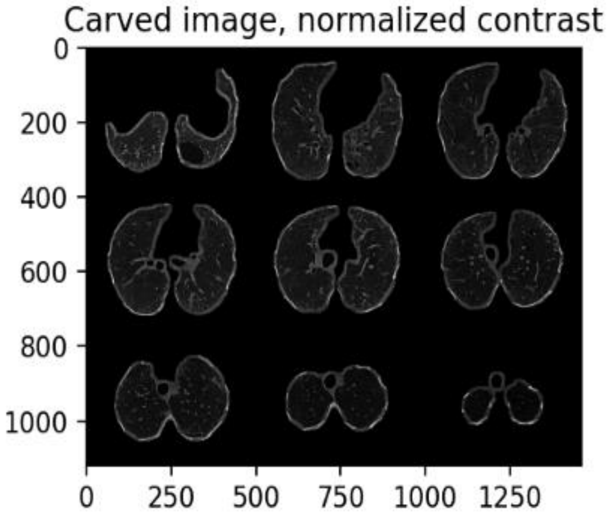
Data Wrangling - CT images (d)

Preparing 3x3 images grids:





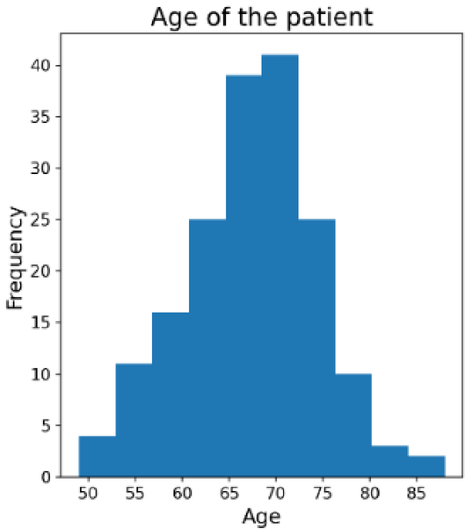


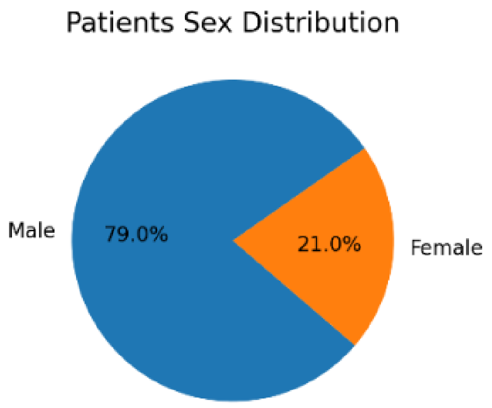


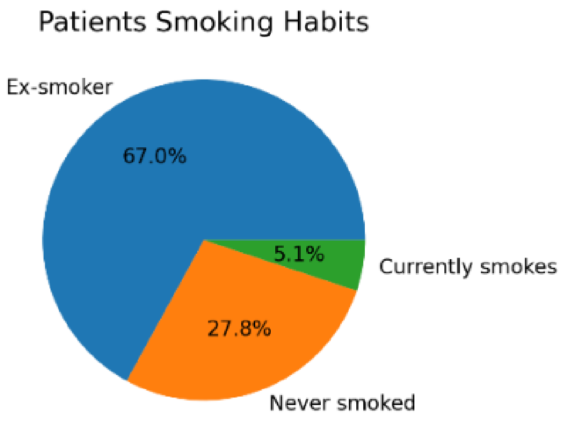
3x3 whole images

3x3 carved images

EDA – Age, Sex, Smoking Status

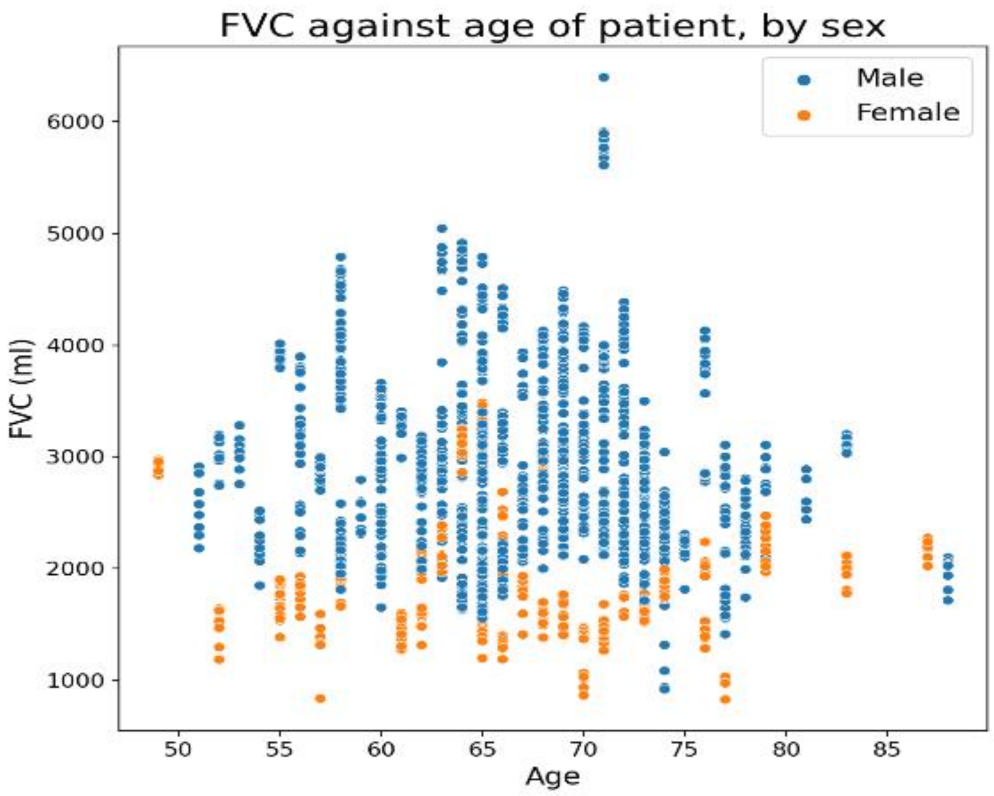






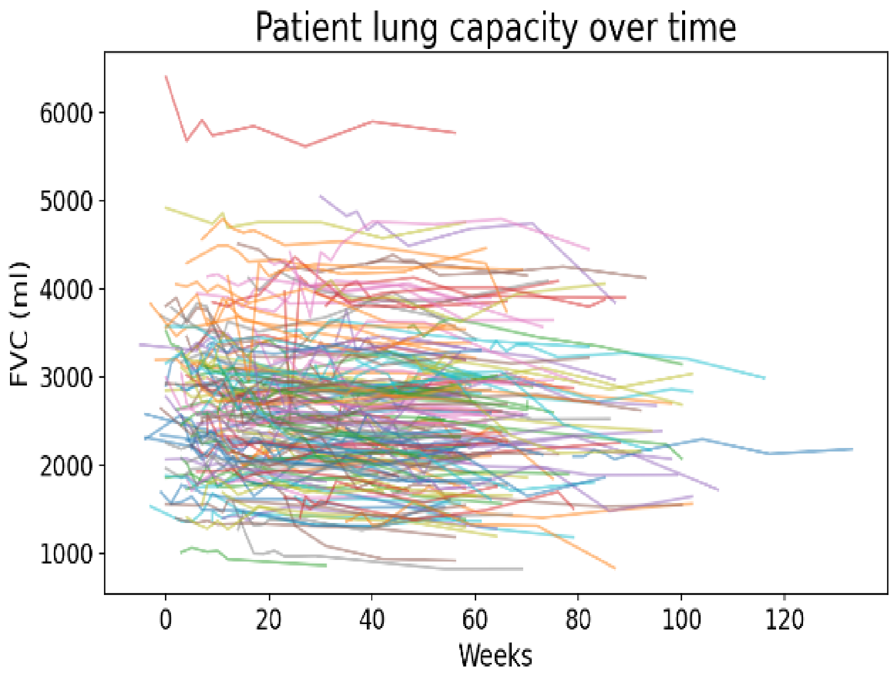
- Age normally distributed (mean 67.3 years)
- Majority of patients are **men, ex-smokers**

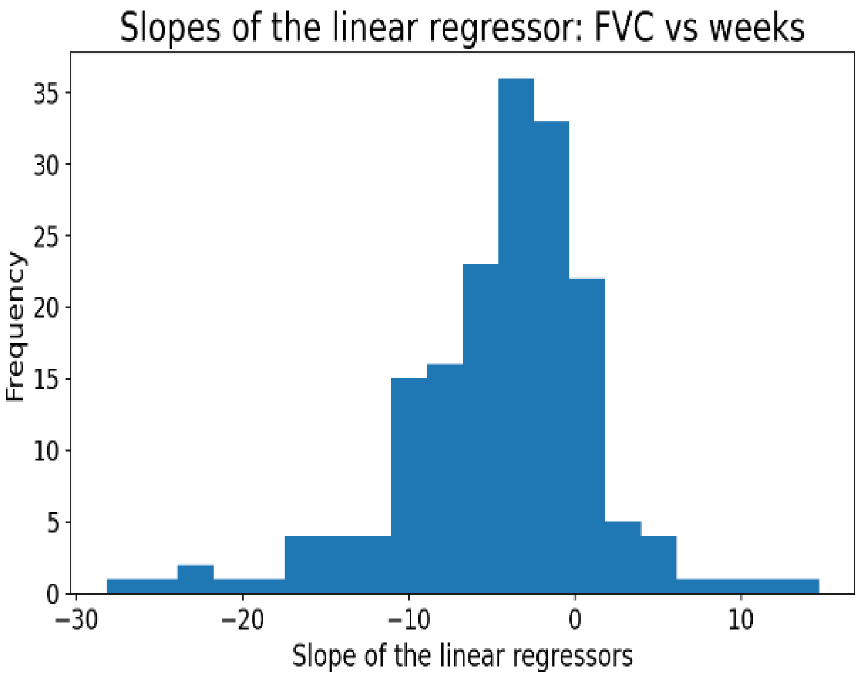
EDA – FVC



Males have higher lung capacity (bigger chest)

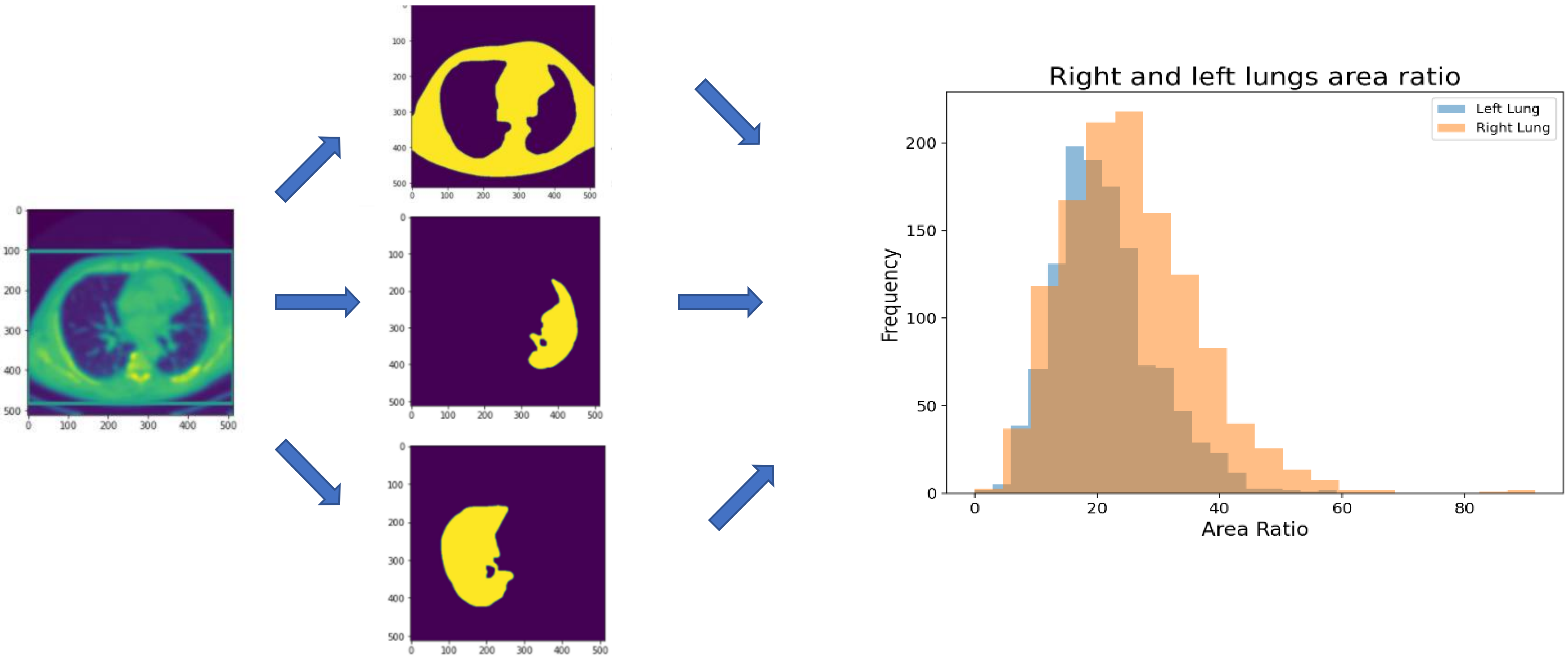
EDA – FVC decay





The lung capacity dropped for most of the patients

EDA – Area of right and left lungs



Modeling – Strategy

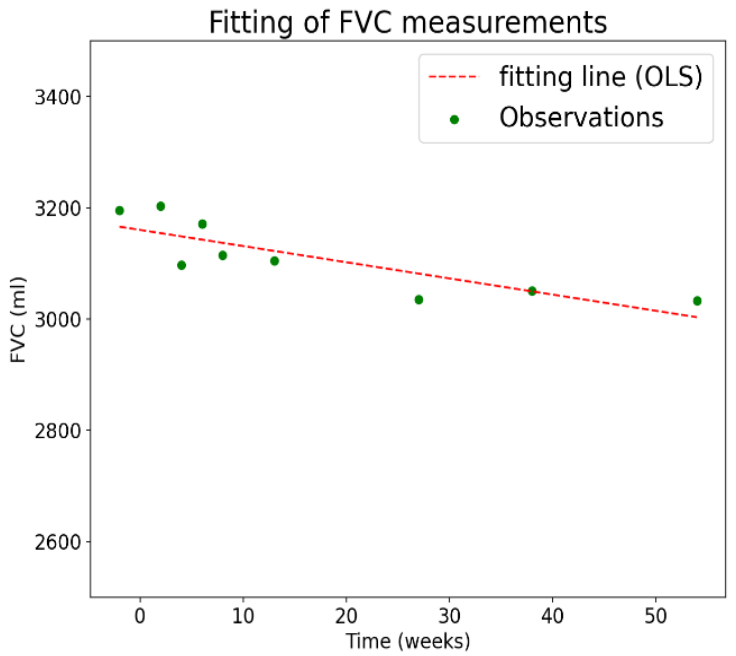
STEP 1: Fit observed FVC measurements with an OLS regressor

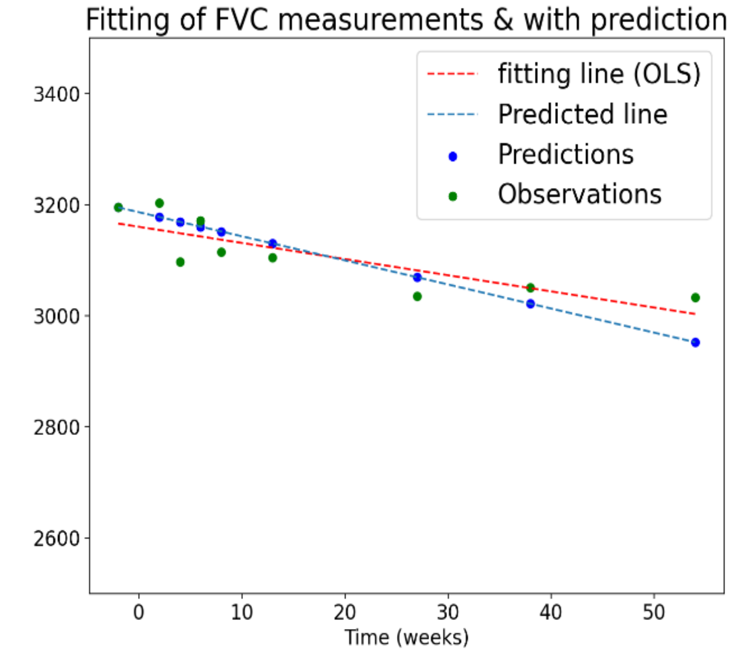
STEP 2: Extrapolate the slope of the best fit line

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

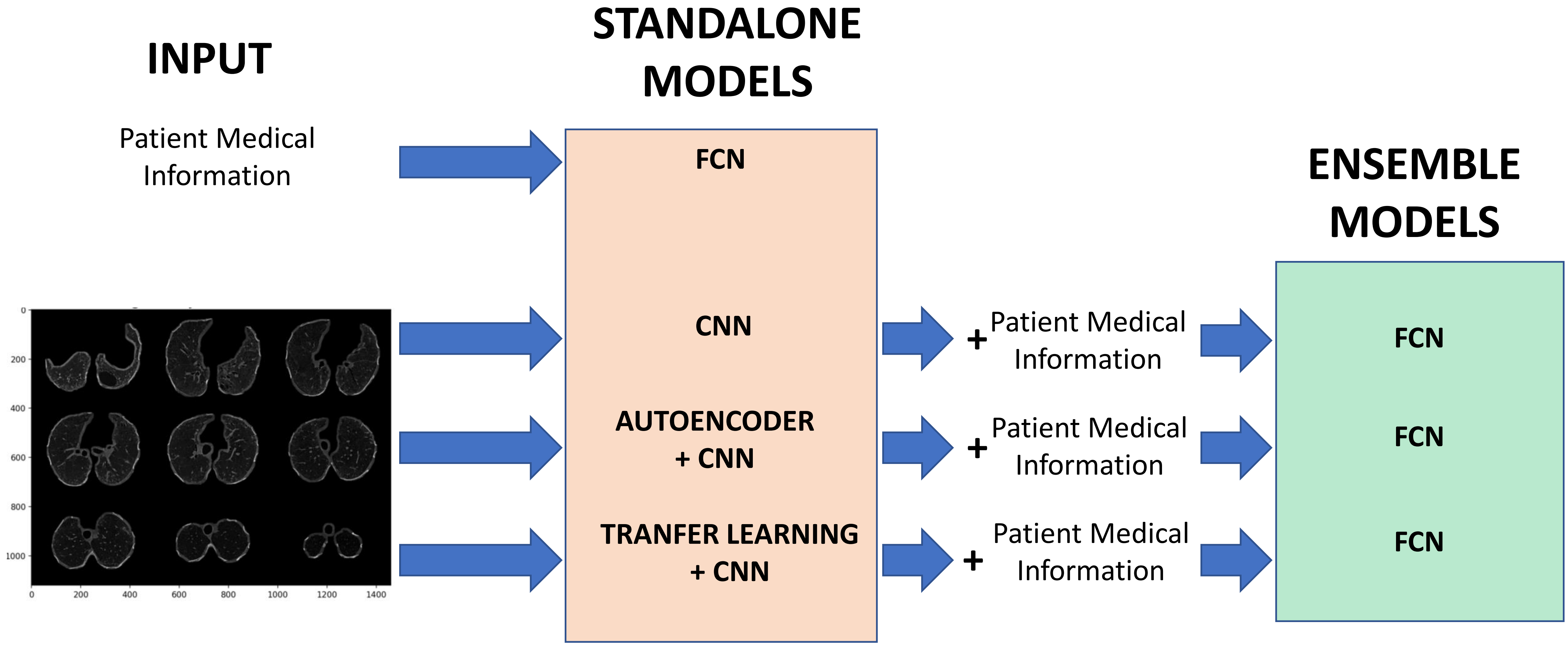
STEP 4: Use the baseline FVC values (1st measurement) to estimate the intercept of the fitting line

STEP 5: Calculate the future FVC values





Modeling – Slope Models



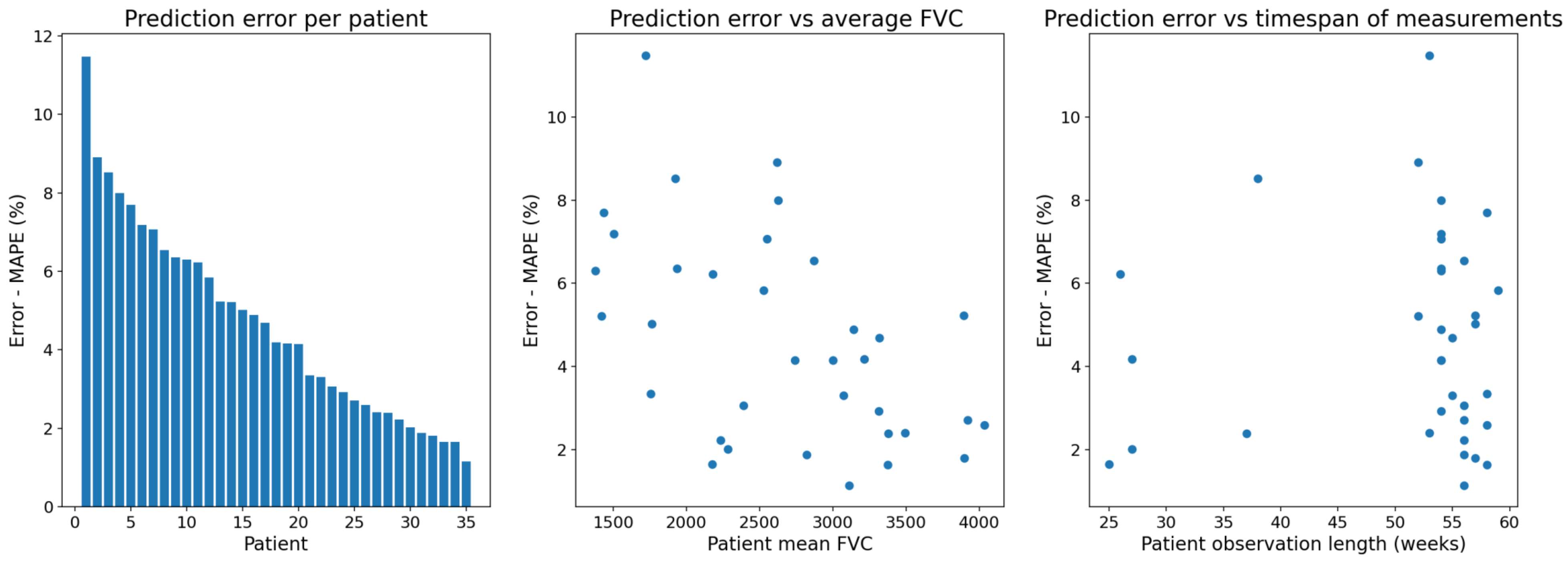
Modeling – Summary

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%****

BASELINE ERROR (average of FVC): 28.17%

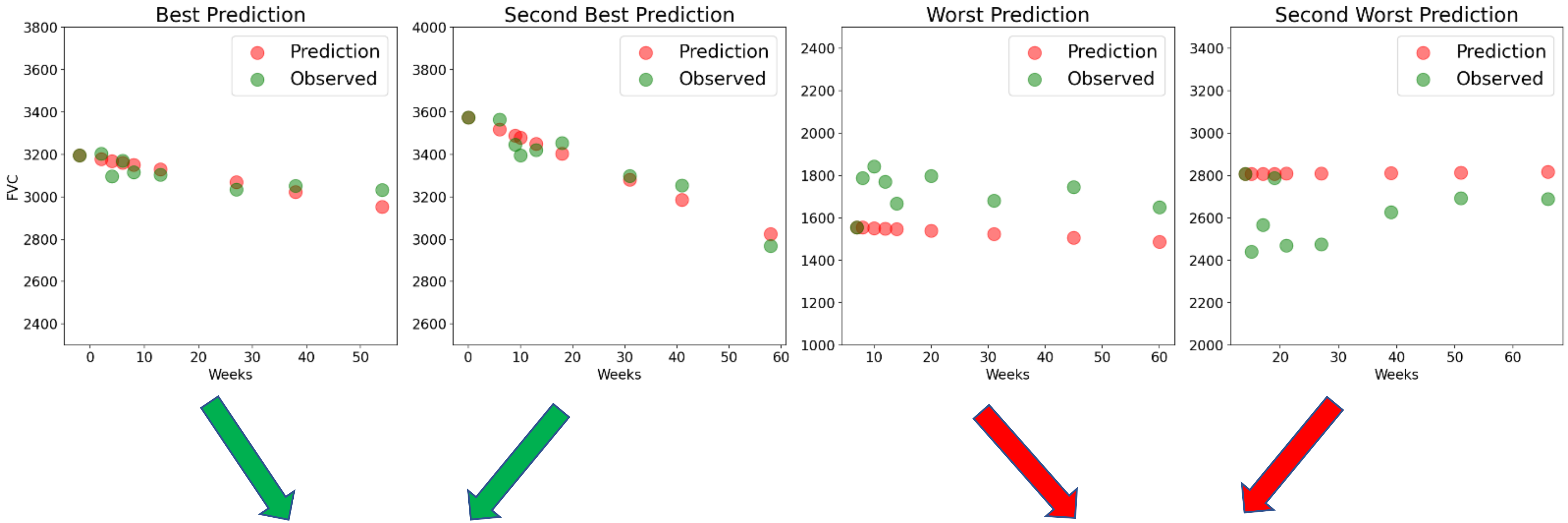
- Both patient medical data and chest CT images **contain key insights** for the prediction of the patient's lung capacity.
- Carving the images **does not consistently improve** the model performance.
- Normalizing the contrast on the images **improve the model predictive power only** when whole images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

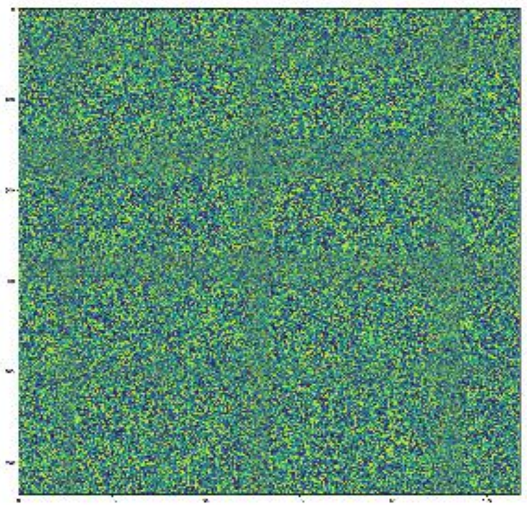
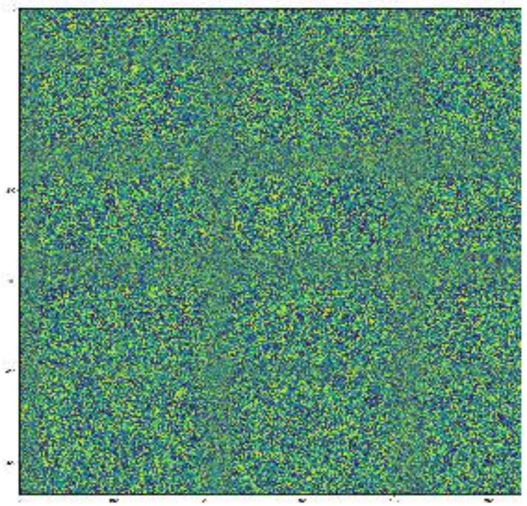
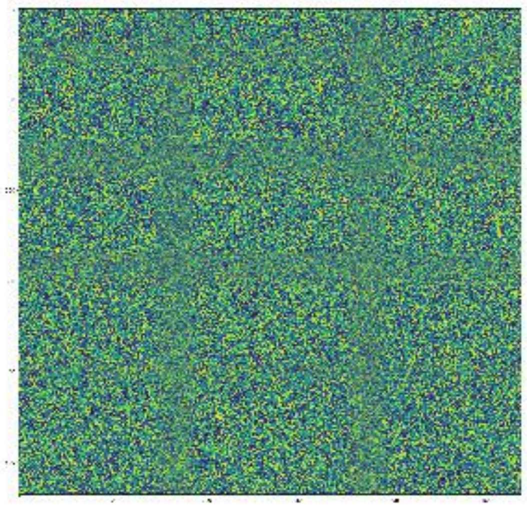
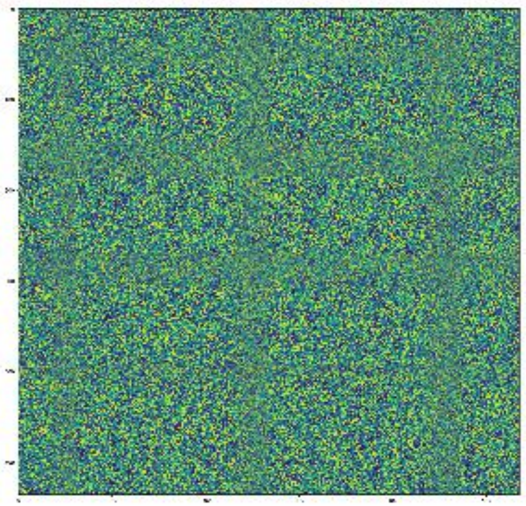


When the lung capacity of the patient changes linearly overtime, <u>the model performs well.</u>

When lung capacity changes drastically, <u>predictions are less accurate.</u>

Modeling – Feature maps of CNN1a

What does the model “see”?

String-like patterns $\xrightarrow{?}$ 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