PROGRESS PREDICTION
6° WEEK

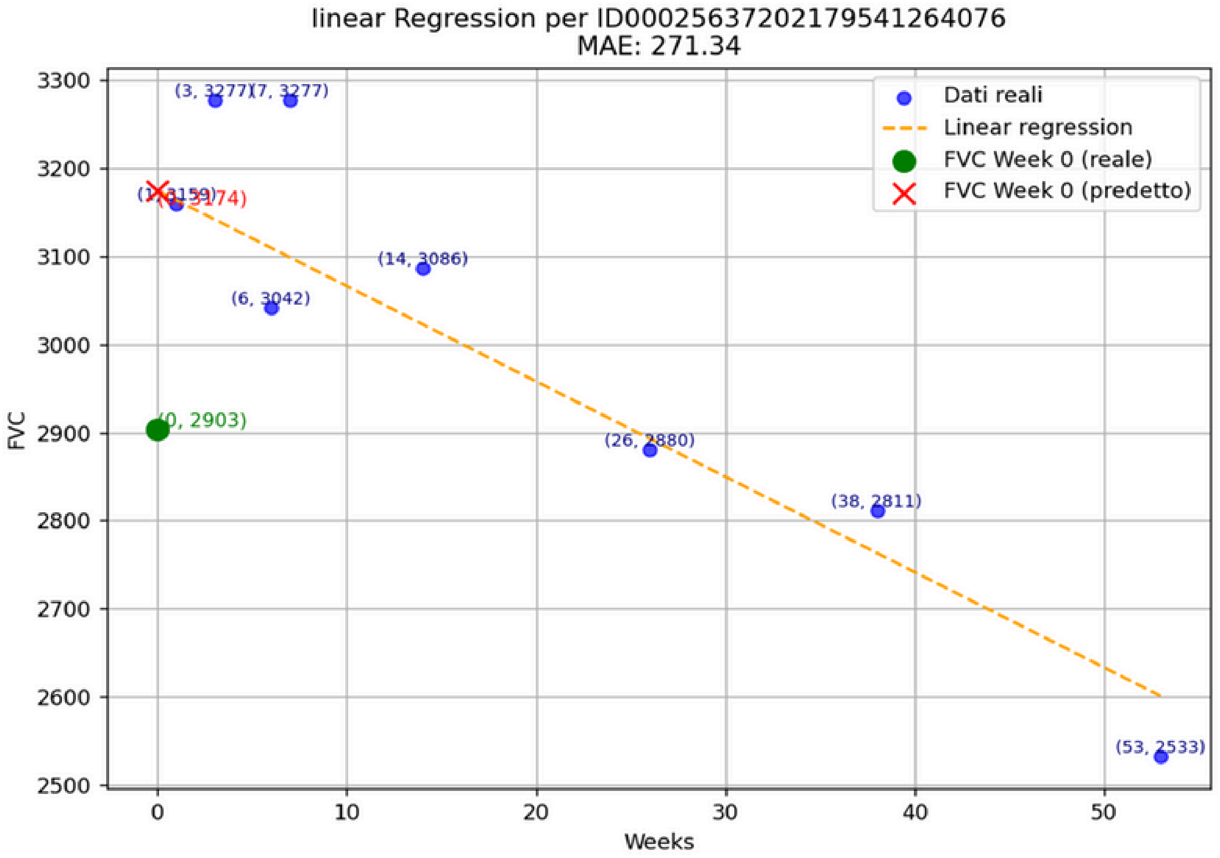
Baseline

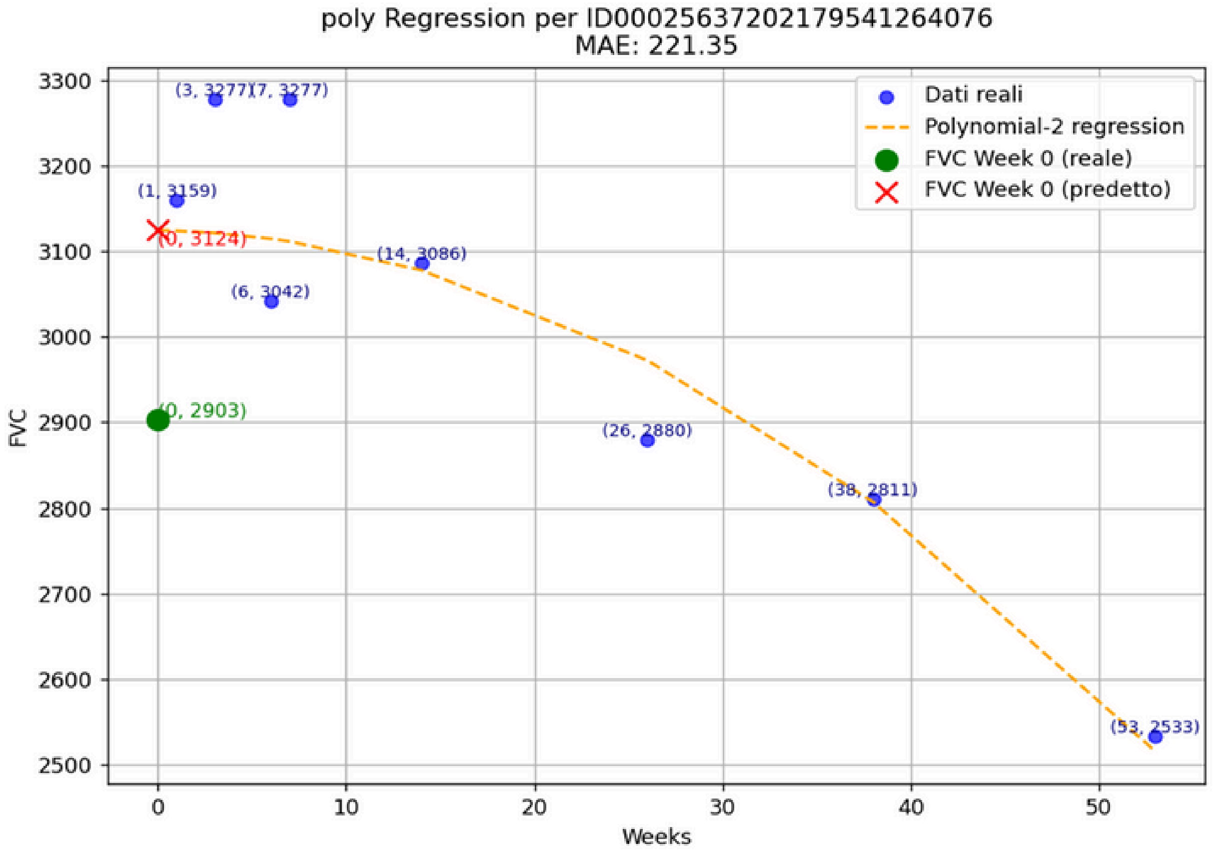
3 models:

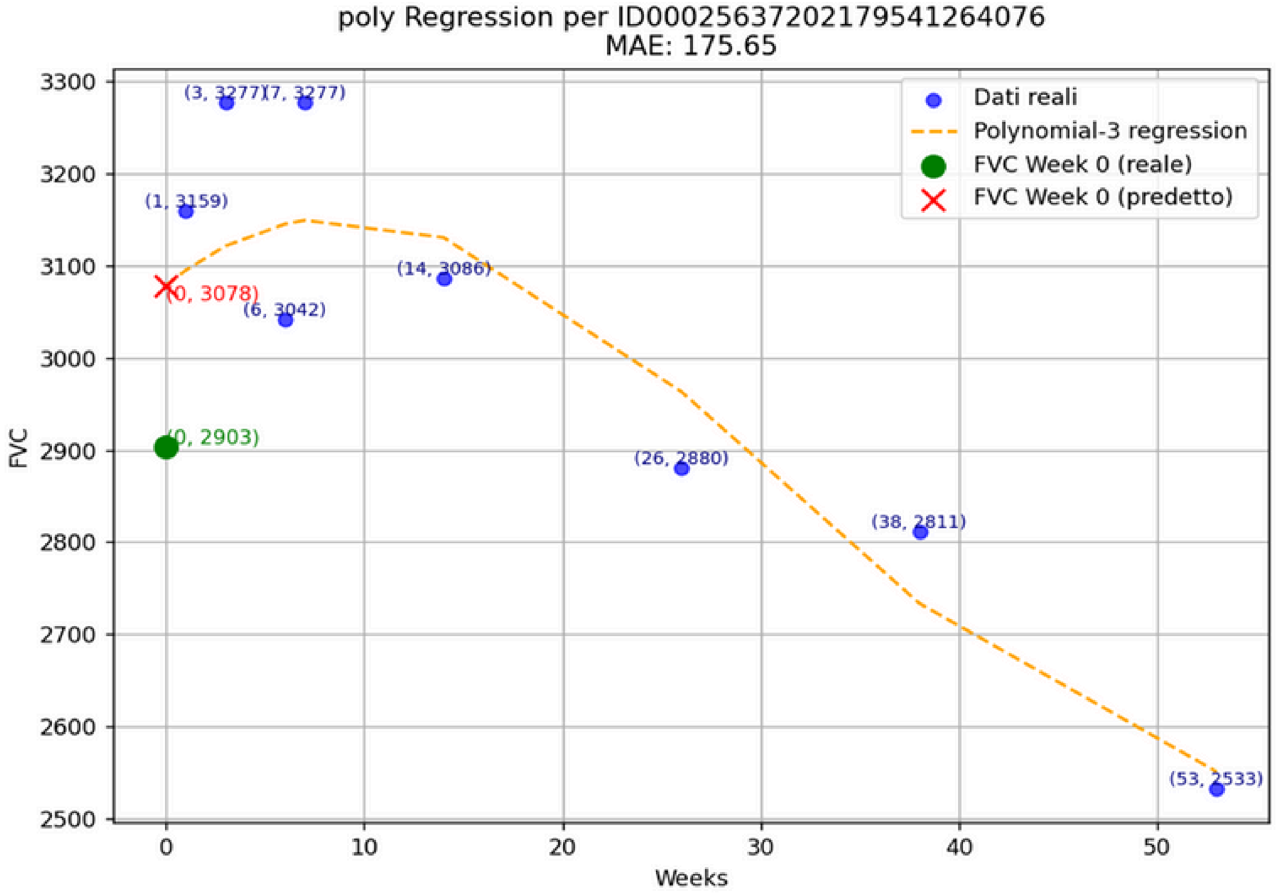
- **Linear Regression**
- **Polynomial regression (degree 2)**
- **Polynomial regression (degree 3)**

Metric (MAE)	Linear Regression	Polynomial 2	Polynomial 3
Average	127.62	93.95	**67.76**
Max value	557.10	359.04	**175.65**
Min value	**1.08**	2.27	6.88
Std	172.49	114.96	**60.51**
Median	**30.70**	32.08	41.26

Baseline comparison







Highlighting how data is nonlinear , therefore a cubic model approximates it substantially better than the linear one.

Feature Extraction

How are features extracted in Kaggle solution?

- 11 slices
- Chosen beween the 30% - 60%

Is it the best way?

Problem → Different number of slices for patient

- Low margin : 12 slices
- Upper margin : 1018 slices
- Average # slices : 187

Feature Extraction

Kaggle
Combination of handcrafted features + CNN extracted features

Extracted features (based on the kaggle solution) :

- SliceThickness (through metadata)
- PixelSpacing (through metadata)
- NumImgBw5Prec (number of slices between percentile)
- ApproxVol_30_60
- Avg_NumTissuePixel_30_60
- Avg_Tissue_30_60
- Avg_Tissue_thickness_30_60
- Avg_TissueByTotal_30_60
- Avg_TissueByLung_30_60

Feature Extraction

Possible adding of more features :

- **Mean, Median, Skew, Kurthosis, HAA of non zero pixels in image**
- **midMean, midMedian, midSkew, midKurthosis, midHAA of pixels in the largest CT slice of lung mask**

Mean → average value higher if fibrous tissue is present

Skew → fibrous lung is skewed to the right (normal lung to the left)

Kurthosis → peak of the low attenutaion pixels is much lower

HAA → high-attenuation area - percentage of lung voxels between -600 and -250 Hounsfield Units, associated to inflammation

Feature Extraction

In a discussion, it was highlighted:

- FVC highly correlated to age,height, sex

Possibility to add other informations like:

- Height → derived from age and gender assuming that in the competiton a european cohort had been diagnosed
- BMI → based on the chest circumference
- Chest circumference as standalone criteria

CNN

Use a pretrained model (EfficientNet/U-Net):

- **extract complex patterns from images**
- **concatenate handcrafted features**
- **Predict Radiological progression and FVC decline**
  - **Ground Truth?**
    - **Option 1 : From CNN predict FVC → % difference**
    - **Option 2: Leverage Survival Analysis ,without FVC prediction , just Event occured or not.**
      Example, if through data of patient decline %FVC > 10% that patient signed as progressed → Event = 1 , so correlate features toif the Event happens or not (Bad for %FVC decline)

CNN

In one proposed solution:

- Use of Concatenate Tile Pooling method, instead of assigning labels, like FVC decay and confidence to each CT layer, assigned to all images together
- Concatenate Tile Pooling extracts from each image one portion and then concatenates with the others extracted
- Avoid using 3D models as we have different spacing between slices
- Trained on masked lungs only and then finetuned on original images

CNN

Loss → Leplace Log Likelihood

Used the following:

FVC = V0*(0.01*a*(w-w0)/134 + b + 0.01*p0)

sigma = V0*softplus(c*w/134 + d)

where a,b,c,d are model predictions

V0 is the full lung volume computed as V0 = 100*FVC/percent