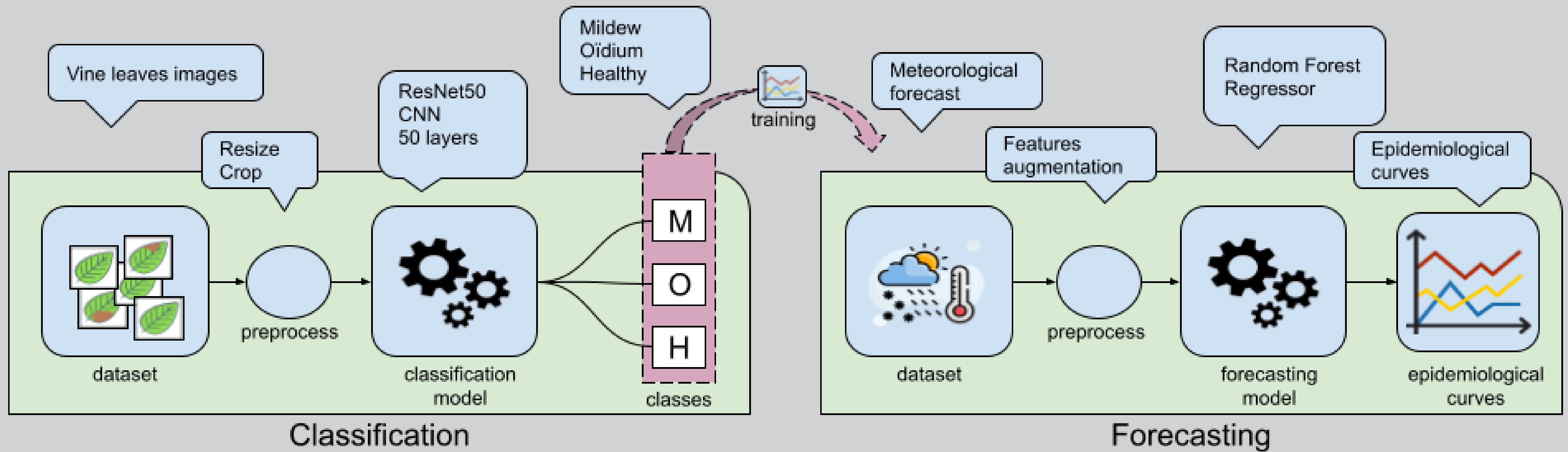


### INTRODUCTION

**Context** Vine cultures have been increasingly targeted by Oïdium and Mildew fungi with the intensification of viticulture on Swiss lands. Therefore, optimizing the treatment of these two diseases is of great economic importance for wine growers. One axis of improvement is the forecasting of outbursts and spreading of those diseases.

**Objectives** To do so, this project consists in the implementation of two models. The first one is aiming at classifying pictures of leaves as either Healthy, contaminated by Oïdium or by Mildew. Those results can then be used as training set for the second model which is forecasting outbursts and the evolution of the diseases, based on weather data.

### MODELS



### METHODOLOGY (CLASSIFICATION)

**Dataset** 9345 labeled pictures of vine leaves

- Healthy : 5555
- Mildew : 136
- Oïdium : 3654

**Training** 80% of the labeled images are used to train different models. Evaluate each of them with 20% of the data .

**Architectures [Pretrained]**

- ResNet 18, 50, 151
- VGG 16, 19
- DenseNet 121, 201

**Other variations [Off/On]**

- Background removal
- Weighting the loss
- Fine tuning (last layer only)

### METHODOLOGY (FORECASTING)

**Dataset** The Forecasting dataset is made of Epidemiological samples:

- Oïdium : 40 samples
- Mildew: 120 samples (additional dataset)

**Training** Epidemiological curves are generated from the leaves (one sample per day) and two models are trained on those curves.

**Technics**

- Feature augmentation (previous days)
- Active learning (pseudo-labeling)
- Grid-search for hyperparameters optimization

### RESULTS (CLASSIFICATION)

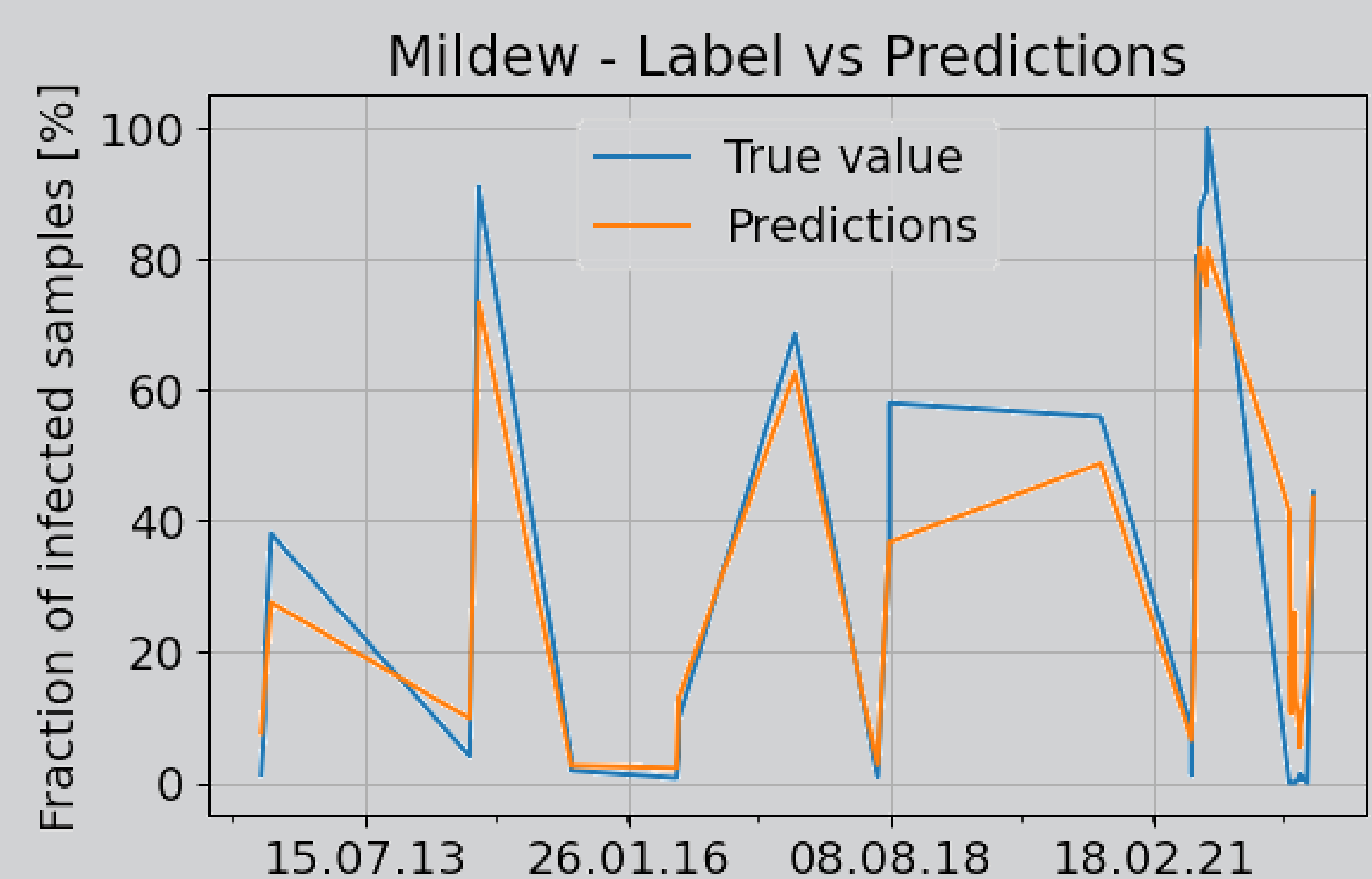
Best Model	
Parameter	Choice
Pretrained model	ResNet50
Background removal	No
Loss weights	No
Fine tuning	No

Class	Support	Metrics		
		Precision	Recall	F1-Score
Healthy	1104	0.87	0.91	0.89
Mildew	26	0.15	0.58	0.24
Oïdium	743	0.89	0.75	0.82
<b>W. avg</b>	-	<b>0.87</b>	<b>0.84</b>	<b>0.85</b>

### RESULTS (FORECASTING)

**Best hyper-parameters:**

- 14 previous days parameters for features augmentation
- 100 estimators (trees).



### CONCLUSION

Globally, the two models responded well to the training and their future utility in concrete cases seems realistic. However, there performances could be improved by adding more samples to the dataset. More specifically, the classification dataset needs more Mildew samples in order to be better balanced and the Forecasting dataset size is not big enough since the number of epidemiological samples is equal to the number of sampling days. This problem could be easily solved by doing more sampling on periods with the adequate meteorological conditions to its spreading.

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