Solar Nowcasting Systems Using AI Techniques

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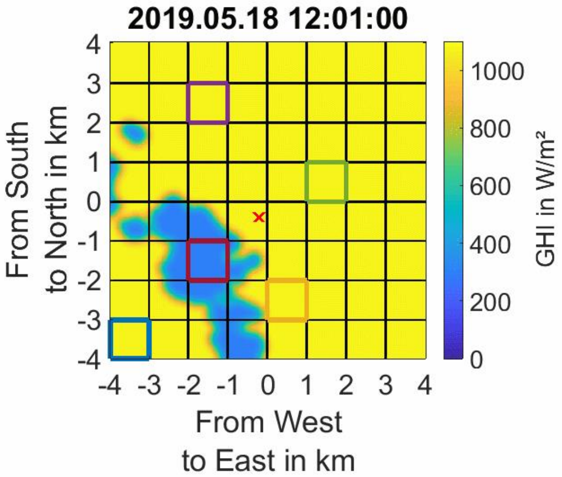
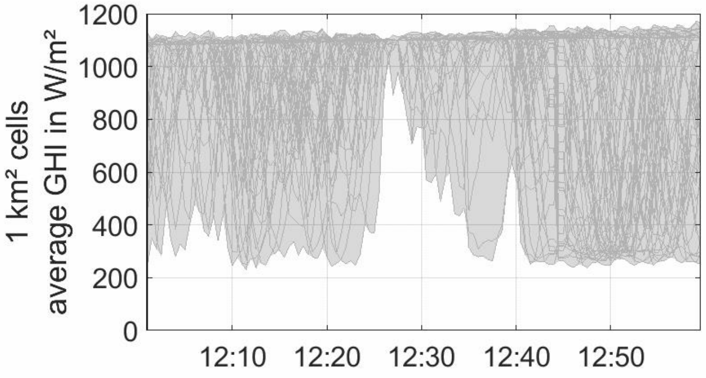
Motivation

Motivation



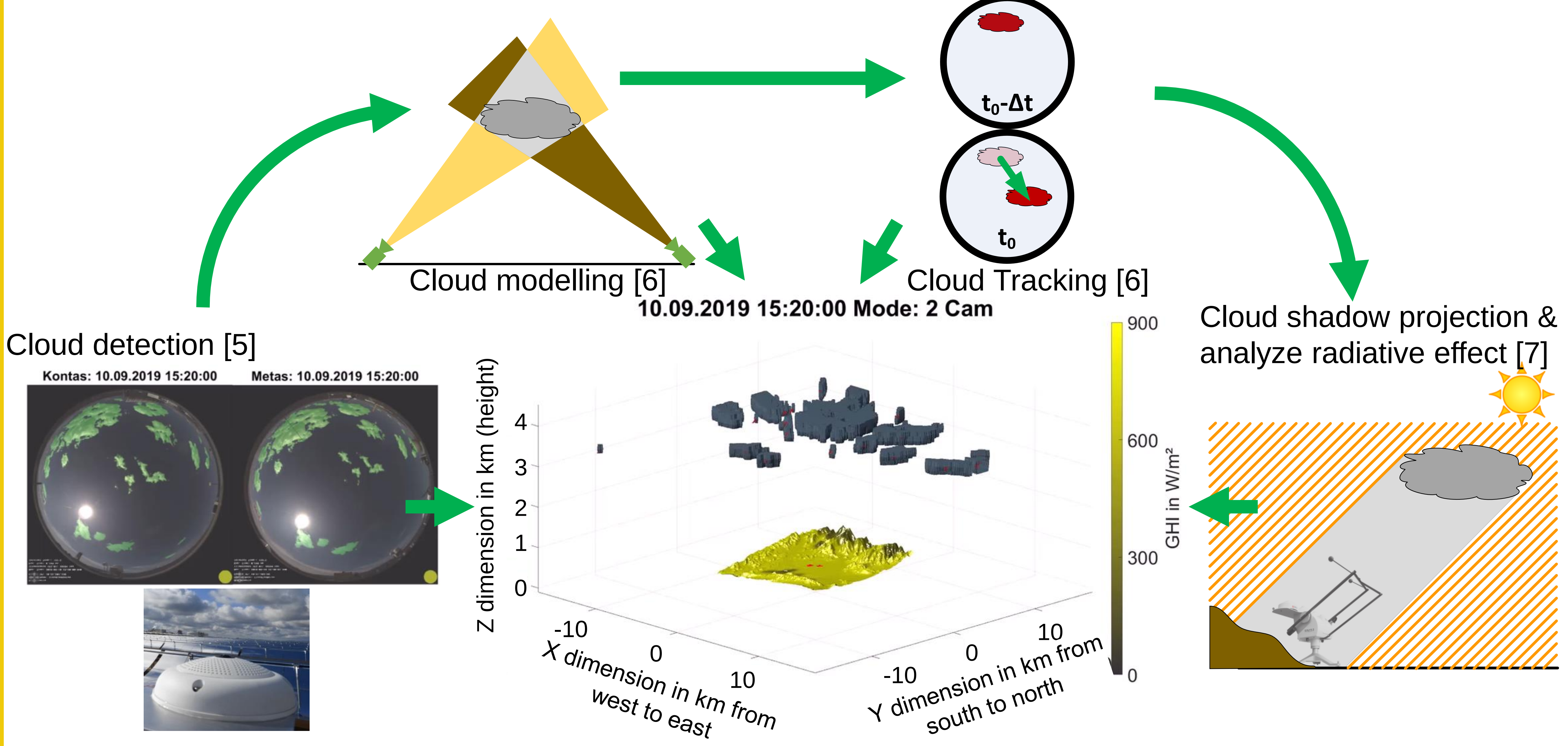


- Why ASI-based nowcasting?
  - Highest variabilities of irradiance on local scale in space and time due to cloud passing
  - Local observations enable irradiance forecasts in high temporal and spatial resolutions
  - Improved situational awareness helps solar power plant and local grid operators to minimize costs and risks (e.g. power plant/solar field control, less curtailment, cheaper balancing, extended battery life,…) [1,2]

- Why using ML for nowcasting?
  - Deep learning has proven to outperform previous state-of-the-art techniques in many computer vision problems [3]
  - ML techniques are widely used in various forecasting problems [4]

Introduction to all sky imager-based nowcasting

Introduction to all sky imager-based nowcasting



Machine learning methods for improving ASI nowcasts – Part 1

Machine learning methods for improving ASI nowcasts

Sky images

Cloud detection

Cloud modelling

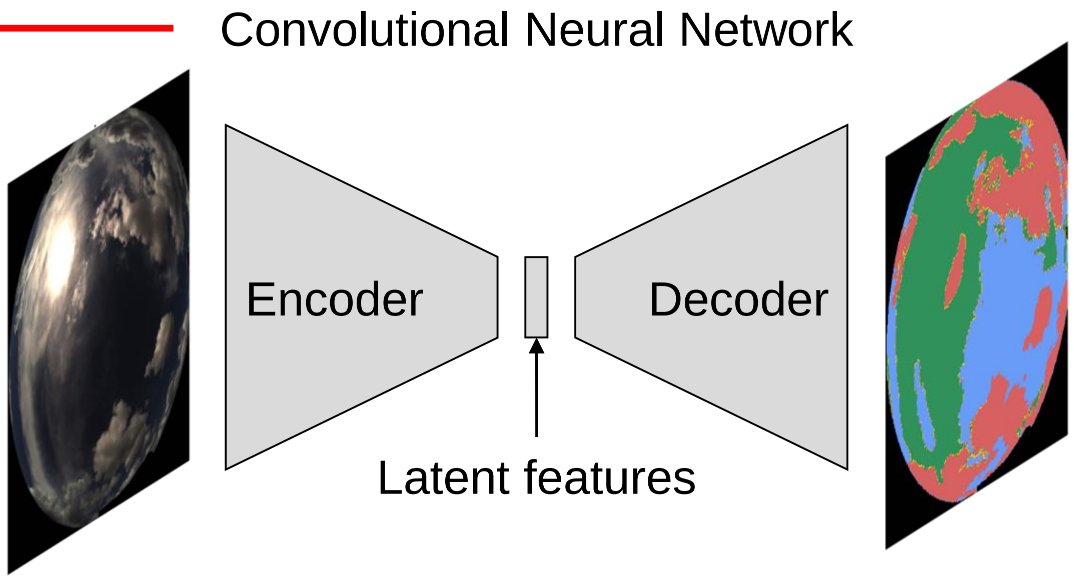
Cloud tracking

Shadow projection

Allocation of cloud transmittance

Irradiance nowcast

- **Option 1: Apply ML to solve individual steps in processing pipeline**
  - E.g. Cloud detection using a Convolutional Neural Network (CNN) for semantic segmentation (pixelwise classification)

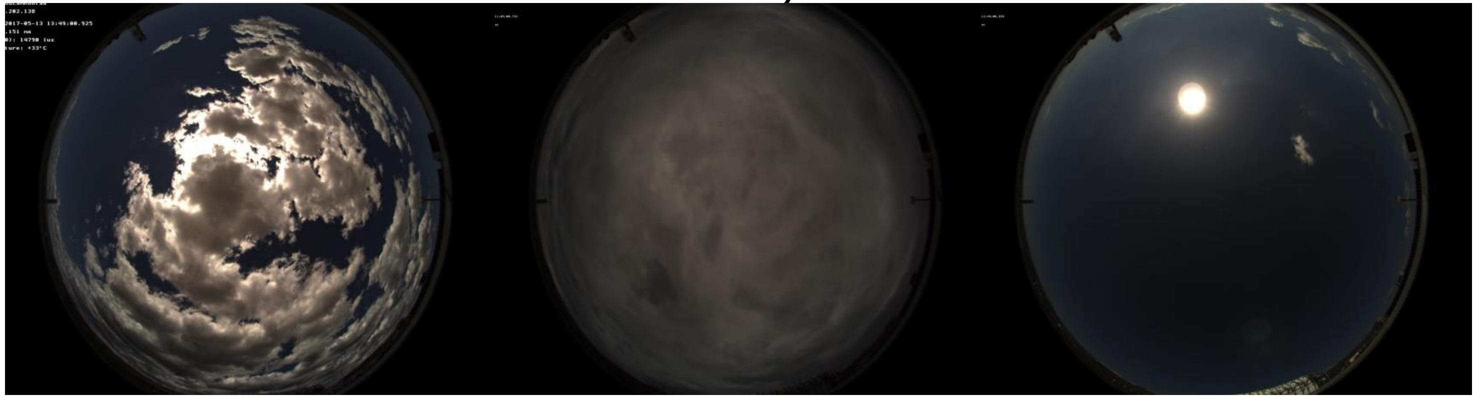


ML-based image segmentation for cloud detection

- **Cloud detection in all-sky images poses a challenging task:**
  - Variable spatial distribution and size
  - Atmospheric conditions and oversaturation of pixels in vicinity of the sun influence visual appearance
  - Distortion effects of fish-eye lens and decreasing resolution towards horizon
  - Multi-layer conditions with high visual similarity of individual layers

➔ Deep learning-based methods proven to handle these challenges best [17], but how to train these models?

Low-layer

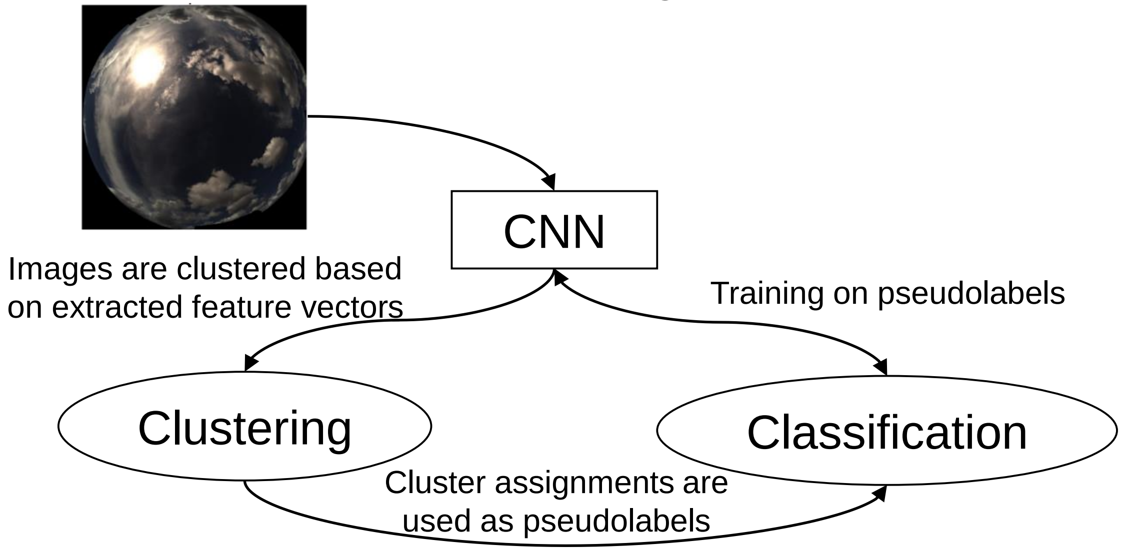


Low-layer | Mid-layer | Low- & Mid-layer

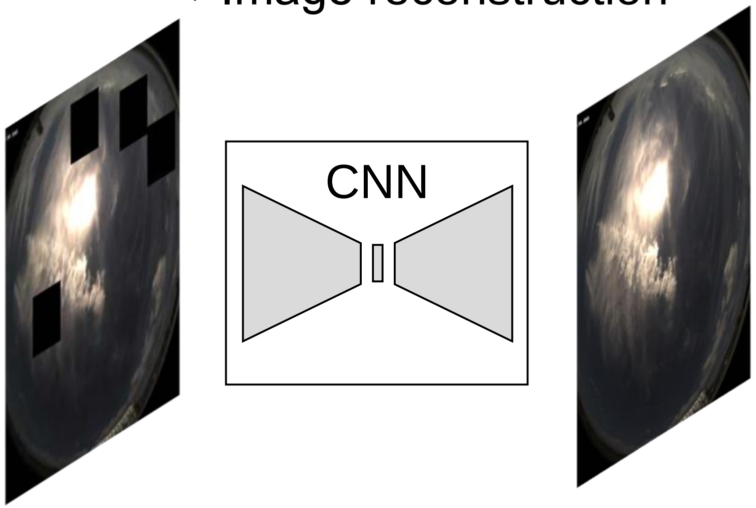
ML-based image segmentation for cloud detection

- Quality of a ML model strongly depends on the amount and quality of data used for training
- Manual creation of segmentation masks is time consuming (770 images from PSA[1] manually annotated)
  → More data could help to increase performance but is infeasible on large scale (>10000)
- **Alternative**: Apply self-supervised learning to enable the model to extract relevant information (latent features) for segmentation
  → Model solves pretext task based on pseudolabels generated from the data itself, e.g.:

Deep Cluster [10]
Alternation of clustering/classification



Inpainting – Superresolution (IP-SR) [8,9]
→ Image reconstruction

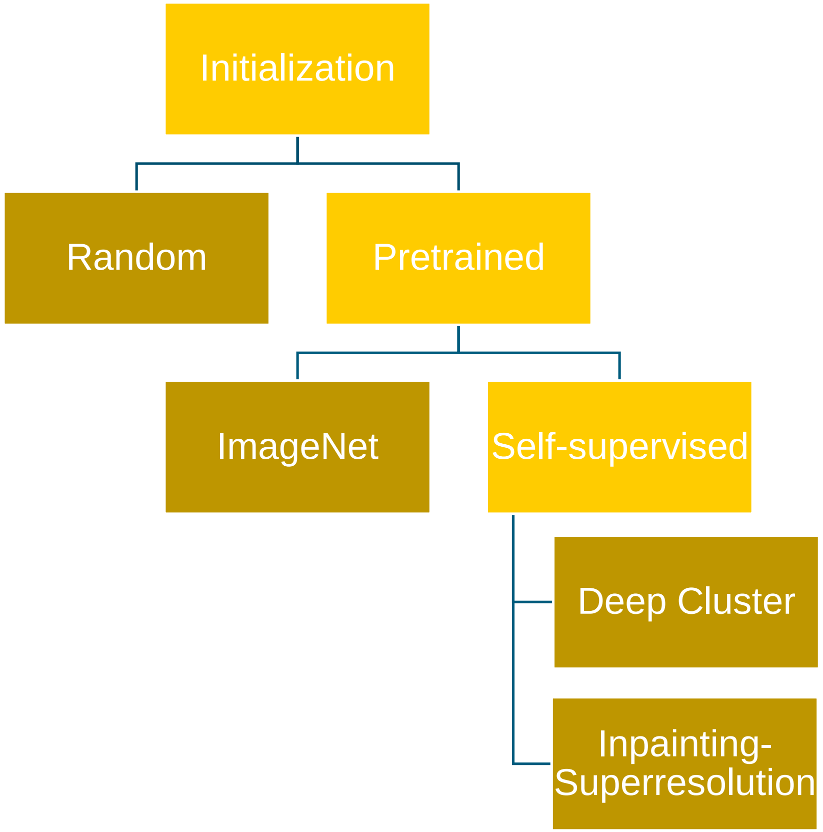


[1] Plataforma Solar de Almería, southern Spain, owned and administrated by CIEMAT

ML-based image segmentation for cloud detection

Evaluation of semantic segmentation by comparing 4 different model initializations [5]

- 4 classes: sky, low-/mid-/high-layer cloud
- Training on 616 images
- Validation on 154 images
- Implemented in python‘s fastai library [11]

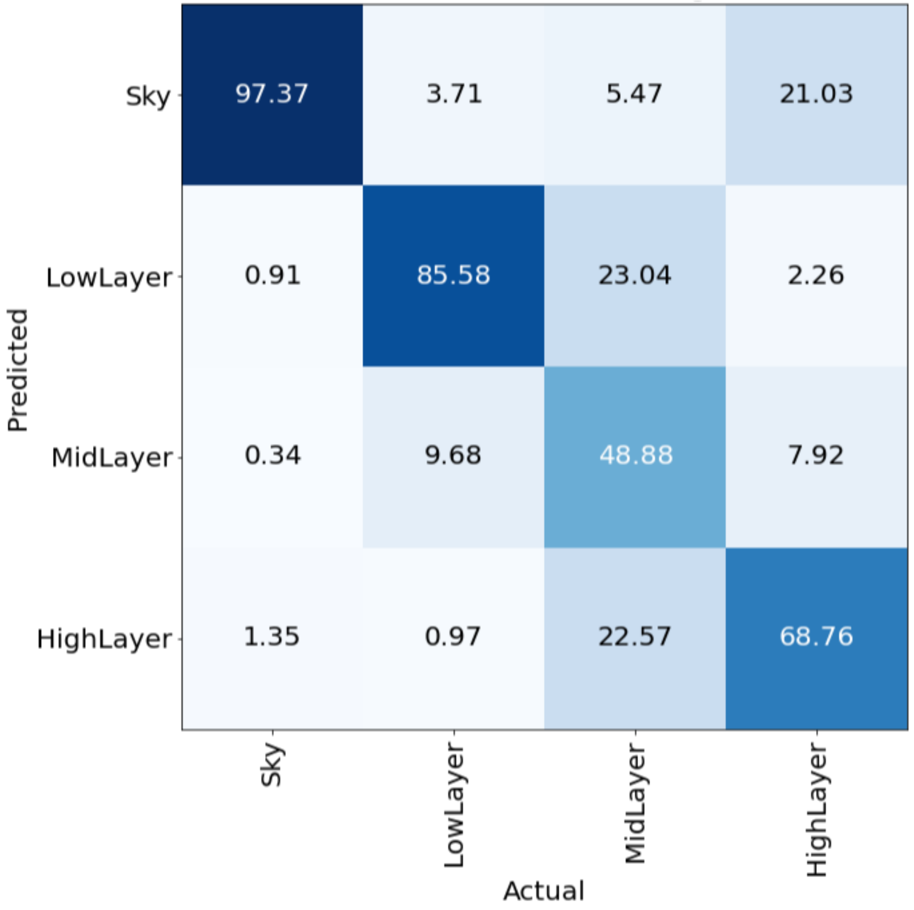


Pixel Accuracy = $\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i + TN_i}{NumPix}$

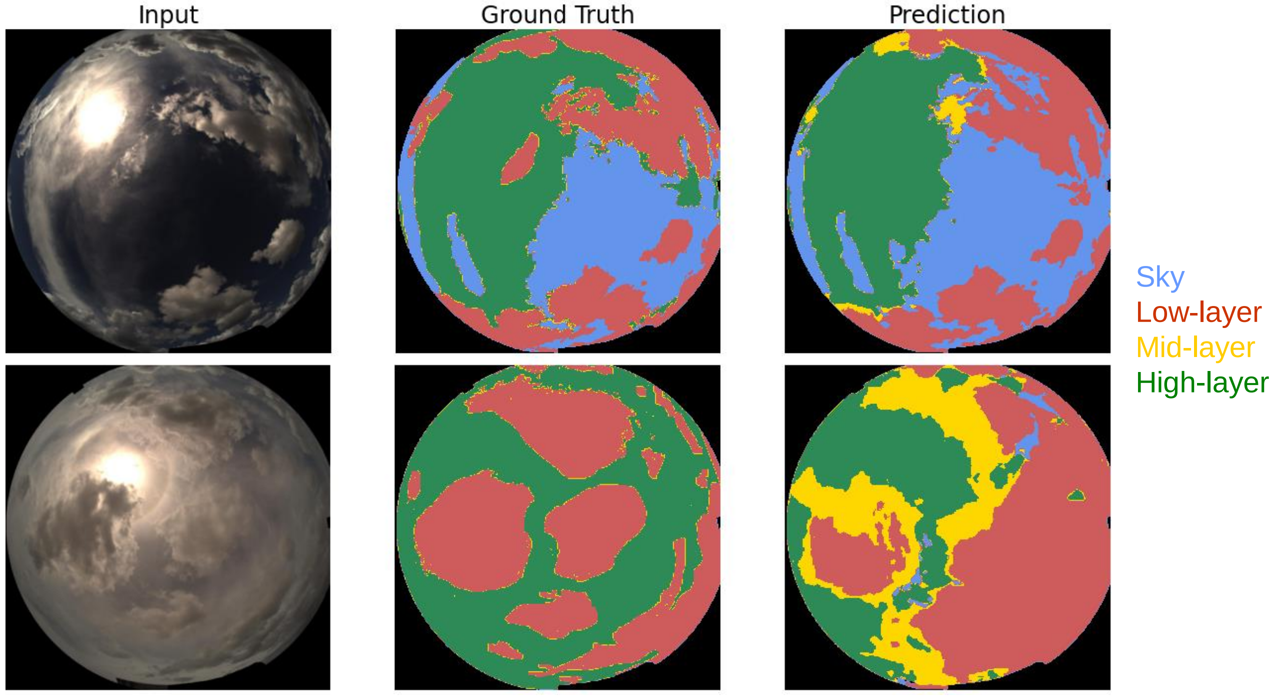
	Random	ImageNet	IP-SR	DC
Accuracy [%]	78.3	82.1	**85.8**	85.2

ML-based image segmentation for cloud detection

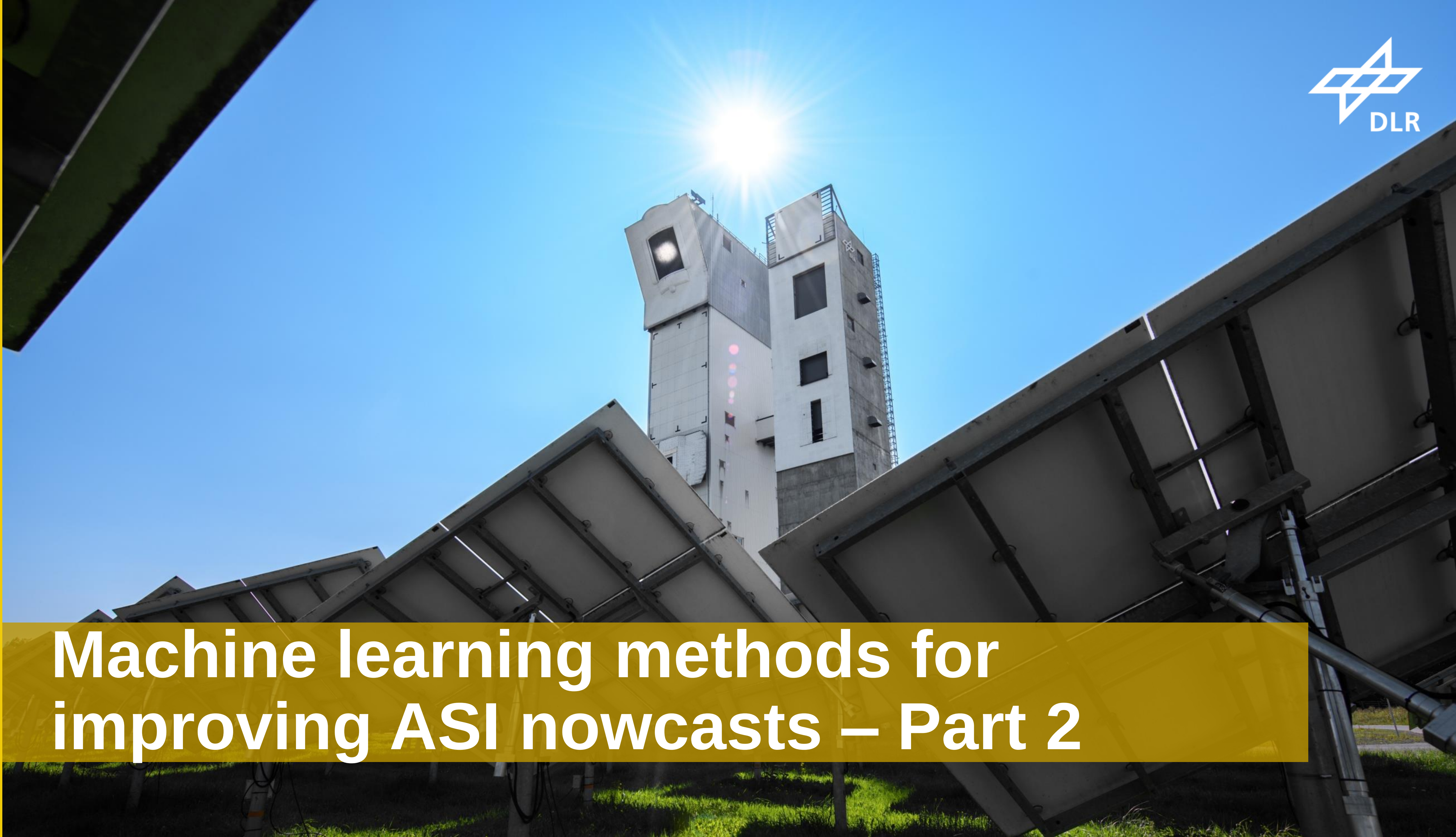
Classwise accuracy of Inpainting-Superresolution initialization [%]



Examples of cloud-layer detection



- Confusions mostly between adjacent cloud layers
- **95.2%** accuracy on binary segmentation outperforming previous non-ML segmentation approach by over 7% points



Machine learning methods for improving ASI nowcasts – Part 2

ML methods for improving ASI nowcasts

Sky images → Time series data

Cloud detection

Cloud modelling

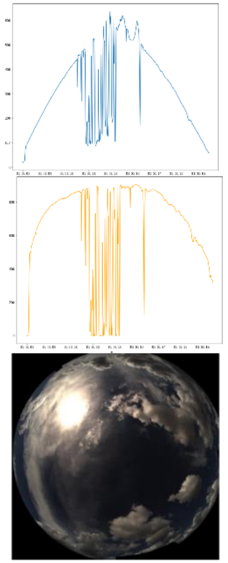
Cloud tracking

Shadow projection

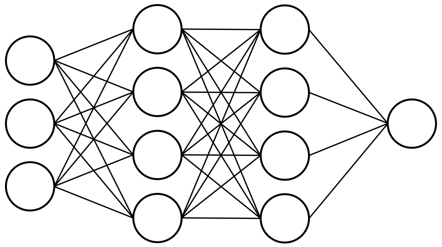
Allocation of cloud transmittance

Irradiance nowcast

- **Option 2: Use ML models to generate nowcast from raw data**
  - ML models are trained on large amounts of observations or features extracted from observations to learn patterns in the data



(Feature Extraction)

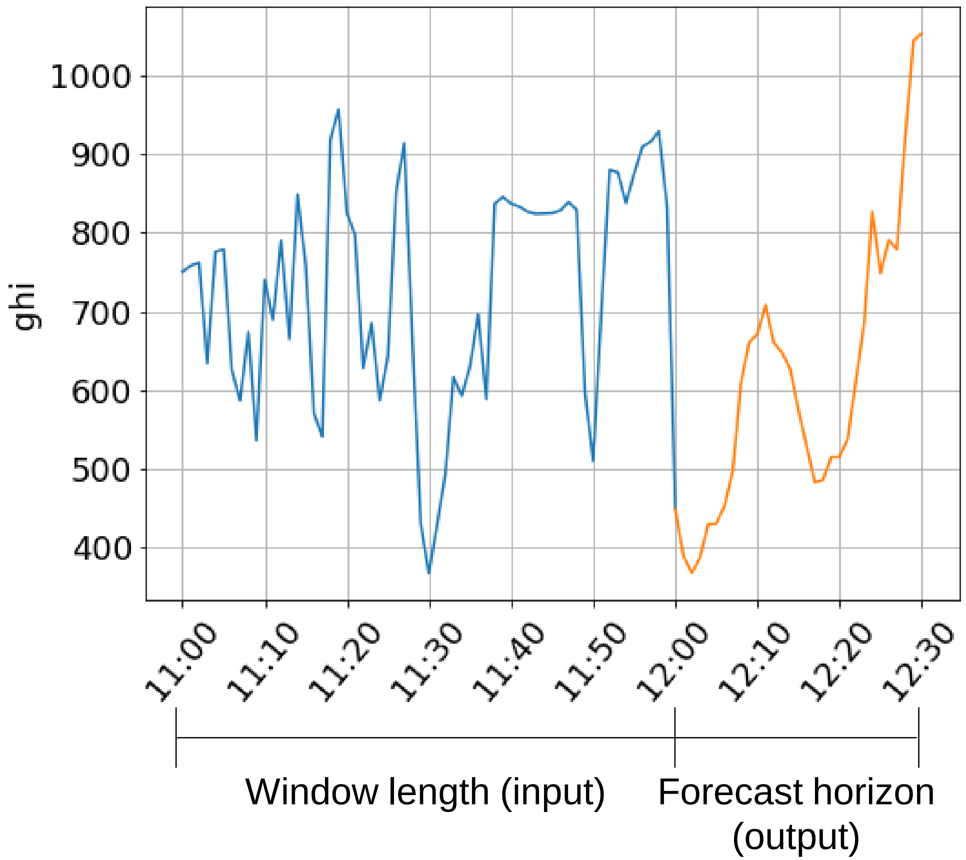


Irradiance nowcast

ML-based time series forecasting for ramp detection

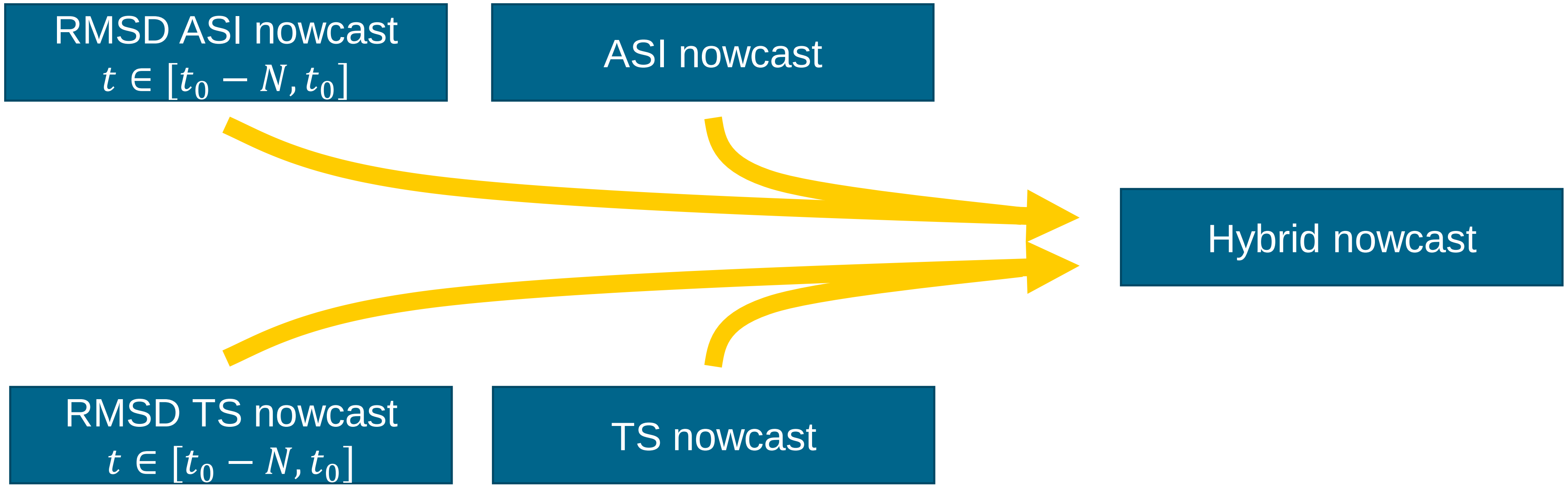
- Possible features for forecasting irradiance:
  - Irradiance measurements: GHI, DNI, DHI
  - Sun azimuth/elevation
  - Weather data: temperature, pressure, Linke turbidity
  - Image data (e.g., cloud coverage)
- 120 days of diverse conditions selected for evaluation
- Analysis of combination of different model hyperparameters and feature sets using tsai library (python) [12]

- Architecture: LSTM
- Window length: 30 min
- Forecast horizon: 20 min
- Feature set: GHI, DNI, DHI, sun elevation, sun azimuth



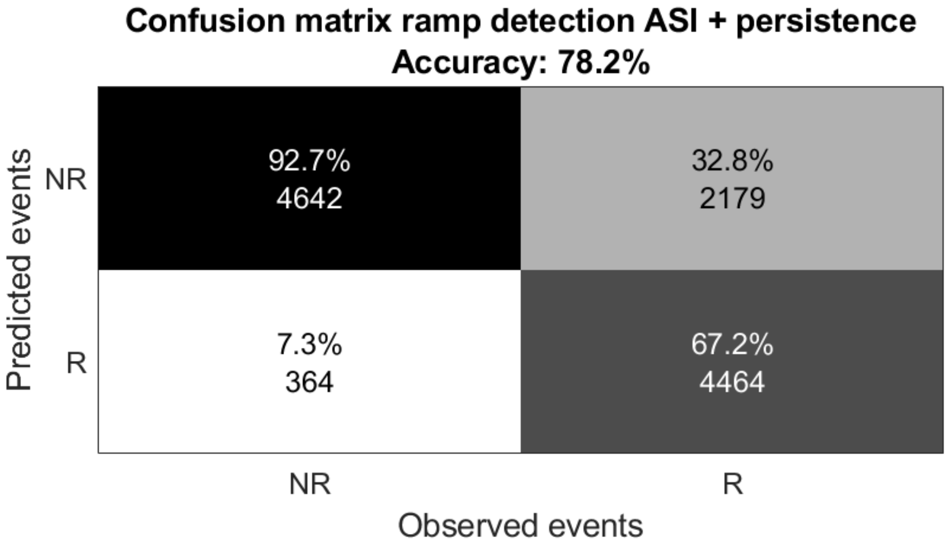
ML-based time series forecasting for ramp detection – Combination with ASI-Nowcasting System

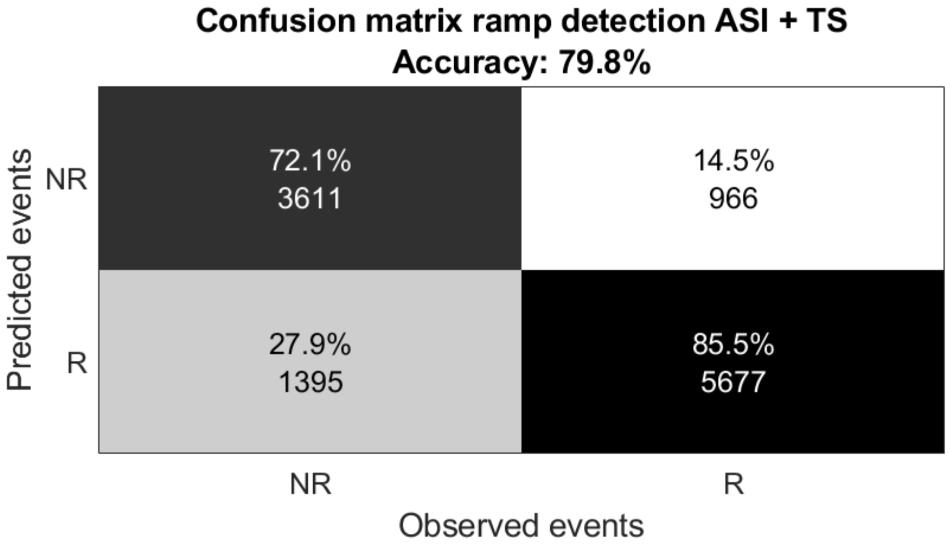
- Combination of physically-based nowcast (ASI) and persistence/time series (TS) nowcast by weighting of RMSD of previous N predictions [13]



ML-based time series forecasting for ramp detection – Combination with ASI-Nowcasting System

- Point-wise evaluation of ramp events [14]:
  - Ramp: Change of normalized irradiance between two points in time exceeds threshold
  - Ramp event: At least one ramp within fixed time horizon (20 min)





- Improved detection of true ramp events for hybrid TS model while increasing the number of falsely detected ramps
  → Fluctuations in irradiance are predicted more frequently
- Same data set as the one used to evaluate various ASI nowcasting systems at PSA [13, 14] allows system comparison
- Advantage ASI system: Areal information of irradiance allows to adjust ramp detection by looking for ramps within irradiance map which further improves the ramp prediction

Summary

Summary

- ML methods can improve forecasting/nowcasting systems by:
  - Replacing other methods for individual tasks of complex physically-based systems (e.g., segmentation)
  - Generating forecasts soley based on measurement data
- New ML techniques as self-supervised pretraining offer great potential for dealing with limited labeled data in computer vision problems
- ML is a fast and efficient tool for time series forecasting and can be combined with other models (e.g., physically-based) to improve the overall performance

Thank you! Questions?

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Impressum

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