Advances in Machine Learning–Based Cloud Detection from IASI Observations

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Machine Learning technique [1,2,3]

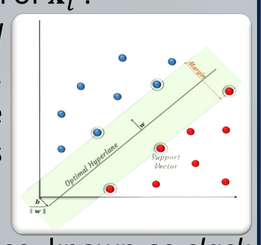
SVM (Support Vector Machine)

The *SVM method* is based on the principles of optimization theory, convex analysis, and linear algebra. This class of algorithms is also used in the case of non-separable data. In this case, the technique, called the *kernel method*, exploits a function, known as a *kernel function*, which transforms the input data into a higher-dimensional *feature space*.

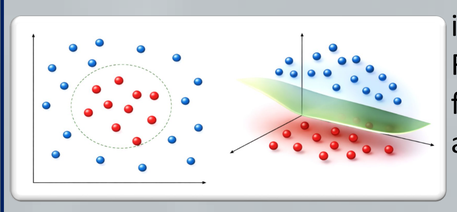
Let:

- $\mathbf{x}_i$ for $i = 1, \dots, l$ is a set of training points, $\mathbf{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_l\}$ represents the measurements (*IASI spectra*).
- y_i for $i = 1, \dots, l$ with $y_i = 1$ (clear) or $y_i = -1$ (cloudy); $\mathbf{y} = \{y_1, \dots, y_l\}$ represents the "truth" values associated with $\mathbf{x}$ and y_i identifies the classification of $\mathbf{x}_i$.

Separable data: there exists an *optimal hyperplane* such that the two data classes, distinguished by their truth values, are included in two different half-spaces separated by the hyperplane.



Non-separable data: by adding new variables, known as *slack variables*, with additional constraints, and using the *kernel method* to map the data into feature space, it is possible to obtain an optimal hyperplane, similar to the case of separable data.

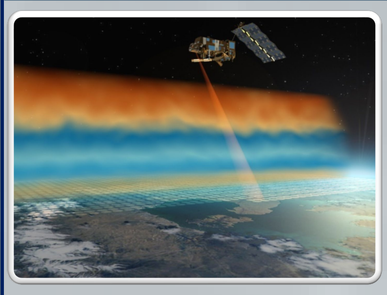


Kernel function

in our case, the Kernel Function is a polynomial function K, of degree q, applied to $\mathbf{X}$

$$K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i \cdot \mathbf{x}_j + 1)^q.$$

IASI instrument [4]



The *Infrared Atmospheric Sounding Interferometer* (IASI) is an instrument onboard the Metop series of satellites.
These measurements are crucial for weather forecasting and climate changing prediction.

The *IASI L1c product* contains infrared radiance spectra at $0.25\ \mathrm{cm}^{-1}$ sampling. The product has, for each sounded pixel, 8461 spectral samples covering the range between $645\ \mathrm{cm}^{-1}$ and $2760\ \mathrm{cm}^{-1}$ wavenumbers.

Variables extracted from L1c IASI product

- '`measurement_date`' – scan date;
- '`lat`' – latitude of scan;
- '`lon`' – longitude of scan;
- '`gs_1c_spect`' – radiance spectra;
  (It is necessary to use the scaling factors to reconstruct spectra in the range of given wavenumbers)
- '`geum_avhrr_1b_cloud_fraction`' – cloud fraction.

ERA5 reanalysis database [5]

The *ERA5* reanalysis database combines model data with observations from different instrument into a consistent dataset. Data has been regridded to a regular latitude-longitude grid with spatial resolution of *0.25° x 0.25°* .

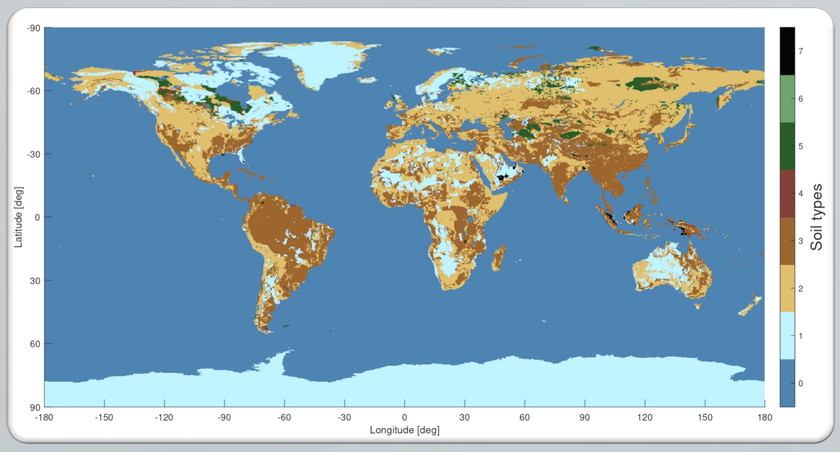
Variables extracted from ERA5 database:

- '`latitude`' – latitude of ERA5 grid point;
- '`longitude`' – longitude of ERA5 grid point;
- '`soil type`' – the texture (or classification) of surface.

The eight *Surface Types* are:

0 – Water	*4* - Fine
1 - Coarse	*5* - Very fine
2 - Medium	*6* - Organic
3 - Medium fine	*7* - Tropical organic

Surface Types from ERA5 database



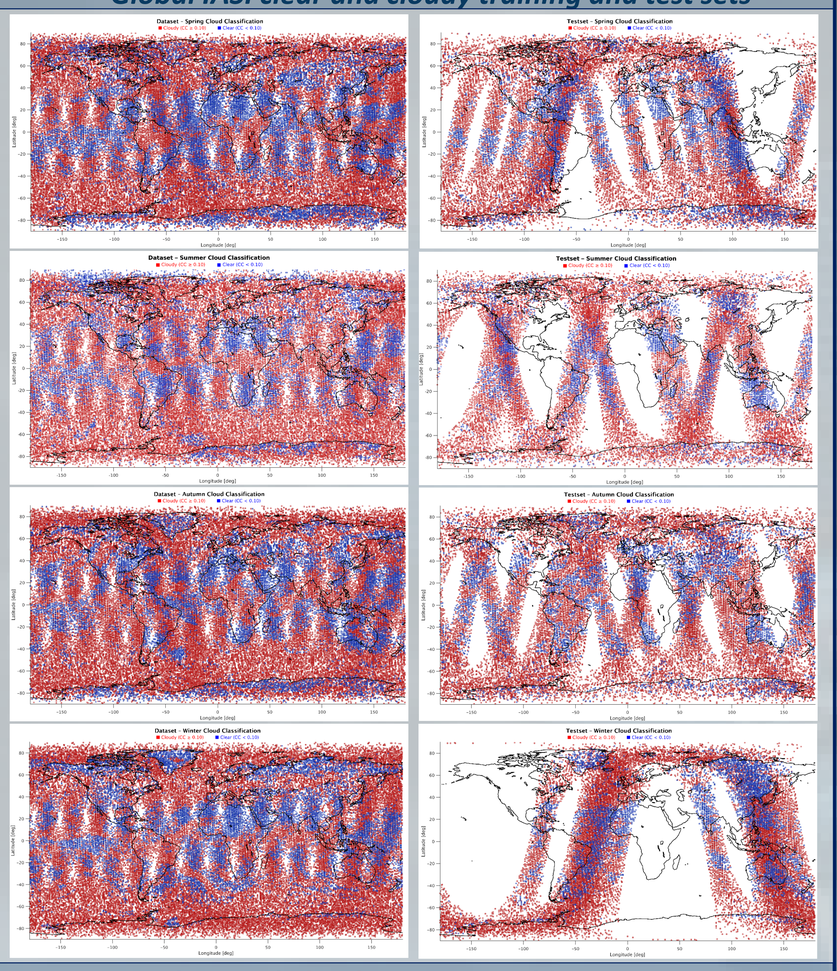
IASI data

Training Sets — *IASI Orbits*	*Test Sets* — *IASI Orbits*
Spring: N. 16 Orbits March/April 2023	*Spring:* N. 8 Orbits March 2020 April 2021
Summer: N. 16 Orbits June/July 2023	*Summer:* N. 8 Orbits June 2020 July 2021
Autumn: N. 16 Orbits Sept./October 2023	*Autumn:* N. 8 Orbits September 2020 October 2021
Winter: N. 16 Orbits Dec. 2023/Jan. 2024	*Winter:* N. 8 Orbits December 2020 January 2021

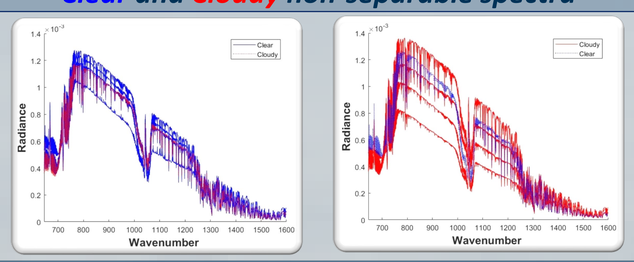
Selected IASI measurements for training set and test set

- For each IASI pixel, a Surface Type is associated using the nearest ERA5 grid point;
- IASI pixels with *cloud fraction<10%* coverage were selected as clear cases;
- IASI pixels with *cloud fraction≥10%* coverage were selected as cloudy cases;
- in the spectral range of IASI $[645; 2760]\ \mathrm{cm}^{-1}$, *different custom range or channels* was selected.

Global IASI clear and cloudy training and test sets



Clear and Cloudy non-separable spectra



SVM applied to IASI measurements

To create a method that works for any geolocation:

1. *Different training sets were created for each surface type and compared with the test sets using the SVM technique.*
2. *The training sets for each surface type were further subdivided in two different ways to reduce the dimensionality.*

SVM Classification Results

Total Training and Test Sets

SURFACE TYPE	N. training sets	N. test sets	SURFACE TYPE	N. training sets	N. test sets
0	~ 650000	~ 300000	*4*	~ 35000	~ 15000
1	~ 130000	~ 66000	*5*	~ 600	~ 250
2	~ 100000	~ 50000	*6*	~ 8000	~ 4000
3	~ 35000	~ 20000	*7*	~ 600	~ 350

High Test Results

Global Dataset + PCA channel selection

↓

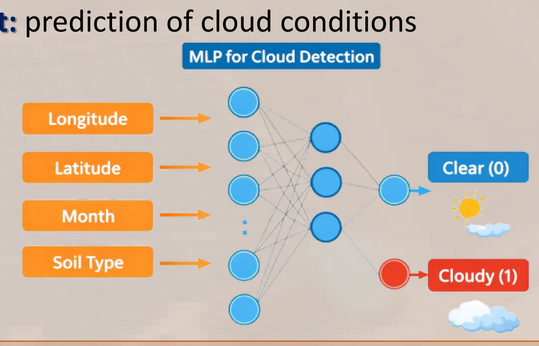
Accuracy > 88%

PCA used for computational efficiency and extraction of the most informative data features

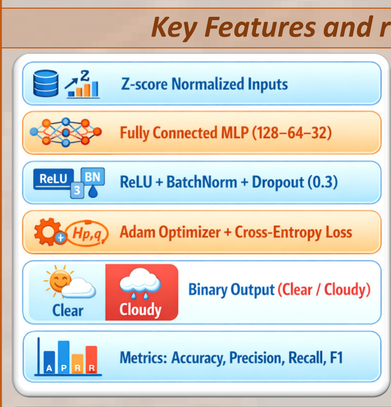
Advanced Mathematical Approach: MLP

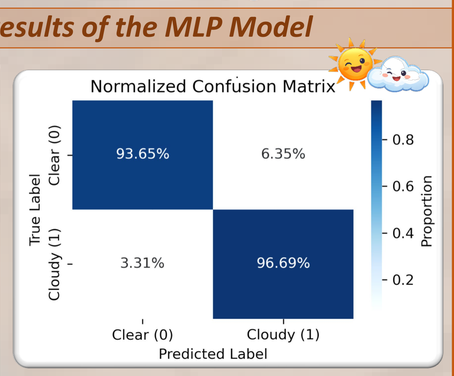
The **M**ulti-**L**ayer **P**erceptron (MLP) cloud detection approach:

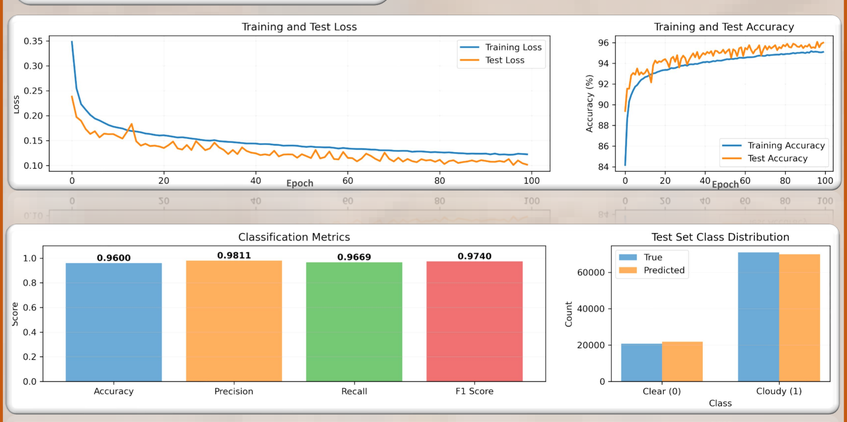
- **Input features:** geospatial data, temporal, and surface type information
- **Feature processing:** inputs are fed into a fully connected neural network
- **Hidden layers:** the MLP learns non-linear relationships among input variables through successive transformations
- **Decision function:** the network maps the extracted features into a binary classification space
- **Output:** prediction of cloud conditions



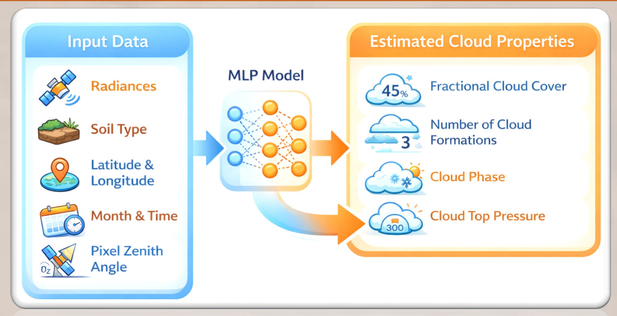
Key Features and results of the MLP Model







Next Steps: Cloud Property Estimation



CONCLUSIONS

*The proposed machine learning framework demonstrates that both SVM and MLP approaches are effective for cloud detection from IASI observations. While **SVM** provides a solid baseline for classification, the **MLP** model shows enhanced capability in capturing complex non-linear relationships between geophysical and radiative inputs. The results highlight robust and generalizable performance across different surface types and global conditions. This work establishes a reliable foundation for future developments toward advanced cloud property retrieval.*

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