

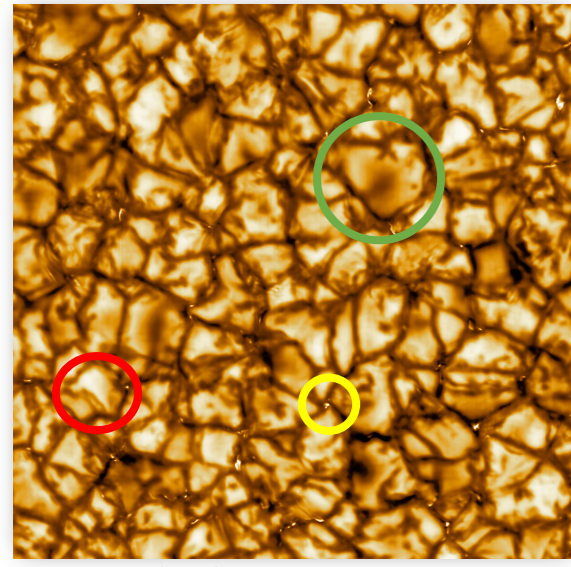
Dense segmentation of solar granulation using deep learning

Saida Milena Díaz Castillo¹, Andrés Asensio Ramos², Catherine E. Fischer³ and Svetlana Berdyugina¹

1. Leibniz-Institut für Sonnenphysik (KIS), Freiburg, Germany, 2. Instituto de Astrofísica de Canarias (IAC), Tenerife, Spain, 3. National Solar Observatory (NSO), Boulder, CO, USA



1. Introduction

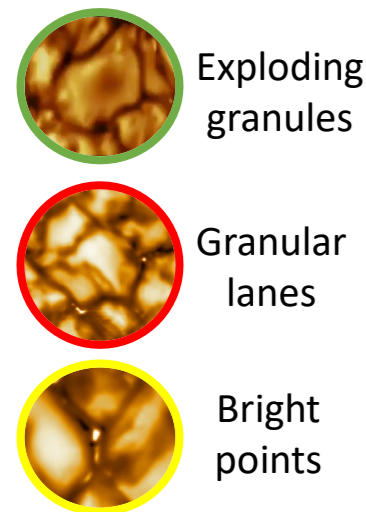


Credit: NSO/NSF/AURA - DKIST first light image

- High-resolution images of the Sun's surface reveal a cellular pattern: **Granulation**.
- Granules are convection cells characterised by various sizes with irregular shapes covering the solar photosphere.
- Highly dynamic with mean lives between 8 to 20 min (Bahng, J. & Schwarzschild, M. 1961).

- Common structures:** Granules (bright patches) surrounded by intergranular lanes (dark surrounding lanes).

- Some special structures:**



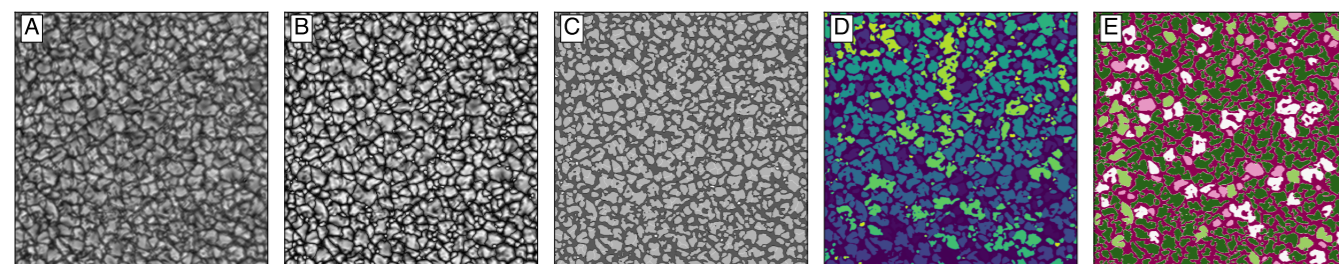
Why it's important to identify and classify this structures correctly?

Statistical studies of *small-scale phenomena in the different layers of the solar atmosphere* are sustained in the effective identification and localization of the different resolved structures.

New solar instrumentation will provide large amounts of data with unprecedented resolution. Fully automatic tools are needed.

2. Ground-Truth data

- Quiet sun solar disc centre - **Sunrise I / IMAx instrument** (Martínes Pillet et al. 2011) 525.02 nm continuum intensity (Stokes I) taken in June 2009. Full maps of 50"x50" (~35Mm x 35Mm) FOV - spatial resolution (~0.15" ~ 100km). Initial sample - 8 maps (768x768 pixels after corrections)
- Labeling procedure:**
 - Multiple-Level Pattern Recognition (MLT4) (Bovelet and Wiehr 2007).
 - Manual selection of 5 different morphologic categories.

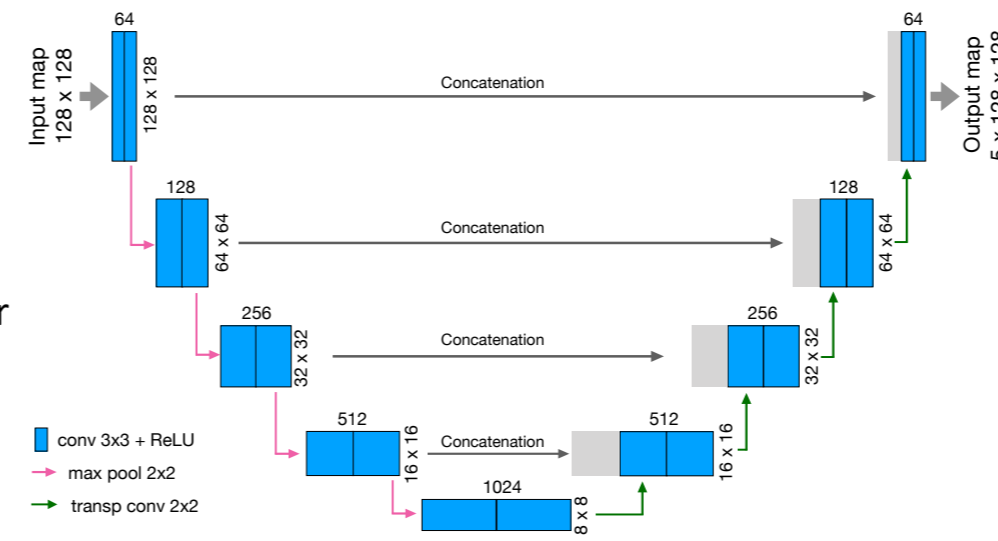


A) Reconstructed continuum intensity map, B) Initial segmentation using 25 descending thresholds, C) Merging and shrinking, D) Intergranular lanes and granules cells as single units, E) Manual selection into categories: intergranular lane (dark violet), uniform-shaped granules (pink), granules with dots (white), granules with a lane (light green) and complex-shaped granules (dark green).

3. Deep learning approach – U-net model

Unet architecture (Ronneberger, Fischer, and Brox 2015).

- Composed by fully connected convolutional blocks.
- Symmetrical: Traditional U-shaped encoder-decoder structure Encoding blocks connected to their decoding counterparts through **concatenation**.
- Our model uses around 31 million of hyperparameters.

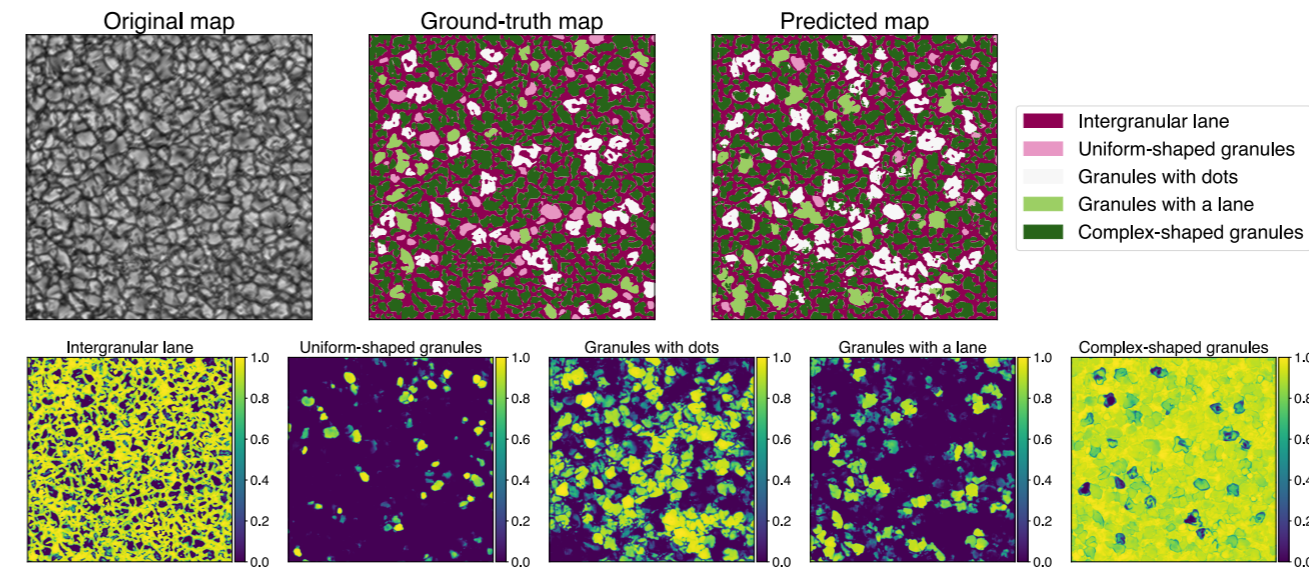
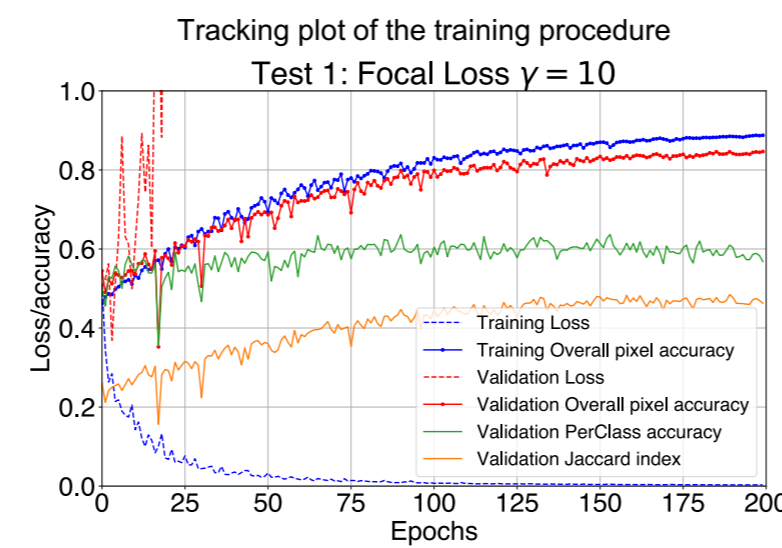


Training strategy:

- Training dataset: 30000 submaps of 128x128 pixels (6.5"x6.5") extracted from the full FOV maps.
- Data augmentation procedure – random rotation and perspective transformation.
- Identified issue: severely **skewed class distribution**:
 - Implementation of **stratified random sub-map sampling**: 7% increase in the pixel proportion of the underrepresented classes.
- Use of **loss functions** commonly applied to imbalanced data problems: Focal Loss (Lin et al. 2017) and mIoU.

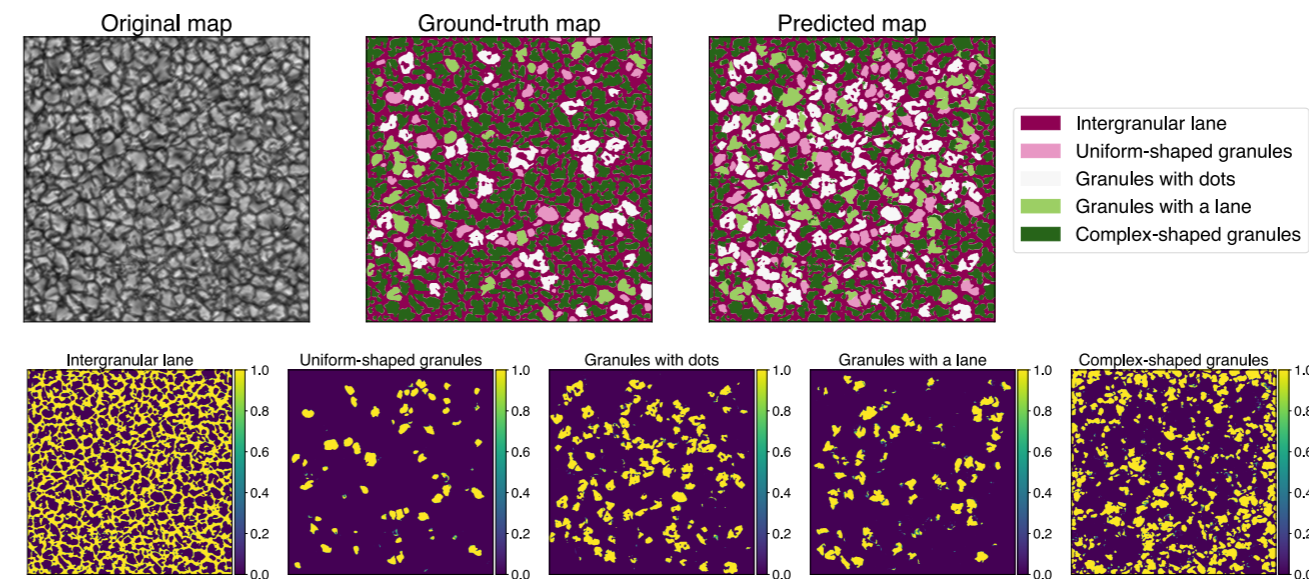
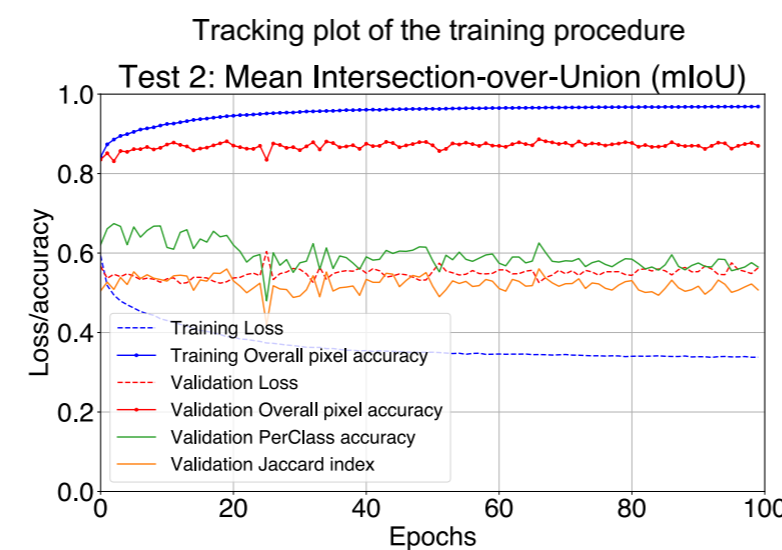
4. Results and Discussion

Test 1: 27000 sub-maps in the training dataset and 3000 sub-maps in the validation dataset, Adam optimization, batches of 32 samples, initial learning rate 0.001 and Focal Loss function with a modulating factor of 10. Training during 200 epochs.



- For the full map, the test 1 model reaches 74% of overall pixel accuracy, a mean accuracy per class of 52% and a Jaccard index of 40%.
- For the full map, the test 2 model reaches 71% of overall pixel accuracy, a mean accuracy per class of 58% and a Jaccard index of 40%.
- High levels of accuracy are achieved in **the identification of the intergranular network** which allows the effective separation of granular morphologies for the proposed models (> 90%).

Test 2: 27000 sub-maps in the training dataset and 3000 sub-maps in the validation dataset, Adam optimization, batches of 32 samples, initial learning rate 0.001 and mIoU function. Training during 100 epochs.



- The network architecture is **sensitive in identifying characteristic patterns in granules**, but it loses efficacy when it comes to discerning between structures with combined morphologies. Low-reliability levels in test 1 and an over-labeling effect in single granules in test 2.

References:

- S. M. Díaz Castillo et al. Frontiers in Astronomy and Space Sciences 2022, in review.
- Bahng, J. & Schwarzschild, M., Astrophysical Journal, 134, 1961.
- Martínes Pillet et. al., Solar Physics, 268, 2011.
- Bovelet B, Wiehr E., Solar Physics, 243, 2007
- Ronneberger O, Fischer P, Brox T., MICCAI, 2015.
- Lin et al. 2017 IEEE 456 ICCV

Come and check out my virtual poster!!! *Ukova*

