

2° Forum della Ricerca Sperimentale e Tecnologica Al astronomical applications development at INAF-OAAb

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Overview

In recent years, the exponential rise of available astronomical data and the contemporary improvement of the accuracy of AI algorithms and models has led to an innovative approach: astronomy research is changing from being hypothesis-driven to being data-driven up to the forthcoming age of exascale data. INAF - OAAb is taking advantage of AI and ML skills in different fields of astrophysics in order to develop innovative software applications which mostly exploit Deep Learning algorithms. They include faint sources detection in IR images and wavefront sensing through optical fibers for Adaptive Optics (currently under development), as well as dwarf galaxy classification and planetary geology data processing and information extraction (currently ideas under evaluation).

Detection of faint sources in IR images

Our research focuses on the identification of **extremely** Low-S/N sources detected by an infrared telescope. Our dataset is made up of images acquired with the SWIRCAM near-infrared camera mounted at the Visible and Infrared Telescope (VIT) in Campo Imperatore Observatory. These images have been compared with the catalog images of the same sky regions from 2MASS.



The developed ML pipeline is composed of the following macro-steps:

- **Data Preparation**: adjust and rescale the two different catalog formats so that they can be suitable as input for Neural Networks.
- **Data Augmentation**: in order to overcome the limitation of a small size dataset, AZT24 backgrounds have been extracted and given as input to a GAN, with the aim of building a consistent dataset of background noise.
- **Denoising CNN**: having built a paired dataset with clean images (2 MASS) and noisy images (2MASS + background noise), a CNN is trained to predict the residual image.
- Testing on AZT24 images: once having built the denoising network, it can be used on the "noisy" AZT24 images, having learnt from the 2 MASS "clean" images to discriminate its extremely faint S/N< 1 sources from the residual noise.

Fiber-fed wavefront sensing for astronomical AO



The synergy between astronomy and photonics is gaining insight in the future era of ground-based telescopes. This research proposes the use of multimode fibers (MMF) as probes of a focal plane wavefront sensor, exploiting a properly trained neural network. Through simulations, numerous aberrated wavefronts have been propagated in a multimodal fiber of known properties. The resulting output images have been saved and fed into a Convolutional Neural Network (CNN) for training and test.



Simulations of aberrated (Zernike modes) wavefront propagating through MMF



Architecture of the CNN with TensorFlow and Keras





AZT24 image (left) and 2MASS image (right) after Data Preparation phase Improving source detection in AZT24 images

Planetary surfaces data handling and processing

Based on the information provided by images, we propose the use of specific computer techniques to **automatically detect impact craters** using the most typical morphological features characterizing bowl-shaped and complex morphologies, such as central depressions and central peaks.





Accuracy Curves

Top: Training accuracy and loss curves Bottom: (A) Confusion matrix for one test set - Test accuracy: 85% , (B) Confusion matrix for second test set - Test accuracy: 87%

Results show the network recognize with good accuracy the input aberrations, except when simulations insert severe fiber bending. Experimental tests are foreseen to verify the model and generalize the problem. The present work is funded by the INAF MiniGrant 2023 and it is part of the R&D activities of the ADONI National Lab.

Dwarf galaxy classification

The human eye is good at detecting dwarf galaxies, but classifying them visually poses several challenges:

a) Kuiper crater (11.3 S, 31.3 W) geologic map. The mapped units are: Kuiper crater peak material (*k-cpm*), Kuiper crater floor and terraces (*k-cft*), Kuiper crater internal melt material (*k-cmm_a*), Kuiper crater external melt material (*k-cmm_b*) and Kuiper crater fresh ejecta (*k-cfe*). Moreover, Kuiper crater rim (*k-cr*) and Murasaki crater rim (*mr*) are defined. b) MASCS coverage over Kuiper crater (11.3 S, 31.3 W). Polygons represent MASCS footprints and have been color coded to match the different geologic units displayed in Fig. 2.4.5a. Both panels use MDIS NAC images EN0223659984M, EN0228372224M, EN0228372226M, EN0228372268M and EN0228372270M overlain on MDIS WAC image EW0223443634I as their background.

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bright dwarfs are easily confused with lenticular galaxies
small dwarfs are hard to distinguish from background sources
irregular dwarfs may be labeled as disrupted spiral galaxies
human bias regarding what constitutes a dwarf galaxy

To avoid these issues, we propose moving to ML techniques to identify dwarf galaxies in future surveys. To prepare for this eventuality, we have identified > 3000 dwarf galaxies in the MATLAS and Euclid ERO optical images, which can be used to train ML algorithms. Examples of some MATLAS dwarfs are shown below; the g-band cutouts are 1' x 1'.

