

# Fiber-fed wavefront sensing with machine learning

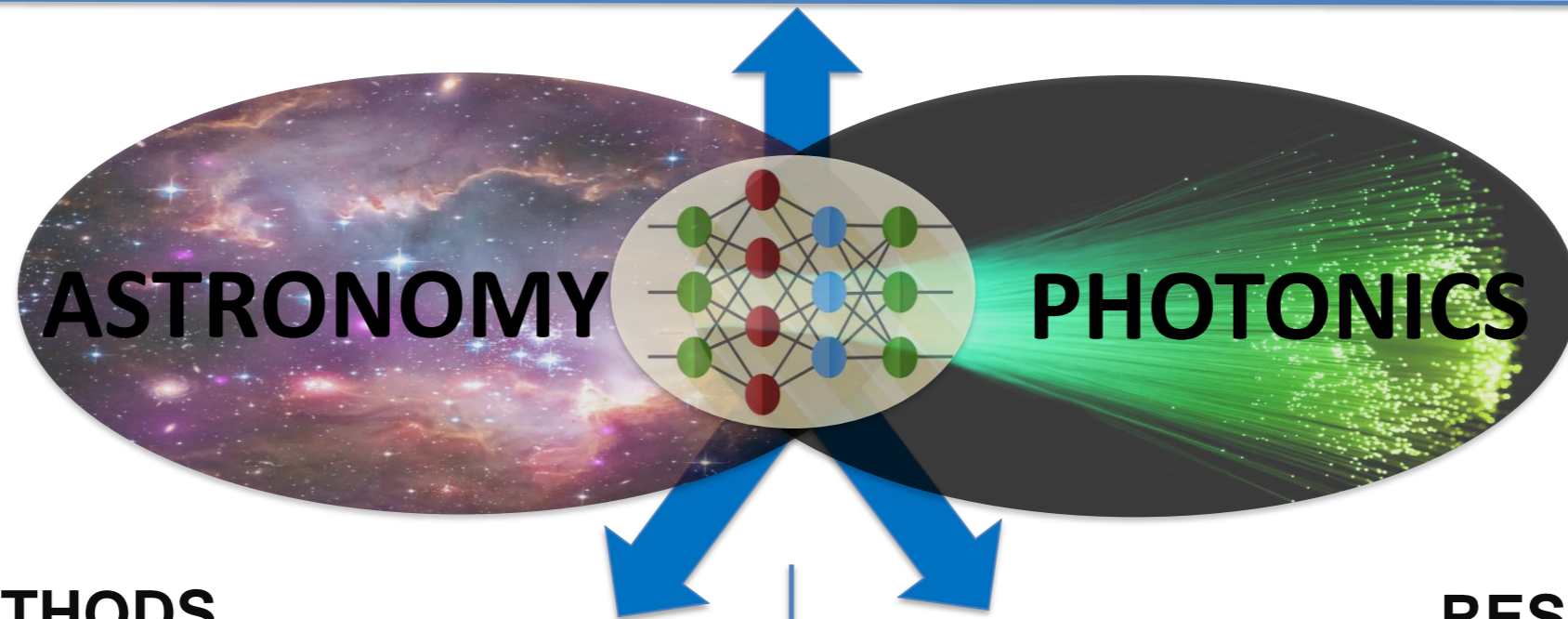
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## SENSING WITH MULTIMODE FIBERS

In recent decades, optical fibers have significantly impacted the field of astronomy, achieving notable success across various applications. In wavefront sensing, photonic lanterns [1] have demonstrated their potential, particularly when integrated with suitable neural networks [2]. This research aims to propose multimode fibers as probes for a telescope focal plane wavefront sensor, employing Convolutional Neural Networks (CNN) to perform sensing. Through simulations, numerous wavefronts with Zernike first orders aberrations, have been propagated in a multimode fiber. The corresponding outputs are used for training a CNN. The validation of the network and the results on the test sets are presented.



### METHODS

#### MMF propagation simulation

We replicated the propagation of an 800 nm light wave through a 50 μm core multimode fiber of length 10 cm using BPM-Matlab software. Starting with a flat wavefront characterized by a Gaussian input field  $U_i$ , Zernike mode aberrations were superimposed as additive phase terms:

$$U = U_i e^{-j\pi b Z_{n,m}}$$

where  $b$  represents the intensity of the aberration and  $Z_{n,m}$  is the corresponding Zernike polynomial.

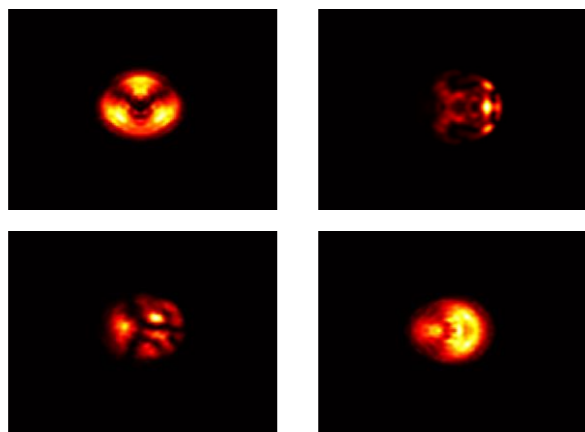


Fig. 1: Fiber output intensities for different aberrations.

#### CNN Architecture

The CNN was developed in Python using TensorFlow and Keras.

The intensity images used for training have been achieved simulating an increasing value of  $b$  and of the fiber radius of curvature ( $RoC$ ).

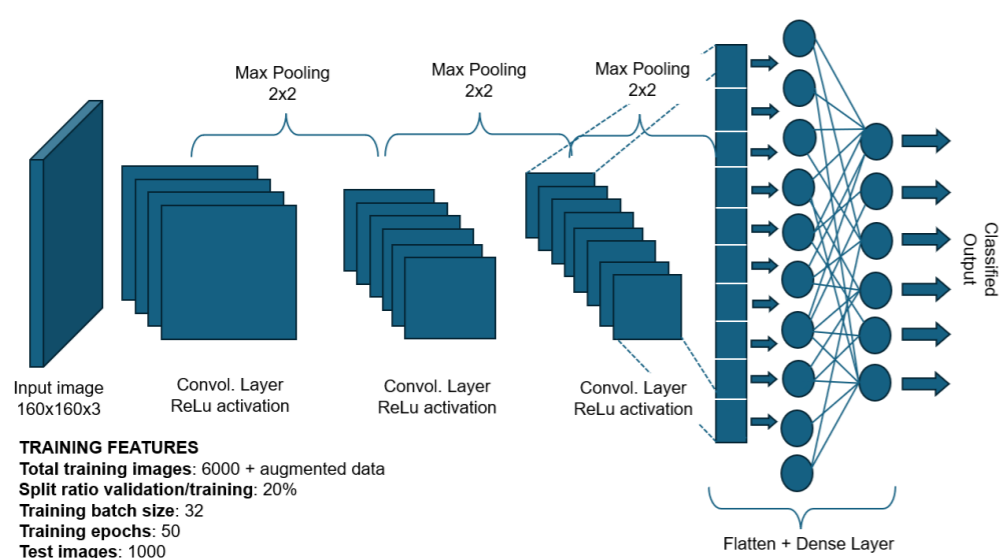


Fig. 2: CNN structured layers

### RESULTS

The first results validate the training performance of the neural network, demonstrating strong learning capabilities and good generalization, achieving up to 90% of training and validation accuracy.

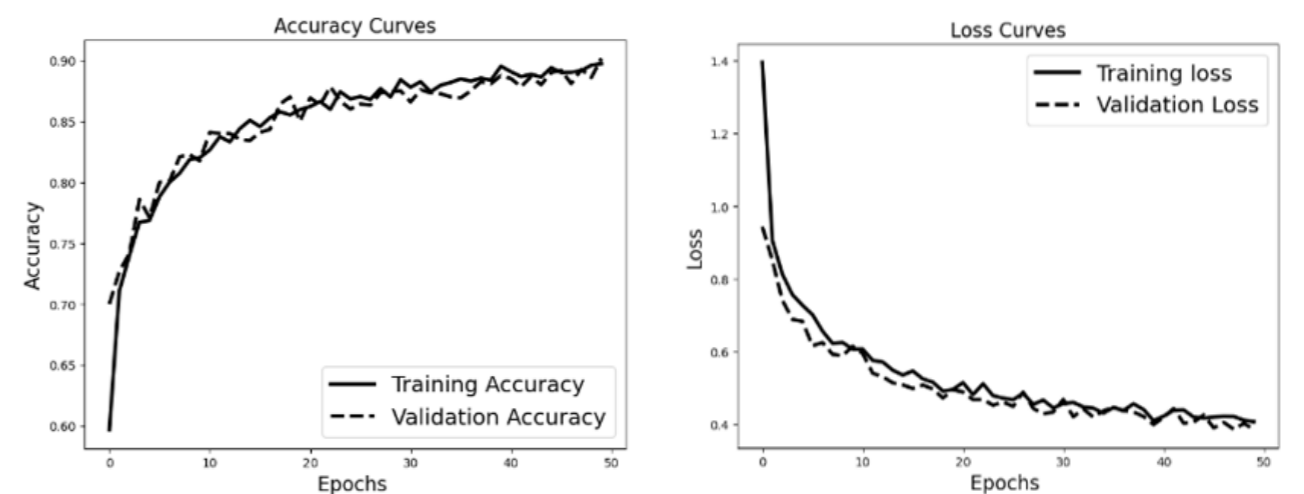


Fig. 3: Accuracy and Loss parameters after network training

For the test accuracy, we used three test sets, changing the parameters of interest  $b$  and  $RoC$ .

- First test set: no bending applied to the fiber and random  $b$
- Second test set: random bending and fixed  $b = 0.2$
- Third test set: random bending and random  $b$

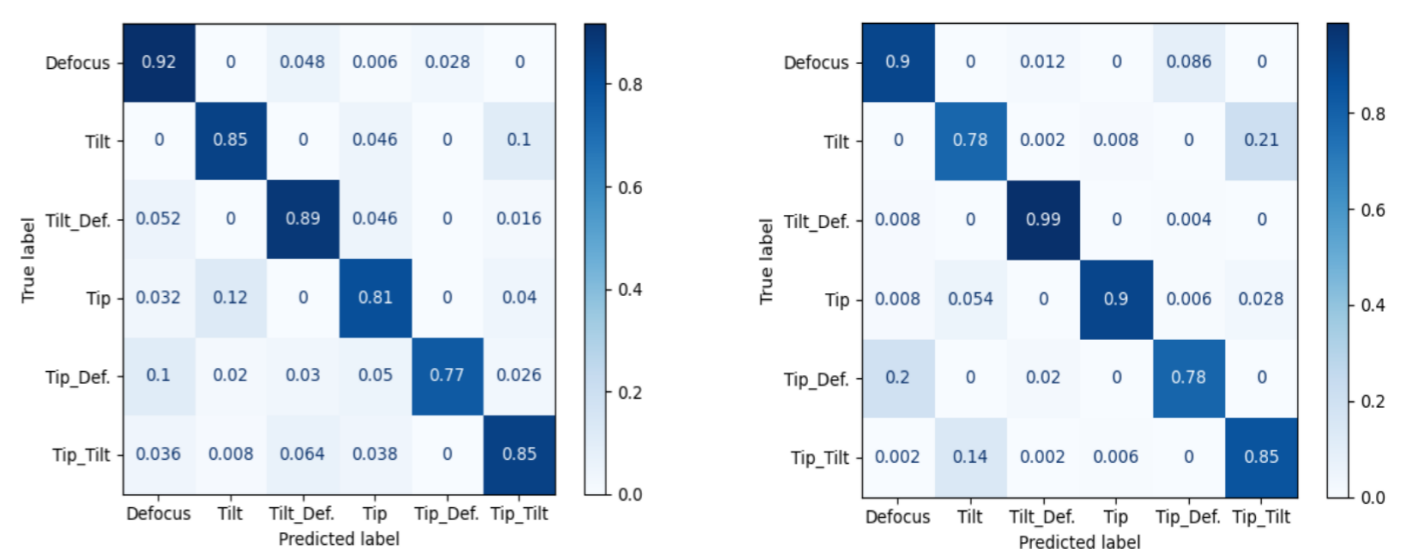


Fig. 4: Confusion matrices for the first and second test sets

The third test set experiences low accuracy, indicating that as fiber bending increases and aberration worsens, the CNN fails. This suggests setting a reliable bending limit and verifying the aberration levels at which the network encounters issues

## FUTURE STEPS

The model shows strong performance, with 90% accuracy in training and validation, and acceptable drops to 85% and 87% in two test sets. However, it struggles when the Zernike contributions are high. To validate the network and generalize the model, experimental tests are foreseen, together with further CNN training.