

**Taras Shevchenko National University of Kyiv
Astronomical Observatory**

**Astronomy and Space Physics
in the Kyiv University**

Book of Abstracts

**International Conference
in part of the Science Day in Ukraine**

May 23 – May 26, 2023

Kyiv, Ukraine

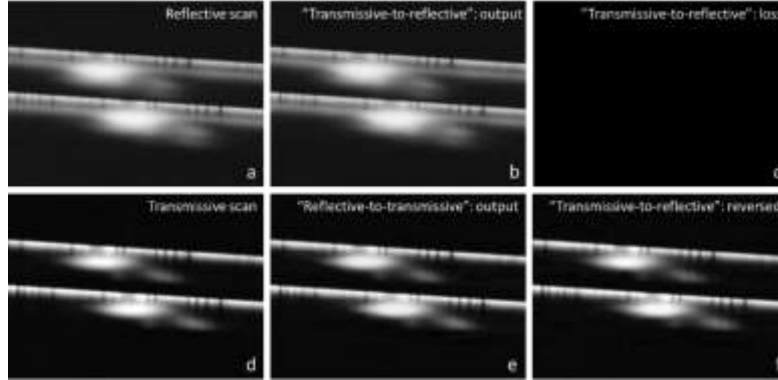


Figure 1. Training results for the $H\gamma$ spectral line of the limb solar flare on July 17th, 1981: (a) target reflective scan for the "transmissive-to-reflective" model, (b) model output, (c) loss function, (d) target transmissive scan for the "reflective-to-transmissive" model, (e) model output, and (f) output from the reversed "transmissive-to-reflective" model.

Detecting and addressing spectral contamination through machine learning

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The study introduces a technique for detecting and excluding impurities from final spectral images using a Convolutional Neural Network (CNN). The CNN transforms spectra between reflective and transmissive scans, effectively learning the relationship between both types of scans. CNNs excel in image processing tasks and minimize the risk of overfitting.

When applied to spectra with impurities, the models adeptly reproduce the true darkness of the photoemulsion while exhibiting high loss for scratches and impurities. Figure 1 illustrates the models' performance on contaminated spectra, revealing that areas of high loss correspond to the

presence of impurities. This approach enables automatic identification and exclusion of scratches, dust particles, and other impurities from the final spectrogram scans, ensuring data integrity.

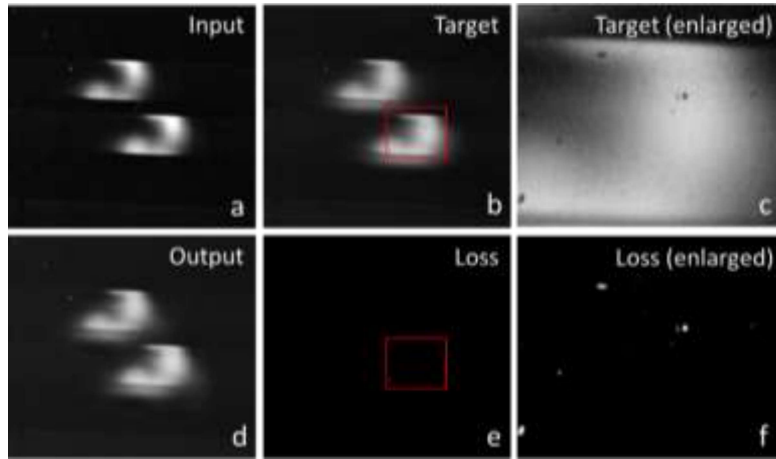


Figure 1. Visualization of the models' performance on contaminated spectra. The figure displays the model's input (a), target (b), enlarged fragment (c), output (d), intensity-normalized loss (e), and an enlarged view of the loss area (f). Comparing panels (c) and (f) reveals high loss areas corresponding to spectral impurities, enabling their reliable detection and exclusion during post-processing.

Compared to other post-processing defect detection methods, this algorithm offers a reliable and user-friendly solution without assumptions about impurity characteristics. The use of reflective scans further aids in detecting impurities that may be challenging to identify using transmissive scans alone. In conclusion, employing a convolutional neural network for transforming spectral images demonstrates promising potential in improving the accuracy of spectral measurements in solar physics and related fields.

The authors would like to express their gratitude to V.G. Lozitsky for generously providing the spectra used in this study.