MACHINE LEARNING FOR HIGH-LEVEL HELIOPHYSICS INSIGHTS USING THE EUROPEAN SOLAR TELESCOPE Thomas Y. Chen[1], [1]Academy for Mathematics, Science, and Engineering (thomaschen7@acm.org)

Introduction: To make meaningful advancements in heliophysics, computer vision techniques based on deep neural networks (DNNs) are a crucial emerging tool. Fundamentally, computer vision is the study of training algorithms to gain high-level insights from imagery and video data, which is especially relevant to a largely observationally-based field such as heliophysics. Machine learning is applied to solar feature detection and phenomenon classification. Utilizing images taken in a multitemporal fashion, computer vision-based approaches can detect solar flares, filament eruptions, coronal jets, etc. and measure properties of our observations over timescales. Data from NASA's Solar Dynamics Observatory (SDO), including Atmospheric Imaging Assembly (AIA) and Helioseismic and Magnetic Imagery (HMI) data, are a useful source of imagery for training computer vision models. In this abstract, we briefly highlight current areas of application at the intersection of artificial intelligence and heliophysics and propose how the solar physics and astrophysics scientific communities can join to fill in interdisciplinary technological gaps.

Surveying Current Work: The emergence of the Daniel K. Inouye Solar Telescope (DKIST) and other solar observatories has enabled unprecedented applications of big data for solar physics. In recent work, [1] presents a methodology of transfer learning using pre-trained deep learning models to classify solar imagery in H-alpha data, while [2] highlights how solar flare prediction facilitated by machine learning comes with challenges such as "difficulties in cross-comparison of flare prediction attempts such as differences in spatial and temporal scales of the constructed data sets." Developing dataset curation tools is another important aspect of the computer vision research process, as relevant pre-processed datasets are the key to training models that can perform inference effectively and yield valuable results. [3] presents a novel Python-based tool that produces sets of machine-learning-ready heliophysics images, including multispectral imagery from the Solar and Heliospheric Observatory (SoHO) and SDO data. Additionally, as [4] discusses, there are exciting opportunities for citizen scientists to play a role in advancing heliophysics through community-oriented machine learning challenges.

Conclusions and Future Work: Upcoming initiatives within the heliophysics and astrophysics communities are paving the way for the collection of more big data and the corresponding development of computer vision models for deployment in multi-stakeholder research projects. For example, the building of the European Solar Telescope (EST) as part of a pan-European project is aimed at observing the Sun's surface in extreme detail and gaining insight into small-scale phenomena including mini-filament eruptions on the solar chromosphere. The rate at which the EST and other planned observatories will produce data is unprecedented, and thus will be difficult to analyze using conventional and statistical approaches. Machine learning and computer vision will therefore fill in the gaps in these areas. Another aspect of the AI-heliophysics connection that should be considered is the introduction of more sophisticated computer vision methodologies into the analysis of solar physics. As the field of pure computer vision advances rapidly, complex generative adversarial networks (GANs) and 3D reconstruction techniques are seeing interdisciplinary applications in adjacent scientific fields as well. In the next decade, it is appropriate to consider whether generative approaches like multilayered GANs can enable further discovery in heliophysics. Reconstructing the Sun via computer graphics can potentially aid in a deeper understanding of relevant phenomena and features in a noninvasive manner. Cross-collaborations between computer scientists involved in high-level deep learning research and solar physicists with inherently domain-specific knowledge are key to the next decade's advancement of research at this burgeoning nexus.

References: [1] Armstrong, J.A., Fletcher, L. Fast Solar Image Classification Using Deep Learning and Its Importance for Automation in Solar Physics. *Sol Phys 294, 80* (2019). [2] Sadykov, V. M. (2019, December). In *AGU Fall Meeting Abstracts (Vol. 2019, pp. SH34B-05)*. [3] Shneider, C., Hu, A., Tiwari, A. K., Bobra, M. G., Battams, K., Teunissen, J., & Camporeale, E. (2021). A Machine-Learning-Ready Dataset Prepared from the Solar and Heliospheric Observatory Mission. *arXiv preprint arXiv:2108.06394*. [4] Musset, S., Glesener, L., Fortson, L., Wright, D., Kapsiak, C., Hurlburt, N. E., ... & Fleishman, G. D. (2020, December). In *AGU Fall Meeting Abstracts (Vol. 2020, pp. SH024-0006)*.