Planetary Nebulae: A Universal Toolbox in the Era of Precision Astrophysics
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AI Techniques for Uncovering Resolved Planetary Nebula Candidates from the VPHAS+ Survey

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Abstract. AI and deep learning techniques are beginning to play an increasing role in astronomy as a necessary tool to deal with the data avalanche. We describe an application for finding resolved Planetary Nebulae (PNe) in crowded, wide-field, narrow-band Hα survey imagery in the Galactic plane.

Keywords. machine learning, artificial intelligence, planetary nebulae, wide-field surveys

1. Introduction

There are currently ~ 3800 Galactic planetary nebulae (PNe) known as recorded in the HASH database, e.g. Parker et al. (2016). These numbers fall far short of the numbers expected from population synthesis. Visual searching for PNe of narrow-band Hα surveys has provided most of the discoveries over the last 25 years, e.g. Parker et al. (2006), Miszalski et al. (2008), Sabin et al. (2014). This is time-consuming due to the large areal coverage and complex and varied nature of Hα emission in these Galactic plane surveys. To facilitate more objective, reproducible, efficient and reliable trawls for PNe candidates we have developed a new, deep learning algorithm for finding resolved Planetary Nebulae in crowded, wide-field, narrow-band Hα surveys in the Galactic plane. These techniques are beginning to play an increasing role in astronomy as a necessary tool to deal with the data avalanche.

Our approach uses a Swin-Transformer model based on Mask R-CNN (regions with convolutional neural networks), e.g. He et al. (2016). Specifically, we replaced the feature extraction network in Mask R-CNN with a transformer network, replaced the ResNet module with a Swin-Transformer, and then constructed a new 'bespoke' deep learning object detection method for PNe.

2. Our Results

We applied the algorithm to several Hα digital surveys, e.g. IPHAS (Drew et al. 2005) and VPHAS+ (Drew et al. 2014). The training and validation dataset was built with true PNe from the HASH database. After transfer learning, it was then applied to the VPHAS+ survey. We examined 979 out of 2284 survey fields with each survey field covering 1×1 degrees. With a sample of 454 PNe from the IPHAS as our validation set, our algorithm correctly identified 444 of these objects, with only 16 false positives. Our model returned ∼20,000 detections, including 2637 known PNe and many other

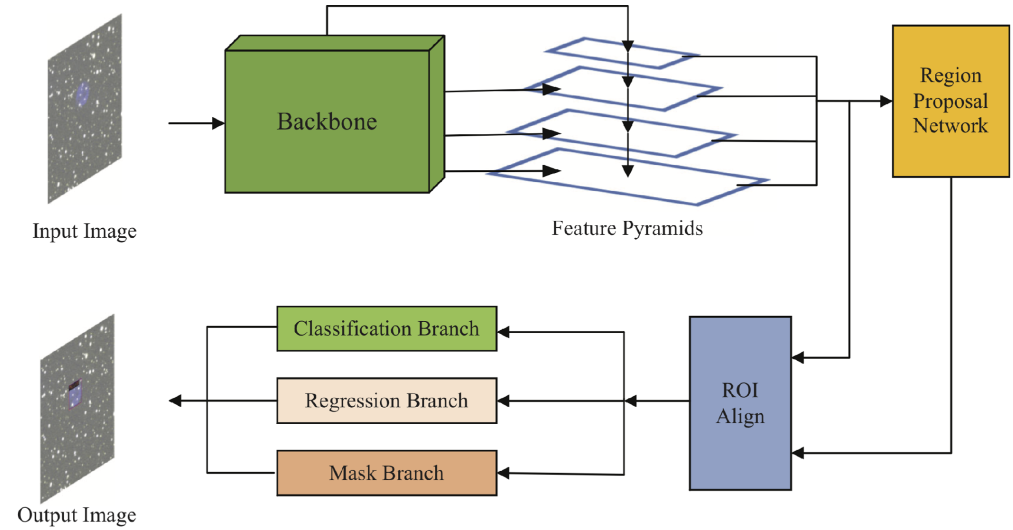

Figure 1. The schematic structure of the Swin-Transformer model used as the basis for this work.

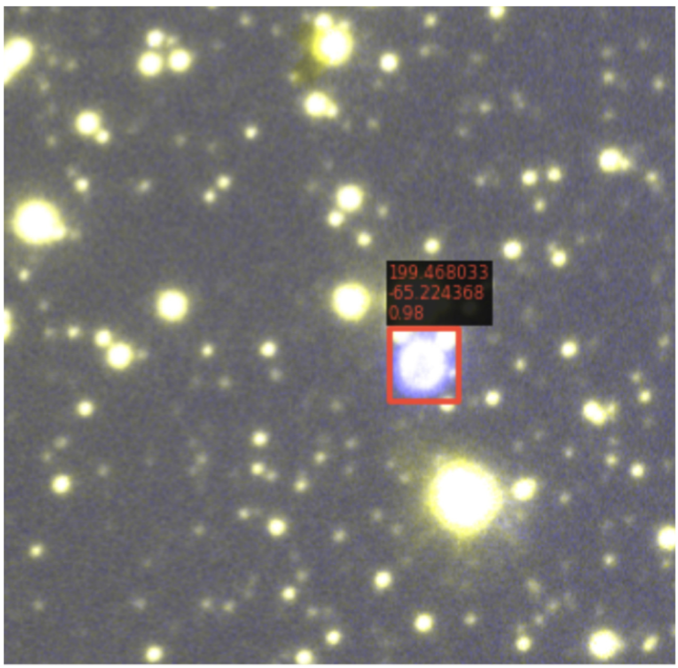

Figure 2. VPHAS+ image of a new PN found from our ML deep learning process.

kinds of catalogued non-PNe such as HII regions. A total of 815 new high-quality PNe candidates were found, 30 of which were selected as top-quality targets for subsequent optical spectroscopic follow-up on the SAAO 1.9m telescope in July 2023. Figure 1 shows the schematic structure of the Swin-Transformer model used as the basis for this work while Figure 2 shows a compact PN candidate uncovered in the VPHAS+ survey data by our process and finally Figure 3 shows a 2-D confirmatory SAAO 1.9m spectrum of one of the first PNe candidates found by our techniques.

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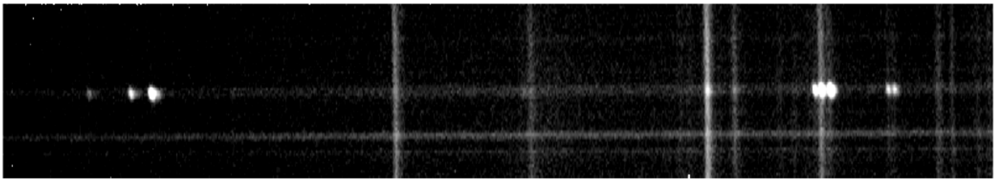

Figure 3. 2-D confirmatory SAAO 1.9m spectrum of a PNe candidate found by our techniques.

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