

Strong Lens Detection 2.0: Machine Learning and Transformer Models

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Abstract. Upcoming large-scale surveys like LSST are expected to uncover approximately 10^5 strong gravitational lenses within massive datasets. Traditional manual techniques are too time-consuming and impractical for such volumes of data. Consequently, machine learning methods have emerged as an alternative. In our prior work (Thuruthipilly et al. 2022), we introduced a self-attention-based machine learning model (transformers) for detecting strong gravitational lenses in simulated data from the Bologna Lens Challenge. These models offer advantages over simpler convolutional neural networks (CNNs) and competitive performance compared to state-of-the-art CNN models. We applied this model to the datasets from Bologna Lens Challenge 1 and 2 and simulated data on Euclid.

Keywords. Gravitational strong lensing, data analysis, image processing, observations

1. Introduction

Strong gravitational lensing is a fascinating prediction of General Relativity (GR). It occurs when a foreground galaxy's massive gravity bends light from a distant source, forming arcs or multiple images. Since the first galaxy-galaxy strong lensing system discovery by Hewitt et al. (1988), numerous applications in cosmology and astrophysics have emerged for strong lenses (SLs). However, strong gravitational lensing is rare, with roughly one lens per thousand galaxies observed. Advanced missions like Euclid (R. et al. 2021) and Legacy Survey of Space and Time (LSST) (Ivezić et al. 2019) are expected to identify about 10^5 strong lensing events among 10^9 galaxies. Analyzing data manually or semi-automatically in future large-scale surveys is impractical and time-consuming, necessitating faster, reliable, and robust alternative approaches.

Recent advancements in natural language processing (NLP) led to the development of transformer models, a breakthrough in NLP introduced by Vaswani (2017). While these transformers have revolutionized machine learning, their application in astrophysics remains largely unexplored. In this study, we investigate the potential of attention-based models, specifically transformers, to identify strong gravitational lenses (SLs). We implemented transformers on Bologna Lens Challenge 1 and 2 data and also assessed their performance on simulated data for the Euclid mission. Additionally, we compared the performance of transformer models with other top-performing models on the same dataset.

2. Methods

We base our Strong Lens (SL) detection Transformer models on self-attention principles. Self-attention, generally expressed as $\text{Attention}(Q, K, V) = \text{softmax}(QK^T/\sqrt{d_k})V$, assigns importance to input features based on their inherent relationships, where Q, K, V

Table 1. ‘Lens Detector 15’ vs. Best CNNs in the Literature.

Dataset	Model	AUROC
Bologna Lens Challenge 1	Lens Detector 15	0.98
	CMU-DeepLens (Metcalf et al. 2019)	0.98
Bologna Lens Challenge 2	Lens Detector 15	0.83
	EfficientNets (Bom et al. 2022)	0.82
Euclid Simulation Data S1	Lens Detector 15	0.98
	Inception (Euclid Collaboration 2023)	0.92
Euclid Simulation Data S2	Lens Detector 15	0.98
	Inception (Euclid Collaboration 2023)	0.88
Euclid Simulation Data S3	Lens Detector 15	0.98
	Inception (Euclid Collaboration 2023)	0.90
Euclid Simulation Data S4	Lens Detector 15	0.97
	Inception (Euclid Collaboration 2023)	0.81

are vectors and $\sqrt{d_k}$ represents the key vector’s dimension. In our study, we consistently employ the ‘Lens Detector 15’ model mentioned in Thuruthipilly et al. (2022) across three different datasets: Bologna Lens Challenge 1, 2, and the Euclid simulation dataset. For the Bologna Lens Challenge 1 dataset, we trained this model with randomly initialized weights. However, we utilized pre-trained weights from our training on the Bologna Lens Challenge 1 for the other two datasets.

3. Results and Conclusions

In Table 1, we conduct a comparative evaluation of the ‘Lens Detector 15’ transformer model’s performance in contrast to the best-performing convolutional neural networks (CNNs) documented in existing literature across diverse simulated datasets. Notably, the transformer models demonstrate exceptional performance compared to the CNNs mentioned in prior studies, highlighting the adaptability of transformers in the context of strong lens detection. For a comprehensive understanding of the datasets, please refer to Metcalf et al. (2019); Bom et al. (2022) for Bologna Lens Challenge 1 and 2, and Euclid Collaboration (2023) for the Euclid simulation datasets.

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