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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR ASTRONOMICAL OBJECT DETECTION AND CLASSIFICATION: APPLICATIONS, CHALLENGES, AND FUTURE DIRECTIONS

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ABSTRACT

Over the past few decades, the role of data analysis using AI has been amplified in the field of astronomy. AI has become increasingly important for the detection and analysis of astronomical objects. This review investigates how Artificial Intelligence and Machine Learning techniques are used to detect and analyse astronomical objects and highlight their performance, with a focus on asteroid detection, exoplanet detection, and galaxy classification. The review highlights the ability of these techniques to perform complex analyses, identify patterns in astronomical data, and improve the efficiency of object detection and classification. However, several challenges including limited training data, noisy or low-quality observations, and computational requirements continue to affect their reliability. Future prospects and directions may focus on resolving these limitations and strengthening collaboration between automated systems and human researchers.

KEYWORDS

Artificial Intelligence, Machine Learning, Deep Learning, Convolutional Neural Networks, Astronomical Object Detection, Asteroid Detection, Exoplanet Detection, Galaxy Classification

INTRODUCTION

There has been an exponential increase in the amount of visual data related to astronomical objects such as asteroids, stars, galaxies, planets, and other celestial bodies. To expand our understanding of celestial bodies, researchers must collect petabytes of data, and analyse it. Traditional methods are not effective enough for the analysis of ever-growing datasets (Saikia, 2025, p. 1). For this purpose, the application of AI and ML has become prevalent in the analysis of astronomical data, enabling us to discover celestial bodies or anomalies and track existing ones. AI offers promising techniques for object detection and processing of astronomical images. However, a few persisting challenges make astronomical data analysis difficult, the most hindering of which have also been discussed in this review.

Limitations of Traditional Methods for Astronomical Object Detection

Traditional methods such as Radial Velocity (Doppler Spectroscopy), Transit Photometry, Direct Imaging and manual inspection of telescope images were used widely for detecting exoplanets as well as other celestial objects before the emergence of AI. However, all of them face challenges with the growth of astronomical data. These techniques often struggle with detecting objects that appear faint, produce false positives (Deljookorani et al., 2020, p. 2), or are simply most precise for detecting massive objects or exoplanets (Saikia, 2025, p. 1). Large datasets contain irrelevant data, known as noise. This noise in the data frequently leads to errors in analysis via traditional methods. The detection of anomalies in astronomical data has become more straightforward with the use of AI tools.

Artificial Intelligence and Machine Learning Techniques

Machine learning techniques are now being used for various processes in Astronomy, such as asteroid detection, exoplanet detection, and galaxy classification. Convolutional Neural Networks (CNNs) are deep learning algorithms central to the analysis of visual data in Astronomy. CNNs eliminate the need for manual extraction of data from images by directly extracting information from raw data. They are widely used for visual analysis. They have been used to extract features from galaxy images, analyse light curves for exoplanet detection, and classify stellar spectra (Irureta-Goyena et al., 2025, p. 3). A few areas of exploration that can harness the potential of AI in Astronomy have been discussed below.

1. Asteroid Detection

The detection of asteroids among NEOs (Near-Earth Objects) is crucial for protecting life on Earth. In large astronomical surveys, the detection of asteroids becomes challenging due to the vastness of the data accumulated. Researchers have applied CNN for automatic detection of asteroid trails. Studies show that CNN-based classifiers and object detection architectures have demonstrated high accuracy in detecting tracklets and trails (Cowan et al., 2023, p. 8).

Researchers deployed a two-step Neural Network on ATLAS (Asteroid Terrestrial-Impact Last Alert System) and found that it effectively eliminates 90% of the NEO candidates that astronomers must screen manually (Rabeendran & Denneau, 2021, p. 11). Evidently, such methods can be used to significantly increase efficiency and reduce time required for analysis, allowing related agencies to act quicker upon the discovery of an asteroid near Earth. However, AI models can produce false positives due to ambiguous observations that resemble the patterns of the target object. Such incorrect detections may lead to inefficient use of observational resources.

2. Exoplanet Detection

An exoplanet is defined as a planet outside of our solar system. In order to detect exoplanets, light curves were traditionally mapped by recording the dips in the brightness of a star. Due to the massive amount of data collected by space telescopes such as NASA's Kepler and TESS, it is impractical to analyse light curves manually. Machine learning models, particularly deep learning models involving CNNs, are increasingly used to evaluate light curves to detect a potential exoplanet. By being trained on patterns observed in light-curve data obtained through transit methods, these models can distinguish exoplanet signals from ordinary fluctuations in the brightness of stars. They are capable of noticing subtle patterns in time-series data.

A deep learning model developed and used by researchers at NASA identifies "exoplanet candidates"—signals that may indicate the existence of a planet and require review (Valizadegan *et al., 2025, p. 14)*. It narrows down the data to be analysed by astronomers. Several studies demonstrate that machine learning methods have the capability to identify potential exoplanets more efficiently than manual approaches, ultimately paving the way for a streamlined detection of exoplanets. Even so, the effectiveness of these models heavily depends on the quality of the training data, which may affect their capabilities.

3. Galaxy Classification

Galaxies are classified into three main categories based on their features: Elliptical, Spiral, and Irregular. The structure of galaxies provides crucial information about their formation and evolution. Galaxy classification allows astronomers to understand how a galaxy may interact and evolve over time. Here, image recognition and classification prove to be useful in recognising common features found in different types of galaxies; such as a lack of spiral arms, presence of central bulges, or chaotic structures. CNNs utilise computer vision to analyse raw telescope images and identify features consistent with the various types of galaxies.

Simple features of the images are first detected and then deeper layers of the neural network identify complex morphological features. Studies show that CNN models show high accuracy for galaxy classification (Eldeen et al., 2017, p. 1) comparable to classifications carried out manually. This has enabled astronomers to classify large collections of galaxy images more consistently. The models can, however, still underperform when presented with low-resolution images and rare galaxy types, as limited training data for uncommon galaxies makes accurate classification more complicated. Through collaborative citizen science programs such as Galaxy Zoo, human volunteers can classify ambiguous images. The resulting human-labeled datasets can be used to train and improve AI models for automated classification.

Table 1. Comparison of AI Applications in Astronomical Object Analysis

Application	Data Analysed	AI Method	Purpose	Key Challenge
Asteroid Detection	Telescope images	CNNs, object detection models	Identify moving celestial objects	Noise and ambiguity in data
Exoplanet Detection	Stellar light curves	CNNs, Deep Learning models	Identify transit signals indicating planets	Noise and quality of training data
Galaxy Classification	Galaxy images	CNNs	Classify galaxy morphology	Rare galaxy types and image quality

Key Challenges

Despite significant growth in Artificial Intelligence, machine learning algorithms and neural networks face frequent limitations. One of the most common challenges is the lack of sufficient labeled training data (Eldeen et al., 2017, p. 1). The efficiency and results yielded by models depend heavily on the training data. Rare astronomical events are underrepresented in astronomical data, and therefore limit model performance. Training CNN models requires a large amount of computational and hardware resources.

Furthermore, astronomical observations often contain noise, low-resolution images, and faint signals that reduce the quality of the data given to the models for analysis, impacting the accuracy of models negatively (Marchant et al., 2024, p. 8). Deep learning models also often lack explainability, making it difficult for astronomers to understand the reasoning behind a particular decision.

There is also a risk of false positive assessments due to ambiguity in data, which may lead researchers to devote valuable resources to incorrect detections and result in a gradual reduction of confidence in discovery systems (Rabeendran & Denneau, 2021, p. 11).

Future Directions

Future developments in Artificial Intelligence and Machine Learning technologies are expected to expand their applications in Astronomy. As astronomical surveys continue to record massive amounts of complex data, AI systems will play a fundamental role in interpreting and observing astronomical data. Future research may focus on increasing the accuracy and reliability of AI models in this field, which is central to the purpose of AI in Astronomy. In addition, collaborative astronomy projects between humans and technology may become more prevalent; improving the classification and discovery of celestial objects. These advancements have the potential to expedite astronomical research and contribute to a deeper understanding of the universe.

CONCLUSION

This review examined the various applications of Artificial Intelligence and Machine Learning in the detection and analysis of astronomical objects. Massive and ever-growing datasets have produced a requirement for a more efficient and streamlined way of analysis. Machine learning and deep learning algorithms have demonstrated considerable potential for contributing to astronomical detection and classification. Despite challenges to data quality and model reliability, these technologies continue to improve the consistency of astronomical analysis. As AI capability advances, it is expected to become essential for exploring and understanding the universe.

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