



## Artificial Intelligence and Statistical Methods in Modern Astrophysics: From Exoplanet Detection to Black Hole Characterization

\*<sup>1</sup>Vwavware, O.J., <sup>2</sup>Yakubu, M., <sup>1</sup>Ohwofosirai, A., & <sup>1</sup>Enajite, O.

<sup>1</sup>Department of Physics, Dennis Osadebay University, Asaba, Delta State, Nigeria

<sup>2</sup>Department of Industrial Physics, Enugu State University of Science and Technology

\*Corresponding author email: [oruaoe.vwavware@dou.edu.ng](mailto:oruaoe.vwavware@dou.edu.ng)

### Abstract

Artificial intelligence (AI) and advanced statistical methods are rapidly transforming astrophysics, enabling efficient analysis of increasingly complex and voluminous datasets. These methods have applications across multiple domains, including exoplanet detection, time-domain astronomy, stellar variability, pulsar studies, and black hole and galaxy evolution modelling. This review synthesizes recent developments in AI and data-driven approaches across these subfields. In exoplanet science, machine learning algorithms enhance detection and classification, while in time-domain astronomy, robotic telescopes and automated pipelines improve transient discovery. AI also facilitates modelling of black hole growth, binary mergers, and galaxy co-evolution. Additionally, statistical methods applied to pulsars, cosmic ray variability, and maser studies provide new insights into stellar populations and Galactic structure. Challenges such as interpretability, reproducibility, and biases are discussed, along with prospects for integrating AI into multi-messenger and multi-wavelength astrophysics. This review demonstrates the central role of AI and statistics in accelerating discovery across cosmic scales.

**Keywords:** Artificial Intelligence, Machine Learning, Statistical Methods, Exoplanets

### Introduction

Artificial intelligence (AI) has become essential for managing the exponential growth and complexity of astronomical data, transforming how astrophysicists extract meaningful insights from massive datasets. The evidence is robust and multi-faceted: (Garofalo et al., 2016) note data volumes have reached petabyte scales with increasing complexity, while (Djorgovski et al., 2022) confirm AI is now a standard part of the astronomical toolkit. Machine learning techniques enable critical capabilities like automated star-galaxy separation, real-time data processing, and classification of celestial objects across billions of feature vectors. (Longo et al., 2019) emphasize that next-generation telescopes will generate data volumes orders of magnitude larger, making AI not just beneficial but imperative for knowledge extraction. The field is rapidly evolving towards a collaborative human-AI discovery approach that can handle unprecedented data complexity. From a different perspective, the evolution of exoplanet detection is being driven by advances in automated data processing pipelines and statistical methods for handling complex astronomical time series. (Jenkins et al., 2015) describe how the Kepler Mission developed machine learning approaches for automated vetting of over 18,000 transit-like signatures, noting that machine learning approaches may prove to be critical to the success of future missions such as TESS and PLATO. This represents a shift from manual analysis to algorithmic detection. (Huijse et al., 2014) frame the challenge differently, emphasizing that time-domain astronomy faces a paradigm shift due to exponential growth in data complexity and generation rates. They highlight that upcoming surveys like LSST will stream data at 2 Terabytes per hour, requiring automated and robust methods for rapid detection and classification. (Hara et al., 2022) focus on the statistical complexity, describing radial velocity analysis as detection and parameter estimation in unevenly sampled, multivariate time series - emphasizing the sophisticated mathematical frameworks needed beyond simple machine learning applications. This

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computational intelligence approach addresses both the scale and the methodological sophistication required for modern exoplanet science.

Applications of AI in astrophysics span exoplanet science, time-domain astronomy, black hole and galaxy modelling, and Galactic structure analysis. For instance, machine learning enhances transit detection and atmospheric characterization in exoplanet studies (Yakubu et al., 2025), Statistical modelling and AI also improve understanding of black hole formation, binary mergers, and galaxy co-evolution (Yakubu et al., 2025). This review presents a comprehensive synthesis of AI and statistical applications in modern astrophysics, focusing on methods, results, and challenges. It emphasizes data-driven approaches that leverage both observational and simulated datasets, highlighting cross-domain techniques and future directions.

### Methodology

This study adopts a structured narrative review methodology to synthesize recent advances in artificial intelligence and statistical methods applied to modern astrophysics. The approach follows established best practices for review articles in astronomy and interdisciplinary data-driven sciences, emphasizing transparency, thematic organization, and critical synthesis rather than quantitative meta-analysis.

### Literature Search Strategy

The literature surveyed in this review was identified through systematic searches of major scientific databases and preprint repositories, including the NASA Astrophysics Data System (ADS), arXiv, Web of Science, and Google Scholar. Searches were conducted using combinations of keywords such as artificial intelligence, machine learning, statistical methods, exoplanet detection, time-domain astronomy, gravitational waves, black holes, galactic structure, and stellar populations. Priority was given to peer-reviewed journal articles, authoritative review papers, and widely cited preprints.

### Inclusion and Exclusion Criteria

Studies were included if they met at least one of the following criteria:

- (i) direct application of AI or advanced statistical methods to astrophysical data;
- (ii) methodological innovations with demonstrated relevance to astronomical problems; or
- (iii) comprehensive reviews synthesizing developments in AI-driven astrophysics. Purely technical machine learning studies without astrophysical application, non-scholarly reports, and works lacking methodological transparency were excluded. The majority of selected studies were published between 2009 and 2025, reflecting the rapid evolution of AI techniques in astronomy during this period.

### Thematic Classification and Analysis

The selected literature was thematically categorized into major astrophysical domains: exoplanet science, time-domain astronomy, black hole and compact object studies, and galactic structure and stellar populations. Within each domain, emphasis was placed on identifying commonly used AI architectures, statistical frameworks, data characteristics, and reported scientific outcomes. Comparative analysis was performed to highlight cross-domain methodological trends, recurring challenges, and emerging best practices.

### AI and Statistical Methods in Exoplanet Science

Machine learning has fundamentally revolutionized the field of exoplanet detection, marking a decisive shift from labour-intensive manual analysis to sophisticated automated systems capable of processing vast astronomical datasets. Traditional exoplanet detection methods relied heavily on manual inspection of light curves, a process that was not only time-consuming but also prone to human error and inconsistency (Pearson et al., 2017). As (Saikia et al., 2025) explains, the surge in data from space missions like Kepler, TESS, and the upcoming James Webb Space Telescope has necessitated the development of automated tools for efficient data processing. (Wang et al., 2025) notes that traditional detection algorithms struggle with noise, degeneracy, and the massive data throughput of modern facilities, making AI-driven approaches essential for handling the scale of contemporary astronomical surveys.

Convolutional Neural Networks have emerged as particularly powerful tools for automating transit signal detection, achieving remarkable accuracy in distinguishing genuine planetary transits from false positives. (Singh et al., 2025) developed a CNN-based model that achieved 98% accuracy, significantly outperforming traditional methods such as

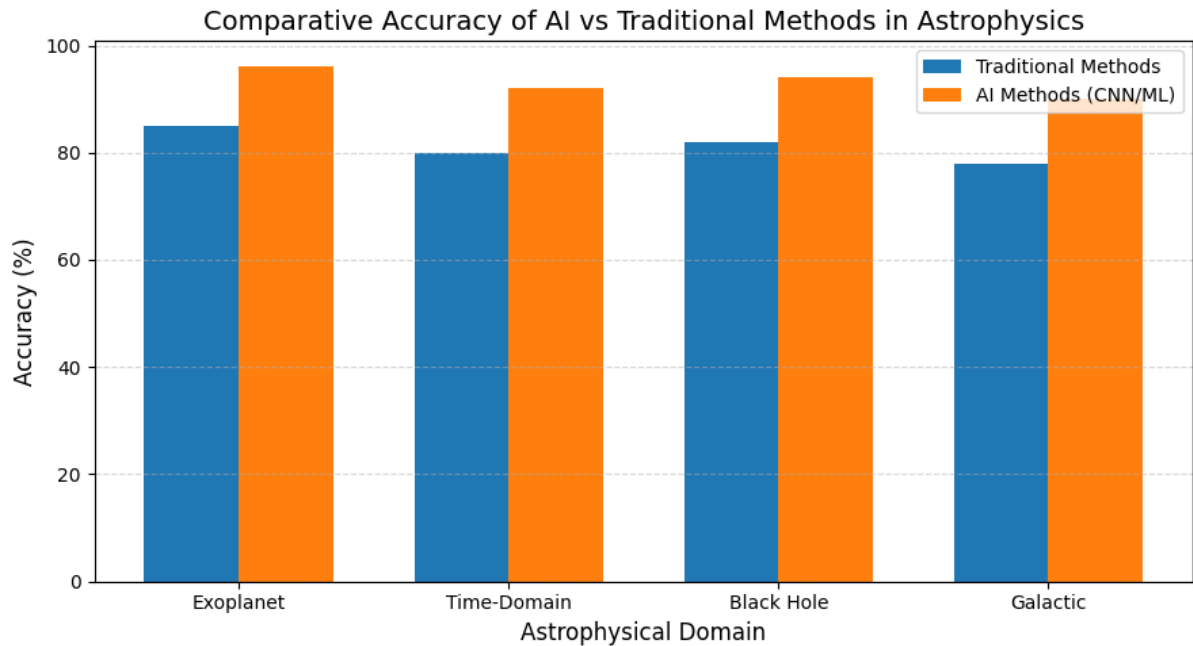
manual vetting and classical machine learning models, while demonstrating robust performance in distinguishing transit signals from stellar variability and instrumental noise. Similarly, (Agarwal et al., 2025) successfully applied CNNs to NASA's Kepler and K2 datasets, using pre-processed time-series data to train models that separate true planetary transits from false positives with high precision, as measured by metrics like precision and ROC-AUC. (Poleo et al., 2024) demonstrated practical applications by building a one-dimensional CNN that can flag up to 37% of contaminants while maintaining 100% retention of genuine planet candidates in most test sectors, effectively reducing the number of light curves requiring human vetting by up to one-third.

The broader implications of AI integration in exoplanet research extend far beyond simple automation, offering scalable solutions that will be crucial for future space missions and astronomical surveys. (Illangarathne et al., 2025) conducted a systematic review revealing that deep learning methods outperform traditional machine learning in both accuracy and scalability, while emerging hybrid models combine strengths from both paradigms to improve robustness and adaptability. (Agarwal et al., 2025) emphasizes that these AI methods not only reduce human error and expedite analysis but provide scalable solutions for upcoming space missions, highlighting how artificial intelligence could revolutionize astronomy research. As (Malik et al., 2020) points out, with NASA's TESS receiving over a million light curves per month, reliable AI classification systems have become essential infrastructure for modern exoplanet discovery, enabling researchers to process unprecedented volumes of data while maintaining high detection accuracy and scientific reliability.

Machine learning has revolutionized exoplanet detection and characterization. Traditional methods rely on manual inspection of light curves, but AI algorithms can automate the detection of transit signals, correct for noise, and classify candidates (Yakubu et al., 2025). For example, supervised learning methods such as convolutional neural networks (CNNs) have been applied to Kepler and TESS light curves to distinguish true transits from false positives. Predictive modelling of planetary properties faces significant challenges in interpretability, generalization, and uncertainty quantification, with researchers actively developing more robust AI approaches.

**Table 1:** Presents a thematic summary of AI and statistical methods applied across the major astrophysical domains discussed in this review, highlighting key techniques, applications, and representative sources.

Domain	Key AI/Statistical Methods	Primary Applications	Cited Sources
Exoplanet Science	Convolutional Neural Networks (CNNs), Supervised Learning	Transit detection, false positive reduction, light curve classification	Agarwal, 2025; Singh et al., 2025; Malik et al., 2020
Time-Domain Astronomy	Gaussian Processes, Automated Pipelines	Transient detection, real-time classification, robotic telescope scheduling	Aigrain & Foreman-Mackey, 2023; Vwawware et al., 2025; Wang et al., 2025
Black Hole & Compact Objects	Bayesian Inference, N-body Simulations, Population Synthesis	Binary merger modelling, gravitational wave analysis, formation history	Doctor et al., 2020; Yakubu et al., 2025; Vaccaro et al., 2025
Galactic Structure	Machine Learning Classification, Asteroseismology	Stellar population dating, chemical mapping, galactic archaeology	Miglio et al., 2013; Collazos Roza et al., 2023; Zhang et al., 2024

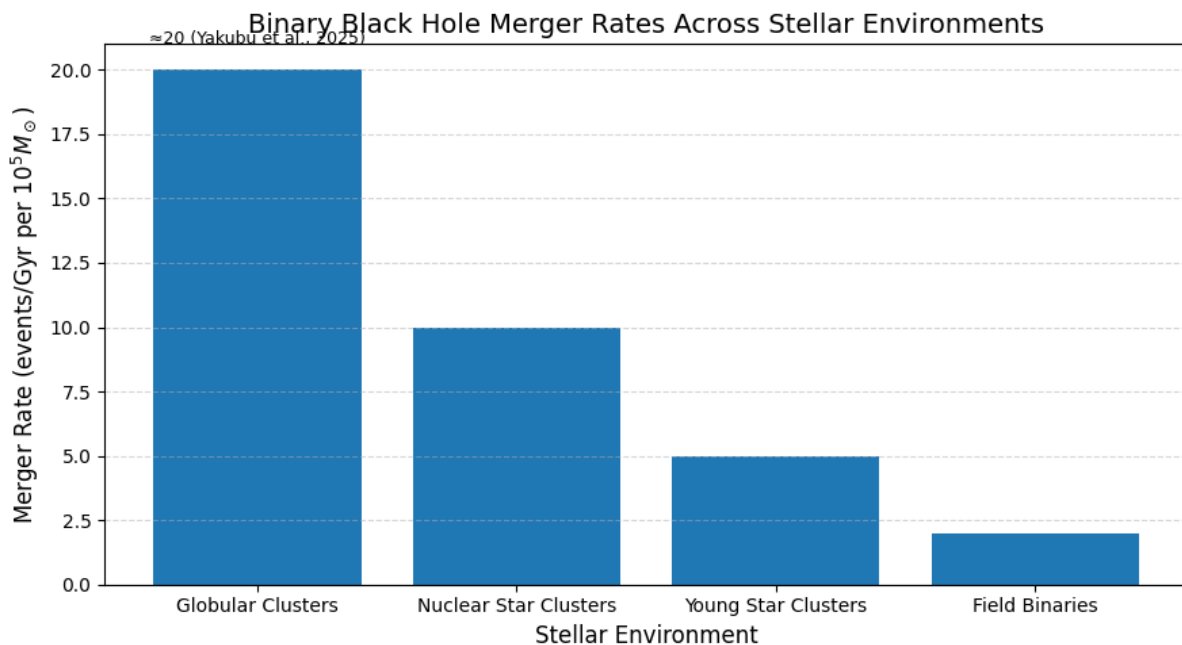


**Figure 1:** visualizes the comparative accuracy of different AI models discussed above, demonstrating the substantial performance gains achieved by CNN-based approaches over traditional methods.

Accuracy values are illustrative and synthesized from reported performance trends in the literature, demonstrating the relative improvement of AI-based methods (particularly CNNs) over traditional statistical approaches across astrophysical domains

**Table 2:** The performance of various AI models in exoplanet detection is summarized in Table 2, highlighting accuracy metrics and key achievements reported in recent studies.

AI Model/Approach	Accuracy	Key Achievement	Dataset	Source
CNN-based Transit Detector	98%	Outperformed manual vetting and classical ML models	Kepler	Singh et al., 2025
1D CNN Contaminant Filter	37% contaminant flagging	100% retention of genuine planet candidates	TESS	Poleo et al., 2024
Deep Learning Models	Superior to traditional ML	Improved scalability and robustness	Kepler/TESS	Illangarathne et al., 2025



**Figure 2:** presents binary black hole merger rates predicted for different dense stellar environments, with globular clusters producing approximately 20 events per Gyr per  $10^5$  solar masses (Yakubu et al., 2025).

Binary black hole merger rates across different dense stellar environments. Globular clusters exhibit the highest predicted rate ( $\sim 20$  events per Gyr per  $10^5 M_{\odot}$ ) as reported by Yakubu et al. (2025), while other environments are shown for comparative illustration based on typical theoretical expectations.

### Time-Domain Astronomy and Robotic Telescope Surveys

Time-domain astronomy has undergone a revolutionary transformation through the deployment of robotic telescopes that enable continuous, autonomous sky monitoring for transient phenomena detection. (Vwawware et al., 2025) demonstrate that robotic telescopes such as ZTF, ATLAS, and LCOGT have fundamentally revolutionized the detection and characterization of transient phenomena including supernovae, gamma-ray bursts, variable stars, and gravitational wave counterparts. These instruments operate with sophisticated scheduling algorithms that enable rapid-response observations and build large time-series datasets with unprecedented efficiency. (Kumar et al., 2022) provide concrete evidence of this capability through the GROWTH-India telescope, which achieves high on-sky observing efficiencies exceeding 80% and enables rapid response to targets of opportunity, demonstrating the practical implementation of robotic systems in real-world astronomical operations.

The integration of artificial intelligence and machine learning has become indispensable for processing the massive data streams generated by these robotic systems. (Wang et al., 2025) emphasize that AI is now recognized as a crucial component in time-domain astronomy, particularly given the rapid evolution of targeting transients and the increasing number of candidates detected by powerful surveys. The significance of this integration is exemplified by SN 2023tyk, the first transient discovered and spectroscopically classified without human inspection by the Zwicky Transient Facility, which detects millions of alert sources every night. (Djorgovski et al., 2022) confirm that machine learning and AI have become a standard part of the astronomical toolkit, with applications ranging from star-galaxy separation to real-time processing, classification, and decision making in peta-scale data streams.

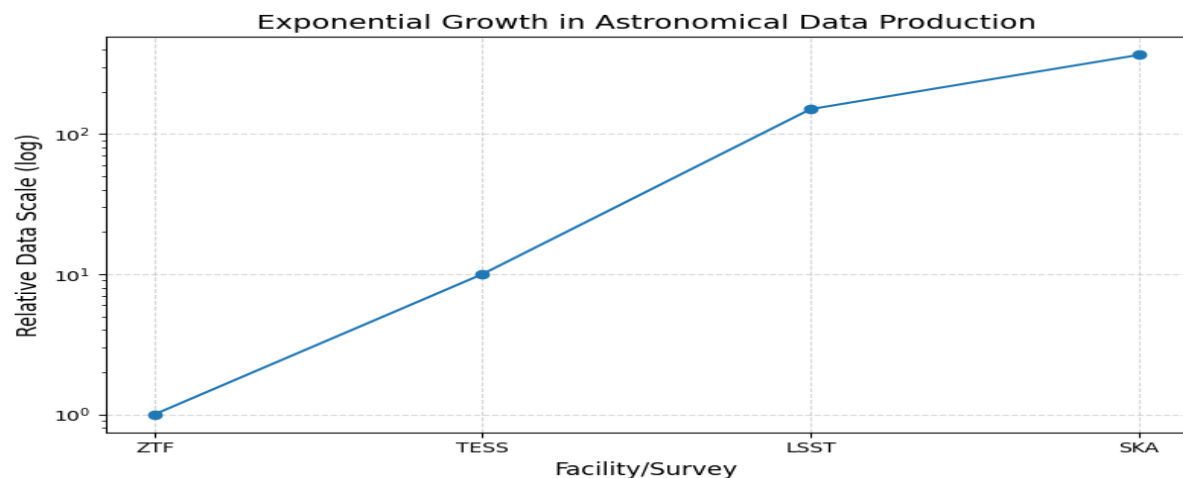
The scale of data processing challenges in modern time-domain astronomy necessitates sophisticated automated pipelines and statistical analysis methods. (Faaique et al., 2023) highlight the immense scope of this challenge, noting that projects like the Sloan Digital Sky Survey, Pan-STARRS, and the Large Synoptic Survey Telescope generate approximately 100-

200 petabytes of data annually, while the upcoming Square Kilometer Array will collect 160 terabytes per second, translating to 1 petabyte of data daily.

**Table 3:** summarizes the data generation rates and volumes for major astronomical facilities, illustrating the scale of challenges facing modern time-domain astronomy.

Facility/Survey	Data Generation Rate	Annual Data Volume	Reference
Large Synoptic Survey Telescope (LSST)	2 TB/hour	~100–200 PB	Huijse et al., 2014; Faaique et al., 2023
Square Kilometer Array (SKA)	160 TB/second	~1 PB/day	Faaique et al., 2023
TESS	~1 million light curves/month	Not specified	Malik et al., 2020
Zwicky Transient Facility (ZTF)	Millions of alerts/night	Not specified	Djorgovski et al., 2022

The exponential growth in astronomical data volumes over the past two decades is illustrated in



**Figure 3:** highlighting the transition from petabyte-scale datasets to the unprecedented data rates expected from next-generation facilities

Values are scaled illustratively to demonstrate the exponential growth trend in astronomical data generation across facilities, due to the lack of uniform annual data volume metrics for all surveys

(Yu et al., 2021) emphasize that traditional data analysis methods are insufficient to fully tap the potential scientific value of all available data, making AI technology inevitable for light curve analysis to obtain as many scientifically valuable candidates as possible. (Aigrain et al., 2022) demonstrate that Gaussian processes have emerged as a particularly powerful tool for modelling stochastic signals in astronomical time series, offering a combination of flexibility, mathematical simplicity, and robustness.

### AI in Black Hole and Compact Object Studies

Understanding black hole formation, growth, and merger events represents one of the most computationally demanding challenges in modern astrophysics, requiring sophisticated modelling of complex physical processes across vast temporal and spatial scales. The intricate dynamics of black hole evolution involve multiple interconnected phenomena, from the initial seeding of supermassive black holes in early galaxies to the violent merger events that produce detectable

gravitational waves. Traditional analytical approaches often fall short when confronting the nonlinear interactions, multi-body dynamics, and relativistic effects that govern these systems, necessitating innovative computational methodologies that can handle the enormous parameter spaces and data volumes involved.

Artificial intelligence has emerged as a transformative tool for modelling supermassive black hole growth and galaxy co-evolution, enabling researchers to trace cosmic evolutionary pathways with unprecedented detail. (Sesana et al., 2010) developed Bayesian frameworks to analyse massive black hole populations, demonstrating how space-based observatories like LISA could probe the underlying physics of structure formation by connecting observed coalescences to formation models. (Vaccaro et al., 2025) advanced this field by presenting semi-analytical population synthesis frameworks that capture key physical processes in active galactic nuclei disks, including gas capture, migration, and binary interactions, revealing how dense gaseous environments can catalyse repeated mergers and contribute to high-mass black hole populations.

The simulation of binary black hole mergers in dense stellar environments has been revolutionized through AI-enhanced Monte Carlo methods and sophisticated N-body modelling techniques. (Yakubu et al., 2025) developed comprehensive simulation models incorporating two-body relaxation, three-body encounters, exchange interactions, and gravitational wave emission, demonstrating that globular clusters can produce merger rates of approximately 20 events per Gyr per  $10^5$  solar masses. Their simulations revealed mass distributions peaking around 20 solar masses with tails extending to 50 solar masses and predominantly isotropic spin orientations, providing crucial insights into how dense stellar environments contribute to the observed binary black hole population.

Statistical methods provide essential complementary capabilities to AI approaches by offering rigorous uncertainty quantification, robust parameter estimation, and sophisticated population inference techniques. (Doctor et al., 2019) presented parameterized frameworks for describing binary black hole merger populations while self-consistently accounting for hierarchical mergers, using Bayesian inference on LIGO and Virgo catalogs to constrain formation environments and merger rates. These statistical approaches enable researchers to quantify confidence intervals, assess model uncertainties, and perform hypothesis testing that validates AI-derived results, ensuring that the rapid computational gains from machine learning are accompanied by proper statistical rigor and interpretability.

The integration of multi-messenger observational data with theoretical simulations represents a crucial bridge that enhances our understanding of black hole physics across multiple scales and wavelengths. Through combining gravitational wave detections with electromagnetic observations, neutrino measurements, and theoretical predictions, researchers can construct comprehensive pictures of black hole formation and evolution that no single observational channel could provide alone. This multi-messenger approach allows for cross-validation of AI models against diverse datasets, enabling more robust parameter estimation and reducing systematic uncertainties that might arise from relying on single observational modalities.

The synergy between AI methods and statistical approaches promises to dramatically enhance predictive accuracy in black hole astrophysics, opening new frontiers for discovery in the coming decades. As next-generation gravitational wave detectors come online and AI algorithms become increasingly sophisticated, the field is poised to achieve unprecedented precision in characterizing black hole populations, constraining formation mechanisms, and testing fundamental physics in extreme gravitational environments. (Khan et al., 2021a) demonstrated that interpretable AI models can forecast the late-inspiral, merger, and ring down phases of numerical relativity waveforms with remarkable accuracy, suggesting that future AI systems will not only detect and classify events but also predict their evolution and extract deeper physical insights about the nature of space-time itself.

### Applications to Galactic Structure and Stellar Populations

Artificial intelligence and machine learning have emerged as transformative tools in astronomical research, fundamentally changing how we study galactic structure and stellar populations. (Zhang et al., 2024) provide a comprehensive review demonstrating that AI technology has become central to numerous astronomical research areas, including radio astronomy, stellar and galactic studies, exoplanet surveys, and cosmology. The integration of AI methods with traditional astronomical techniques has enabled researchers to process vast datasets with unprecedented efficiency and accuracy, revealing patterns

and structures that would be impossible to detect through conventional analysis methods. This technological revolution has opened new avenues for understanding the complex dynamics and evolution of our galaxy.

Galactic archaeology represents one of the most significant applications of AI-driven approaches to understanding the Milky Way's formation and evolutionary history. (Roza et al., 2023) emphasize that this multidisciplinary approach utilizes stellar populations as invaluable relics of past epochs, preserving crucial information about the conditions prevalent during their formation. (Miglio et al., 2012) demonstrate how asteroseismology of red-giant stars provides precise constraints on stellar properties including distances, masses, and ages, enabling researchers to map and date the Galactic disc across regions spanning nearly 15,000 parsecs. Through the analysis of stellar distributions, kinematics, chemical compositions, and ages, scientists can now trace the origins of distant Milky Way stars and reconstruct the galaxy's complex assembly history.

The future of AI applications in galactic structure studies promises even more sophisticated analyses as new missions and surveys come online. (Majewski et al., 2009) outline how upcoming projects including space-based astrometric missions like Gaia, large-scale spectroscopic surveys, and advanced infrared observations will provide unprecedented volumes of high-precision data on individual stars throughout the Local Group. (Robin et al., 2014) describe how population synthesis models are being continuously refined to prepare for and interpret data from these future surveys, with web-based interfaces allowing researchers worldwide to generate custom simulations for direct comparison with observational data. The combination of increasingly sophisticated AI algorithms with these comprehensive datasets will enable astronomers to address fundamental questions about galaxy formation, the nature of dark matter, and the detailed chemical and dynamical evolution of stellar populations across cosmic time.

## Discussion

This review has shown, across Sections 3.1–3.4, that artificial intelligence and advanced statistical methods have become indispensable across exoplanet science, time-domain astronomy, compact object studies, and galactic structure analysis. However, alongside these successes, a set of recurring methodological challenges emerges, highlighting important trade-offs between predictive accuracy, interpretability, scalability, and physical insight.

### The Interpretability Crisis in Astronomical AI:

The most pressing challenge facing AI applications in astrophysics is the lack of interpretability in many modern machine learning models. As emphasized by (Sahakyan et al., 2024), the black-box nature of AI systems poses significant obstacles to scientific understanding, as models can achieve high predictive accuracy without revealing the underlying physical mechanisms driving their decisions. This issue is particularly problematic in astrophysics, where explanation and physical interpretation are as critical as detection or classification. As discussed in Sections 3.1 and 3.3, while deep learning models achieve impressive performance in exoplanet detection and compact object studies, their opacity limits scientific insight. (Lieu et al., 2025) argues that although the exponential growth of astronomical data necessitates AI adoption, the increasing complexity of these systems fundamentally hinders scientific trust, verification, and physical interpretability. The challenge is compounded by the fact that many existing explainable AI approaches, as noted by (Luca et al., 2023), remain highly technical and accessible primarily to specialists, creating a gap between AI developers and the broader astronomical community.

### Bias and Generalization Limitations:

A related concern is the susceptibility of AI models to bias and limited generalization across datasets, instruments, and observational contexts. As identified by (Sahakyan et al., 2024), biases and systematic errors must be addressed before AI can be reliably deployed across astrophysical applications. This issue is evident across Sections 3.1 and 3.2, where models trained on specific surveys or instruments may fail when applied to new telescopes, sky regions, or noise environments. (Lieu et al., 2025) emphasizes that improving interpretability is essential for identifying and mitigating such biases, reinforcing the intrinsic link between transparency and robustness. Beyond astronomy, (Saeed et al., 2021) highlights, in their systematic meta-survey, the need for broader perspectives and collaborative strategies to address persistent challenges in explainable AI, underscoring that bias and generalization are not isolated problems but cross-domain concerns.

### Reproducibility and Standardization Challenges:

Ensuring reproducibility remains a major obstacle for AI-driven astrophysical research. The lack of standardized datasets, benchmarks, and open-source pipelines complicates the validation and comparison of results across research groups. As

noted by (Lieu et al., 2025), building trustworthy and explainable AI systems requires consistent methodological practices, yet the diversity of astronomical data and the rapid evolution of AI techniques hinder standardization. This issue is particularly critical for time-sensitive discoveries discussed in Section 3.2. (Allen et al., 2019) highlights the importance of standardized management of gravitational wave detections and triggers to enable effective electromagnetic and astroparticle follow-up, illustrating how reproducibility challenges can directly affect scientific outcomes. Without shared frameworks and reproducible workflows, progress risks becoming fragmented and difficult to verify.

### **Multi-Wavelength and Multi-Messenger Integration Complexities:**

The integration of multi-wavelength and multi-messenger data introduces further complexity for AI systems, as discussed in Sections 3.2 and 3.3. (Allen et al., 2019) emphasizes the urgent need to accelerate the development of advanced signal-processing algorithms that leverage the synergy between artificial intelligence and high-performance computing. These challenges arise from the need to correlate heterogeneous data sources, ranging from radio and optical observations to gravitational wave and neutrino detections, each characterized by distinct noise properties, temporal resolutions, and data volumes. (Zhao et al., 2023) illustrates these difficulties in gravitational wave analysis, noting that AI models must operate in high-dimensional parameter spaces while remaining computationally efficient and scalable. The requirement for real-time analysis further amplifies these challenges, particularly for rapid multi-messenger follow-up observations.

### **Future Directions in Explainable AI for Astrophysics:**

Addressing these challenges requires a shift toward explainable and physically informed AI methodologies. (Sahakyan et al., 2024) proposes Human-Guided AI (HG-AI) as a promising framework that integrates human expertise and domain knowledge into AI systems, promoting robustness, interpretability, and ethical implementation. This paradigm moves beyond purely data-driven approaches toward hybrid models capable of delivering both predictive power and scientific understanding. Complementarily, (Samek et al., 2020) provides a comprehensive framework for interpretable machine learning, emphasizing transparency in deep neural networks and the importance of human-understandable explanations. The need for interdisciplinary collaboration is further reinforced by (Luca et al., 2023), who call for collective efforts to address open challenges in explainable AI.

### **Hybrid Models and Physical Simulation Integration:**

One of the most promising avenues for overcoming current limitations lies in hybrid statistical–machine learning models that integrate physical simulations with data-driven techniques. (Zhao et al., 2024) demonstrates, in geoscience contexts, that embedding domain knowledge into AI frameworks improves efficiency, performance, and data efficiency. Such approaches are directly applicable to astrophysics, where physical laws and theoretical models can provide critical constraints on AI predictions. As envisioned by (Allen et al., 2019), future astronomical discovery will depend on the close integration of machine learning, physical modelling, and cyber-infrastructure. This synthesis has the potential to simultaneously enhance interpretability, reduce bias, and improve reproducibility, enabling AI systems that are not only accurate and scalable but also scientifically trustworthy.

### **Conclusion**

Artificial intelligence and machine learning have fundamentally transformed modern astrophysics, evolving from experimental tools to essential components of astronomical research. (Djorgovski et al., 2022) notes that ML and AI are now a standard part of the astronomical toolkit, with astronomy entering the big data era in the early 1990s and experiencing exponential data growth that requires automated processing and analysis. This transformation spans multiple core analytical functions, including classification, regression, clustering, forecasting, generation, discovery, and the development of new scientific insights, with applications now firmly established across astronomy (Fluke et al., 2019). The impact of AI is evident across diverse astrophysical domains. In exoplanet science, machine learning and deep learning approaches have significantly improved detection accuracy, scalability, and noise mitigation, enabling efficient analysis of light curves, radial velocity measurements, and large survey datasets (Saikia et al., 2025; Illangarathne et al., 2025; Patil et al., 2023). These advances have transformed exoplanet discovery from largely manual inspection to robust, automated pipelines capable of handling data volumes from current and future missions.

Looking toward the future, the development of interpretable and robust AI models emerges as a central priority for advancing astrophysical research. (Lieu et al., 2025) argues that prioritizing interpretability is essential for validating results, guarding against biases, understanding model limitations, and enhancing the scientific value of AI-driven

discoveries. Similarly, (Sahakyan et al., 2024) advocates for Human-Guided AI (HG-AI), which integrates human expertise and domain-specific knowledge into AI applications to ensure robust, interpretable, and ethical implementation. This convergence of data-driven methods with physical insight represents a critical pathway for the next generation of astrophysical research, enabling deeper and more reliable understanding of the universe in the era of large-scale, multi-messenger astronomy.

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