

How Is Artificial Intelligence Transforming Astronomy?

Name: Gauri Nikhil Rao

Institution: Greenwood High International School, Bangalore, India

Mentor: Divya Singh

ABSTRACT

Astronomers are using Artificial Intelligence (AI) in a new way to investigate the universe. Each day, modern telescopes gather enormous amounts of data about galaxies and distant stars as well as all the signals received from space. Because the data collected exceeds what scientists can analyze with their existing techniques, AI is being utilized to analyze the massive amounts of data collected. AI will assist scientists in identifying patterns, sorting through large amounts of data, and identifying objects/phenomena in a faster, easier, and more efficient way than performing these tasks by hand or with traditional means.

This paper will analyze and describe how the incorporation of AI into modern-day astronomy will impact how astronomers make discoveries. The introductory section will provide a basic understanding of AI and ML as well as explain how these technologies will enable astronomers to make discoveries. There are four case studies that will be analyzed: (a) Exoplanets found with AI in Kepler-based data; (b) AI-assisted galaxy classification with Galaxy Zoo; (c) AI used for supernova detection with the Dark Energy Survey; and (d) AI detection of fast radio bursts using radio telescope data.

The conclusion of the paper is that through the use of AI, researchers will be able to quickly process an unprecedented volume of data and find those objects/events that they would not have otherwise been able to find via traditional data processing methods.

Similarly, AI systems are not inherently good and may make errors based on incomplete or biased datasets. Scientific verification of findings will continue to be performed by human researchers. Thus far, research has shown that AI has been valuable to astronomy; as larger amounts of data are collected via telescopes, AI will have greater influence in assisting scientists to investigate and understand our universe.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Astronomy, Exoplanet Detection, Galaxy Classification, Supernova Detection, Fast Radio Bursts, Astronomical Data Analysis

INTRODUCTION

Society has never examined the universe more closely than it does today, yet the greatest challenge facing modern astronomy is no longer collecting data but making sense of it. Advances in telescope technology, space missions, and large sky surveys have enabled scientists to gather unprecedented amounts of data. Modern observatories produce large datasets related to stars, galaxies, exoplanets, and other celestial objects. Today, surveys produce tera-scale to peta-scale streams of images, spectra, and time-series signals each night and this volume continues to increase (Smith & Geach, 2022). These observations can help astronomers make new discoveries about the universe. While these datasets offer research opportunities, their sheer size and complexity have made them difficult to analyze using traditional methods (Djorgovski et al., 2022).

Manual analysis of this data is often impractical because human researchers and traditional statistical techniques can be overwhelmed by billions of individual measurements and observations (Djorgovski et al., 2022). It is this challenge that has led to the rise of AI as a scientific tool that can automate the tasks which previously took up enormous amounts of researcher time and effort (Baron, 2019). AI is no longer being used just as a supplementary tool. It is now being applied throughout the astronomical research process, helping astronomers process data more efficiently, identify patterns and gain new insights into the universe (Djorgovski et al., 2022).

One of the most important developments in this field has been the use of deep learning, a branch of machine learning that employs artificial neural networks in order to process data. Deep learning models can process astronomical images and signal data directly from raw observations, reducing the need for manual feature extraction, while classifying objects more quickly and accurately (Smith & Geach, 2022).

In contrast to traditional rule-based analysis, AI, specifically machine learning systems, can process much more data and find unexpected patterns that may not be immediately obvious to human researchers. Automated tools can help perform tasks like cluster analysis, dimensionality reduction, and outlier removal on large data sets that usually demand substantial manual effort (Baron, 2019). Such approaches have been incredibly successful in finding new patterns in astronomical data and have contributed to many scientific discoveries across several areas of

astronomy. AI has played an important role in exoplanet discovery, galaxy classification, detection of space events and the analysis of radio signals (NASA, 2025).

Importantly, AI is not used to replace astronomers but to assist them. Automated systems typically screen the data first, identifying candidates, anomalies, or things of interest, and leave it to experts to verify results (Smith & Geach, 2022). This collaborative approach also enables astronomers to concentrate on the most interesting or unusual results, rather than spending time sifting through raw data.

AI is also playing an important role in time-domain astronomy which studies objects and events in space that change over time like exploding stars, fast radio bursts, and variable stars.

Automated systems can quickly analyze new incoming data, detect anomalies, and alert scientists when immediate follow-up and investigation is required. As new observatories continue to increase the volume, speed and complexity of data, AI systems will become even more critical for astronomical data management and interpretation (Wang et al., 2025).

Furthermore, leading scientific organizations consider AI a key technology for future astronomical and astro biological research. NASA has identified artificial intelligence as a valuable tool for future scientific discovery, particularly as upcoming missions are bound to generate increasingly complex datasets (NASA, 2025). As AI penetrates deeper into scientific research, its influence on astronomy is expected to increase, making it an important area of study. However, the adoption of AI also raises important concerns. Issues such as model transparency, reliability, interpretability, and potential bias (Smith & Geach, 2022) remain persistent areas of discussion within the scientific community. Understanding both the benefits and limitations of AI is essential to determine its overall impact on astronomical research.

The majority of existing literature focuses on specific applications or technological advances rather than examining how these different uses are collectively transforming modern astronomy. Much of this literature is also written at a highly technical level, making it less accessible to students and other non-specialist readers. Although many studies highlight the benefits of AI, very few discuss both its strengths and limitations. As a result, a more balanced evaluation is needed.

Additionally, although scientists often tout the benefits of AI analysis, there is a need for a thorough examination of the benefits and drawbacks of the growing use of artificial intelligence in astronomical research. As AI systems are increasingly integrated into scientific workflows, the

impact of AI on discovery, decision-making, and future research practices has become increasingly important.

The rapid development of AI applications raises important questions about how AI is changing modern astronomy. By analyzing current applications, successes, and limitations of AI in astronomy, this study hopes to give a broader understanding of how AI is changing astronomy.

This study is guided by the following research question: How is artificial intelligence transforming modern astronomy, and what benefits and challenges does it create for astronomical research?

The central thesis for the paper is: Artificial intelligence has transformed modern astronomy by helping with the analysis of large datasets, the discovery and classification of astronomical objects, and the making of new scientific discoveries. However, challenges related to accuracy, transparency, interpretability, and the need for human oversight remain important considerations for the future use of AI in astronomy. Figure 1 shows the increase in astronomical data and AI-related research between 2017 and 2023.

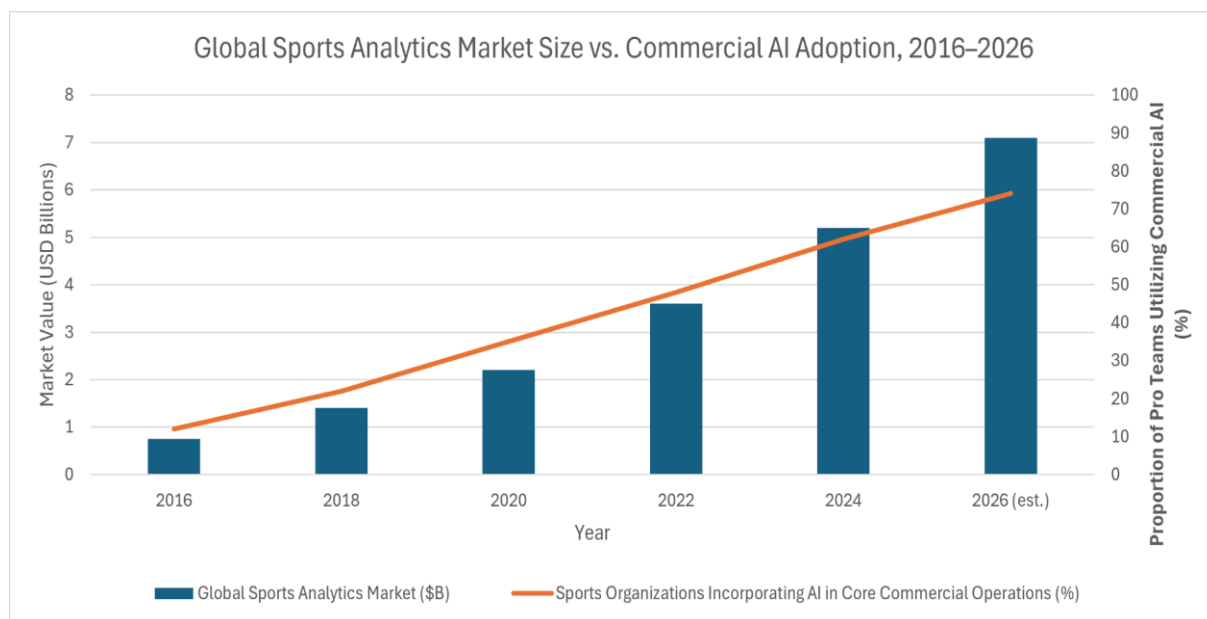


Figure 1. Growth in Astronomical Data volume and AI Research (2017–2023)

Note. Created by the author using information from Smith and Geach (2022) and Fotopoulou (2024).

LITERATURE REVIEW

Artificial Intelligence as a Tool for Astronomical Research

AI systems have the unique ability to learn directly from data. Thus, they can solve multiple scientific problems without being specifically programmed for each one (Djorgovski et al., 2022). This adaptability makes AI especially useful in modern astronomy where vast amounts of data are collected everyday by modern telescopes and sky surveys. AI helps researchers process and analyze this large volume of data much faster than would be possible manually (Djorgovski et al., 2022).

Machine learning which is a major branch of AI can be used for solving problems in multiple areas of astronomy. One common branch of machine learning is supervised learning which uses labeled data to classify astronomical objects or predict their properties. In contrast, unsupervised learning does not rely on labeled data. Instead, it studies the data itself and groups together objects that have similar properties. This is particularly useful in astronomy, where many objects have not yet been classified and labeled catalogs are not available. For example, unsupervised learning in astronomy can be used to group galaxies with similar morphology, identify unusual objects and efficiently organize large datasets. More broadly, machine learning is used widely in astronomy, including classification, prediction, clustering and anomaly detection. In particular, deep learning has been very useful in analyzing images and signals collected by telescopes which make up most of the observational astronomical data (Smith & Geach, 2022).

Deep learning can extract useful information directly from raw telescopic data and identify subtle details in telescope images or spectral signals that may be missed by traditional methods. As a result, deep learning has improved tasks such as classifying galaxies, detecting exoplanets and identifying short-lived astronomical events in real time. This has allowed astronomers to study larger volumes of data and make new discoveries more quickly (Djorgovski et al., 2022).

It is also important to point out the limitations of AI. AI models are becoming increasingly complex and researchers are finding it harder to understand the logic behind their predictions and classifications (Buchner & Fotopoulou, 2025). Other concerns relate to reliability, biased training data, and overfitting.

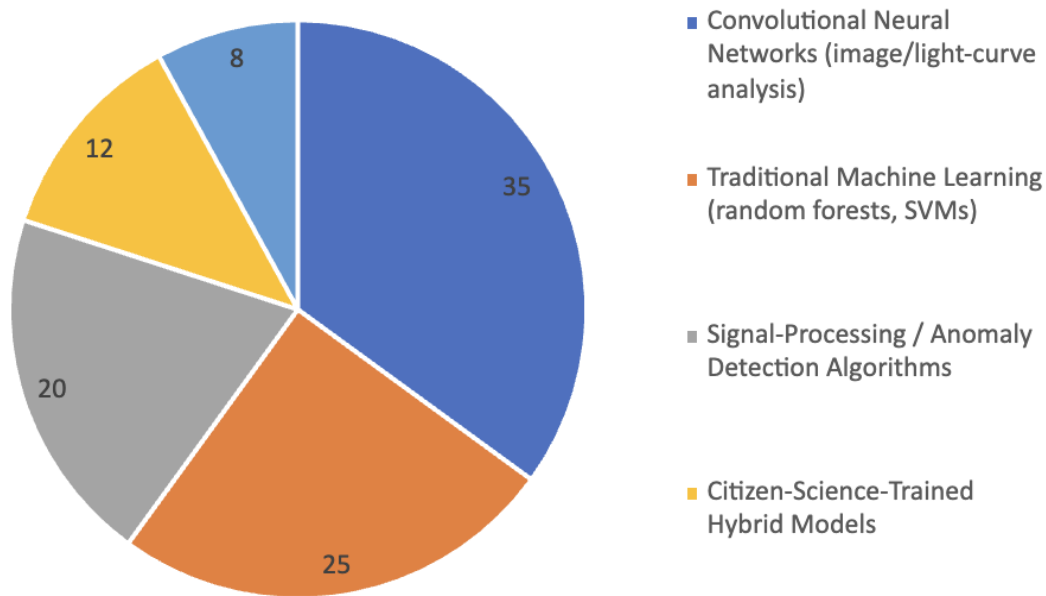


Figure 2. *Distribution of AI Techniques Used Across Astronomical Applications*

Note. Created by the author using information from Fluke & Jacobs (2020); Baron (2019)

Astronomy in the Era of Big Data

In the modern age, astronomy has become a science that is based on an enormous amount of data from the large sky surveys and space observatories. As observatories become more advanced, both the volume and complexity of astronomical data keeps increasing. Modern wide-field surveys collect millions of images, spectra and time series observations. These produce datasets that include billions of celestial objects (Smith & Geach, 2022). Projects like Sloan Digital Sky Survey (SDSS), Zwicky Transient Facility (ZTF), and the Vera C. Rubin Observatory Legacy Survey of Space and Time (LSST) have provided researchers with far more astronomical data than ever before.

While Sloan Digital Sky Survey mapped millions of celestial bodies, the focus of Zwicky Transient Facility was on detecting short-lived astronomical events that keep changing quickly over time. The Vera C. Rubin Observatory is expected to further build on these efforts by providing researchers with unprecedented amounts of astronomical data (Smith & Geach, 2022). Handling such vast amounts of information has become very challenging for astronomers. The sheer volume of data generated by modern sky surveys is too large for manual analysis in which researchers visually inspect images or spectra in order to locate and classify objects of interest

(Baron, 2019). A single night of observations can produce hundreds of thousands of detections, making manual analysis tedious, time consuming and impractical. Without the help of automated tools, important discoveries may be missed within these large volumes of data (Baron, 2019). Time-domain astronomy has added another layer of complexity and challenge for astronomers. It deals with objects such as supernovae, variable stars, and other short-lived events that change over time. Monitoring the sky for such events is particularly challenging for researchers, as it requires continuous data streams and rapid data processing systems which can detect and classify sources in near real-time (Wang et al., 2025).

This growing volume of astronomical data has necessitated the use of AI-based automated tools that can analyze information quickly and more efficiently (Fotopoulou, 2024).

AI in Exoplanet Detection

An exoplanet is any planet that orbits a star outside our Solar System. The search for these planets is one of the most data-intensive areas of modern astronomy as space missions such as the Kepler mission provide enormous amounts of data related to exoplanets (Shallue & Vanderburg, 2017). Most exoplanet searches are based on the transit method, which involves measuring the periodic dips in a star's brightness as a planet transits in front of the star and blocks a small portion of its light (Shallue & Vanderburg, 2017). This concept seems fairly straightforward, but in practice the dips are so minuscule that they may be confused with noise, measurement errors (instrumental artifacts) or natural changes in a star's brightness (stellar variability), making a manual inspection of all the light curves nearly impossible.

To overcome this challenge, researchers trained AI-based deep learning models to recognize the shape of a real transit signal, and search through thousands of stellar light curves in a fraction of the time required by human effort (Yu et al., 2019). In fact, researchers were able to train these models using large amounts of labeled data collected by the Kepler mission helmed by NASA (Shallue & Vanderburg, 2017). For example, NASA's ExoMiner system employed deep learning to confirm 301 previously unidentified exoplanets from a sample of survey data (Valizadegan et al., 2022).

However, automatic discovery of exoplanets using AI is far from perfect. Models can sometimes mistake unusual or noisy signals for real planets and ultimately, their successful performance depends on the quality of the data used to train them. Despite these limitations, AI-based vetting

has enabled astronomers to scan a much larger pool of potential exoplanets than ever before, making the process of finding new worlds beyond our solar system faster and more efficient.

AI in Galaxy Classification

A key to understanding galaxy formation and evolution is studying the shape, or morphology of galaxies. Galaxies are generally classified by their appearance: spiral, elliptical and irregular (Willett et al., 2016). Until recently, this classification was made manually by astronomers, a process which worked well for smaller catalogs, but became increasingly impractical as the size of sky surveys grew and they began to produce images of millions of galaxies.

To overcome this challenge, projects such as Galaxy Zoo invited members of the public to help in the classification of galaxies by eye, through an online website. This initiative was highly successful and it helped classify more than 120,000 galaxies for the Hubble Space Telescope Galaxy Zoo project alone. (Willett et al., 2016).

Citizen science helped address part of the scaling challenge, but it still required considerable coordination and time. Additionally, the newer, modern sky surveys now create images so rapidly that even large groups of citizen science volunteers struggle to keep up with the ever-increasing volume of data.

AI based deep learning has helped address this problem. Using data sets such as Galaxy Zoo, models have been found to classify galaxy morphology with a similar degree of accuracy as human volunteers, but at a much quicker pace (Walmsley et al., 2021; Cavanagh et al., 2021).

Whereas it takes weeks or months for volunteers to analyze images, AI-models can analyze large batches involving thousands of galaxy images almost immediately. This has enabled researchers to investigate the evolution of galaxy structure over a much larger sample of galaxies than previously possible, providing a more detailed understanding of galaxy evolution throughout cosmic time.

AI in Event and Signal Detection

Some of the most valuable information in modern astronomy comes from short lived events that can be hard to detect. One important example is a supernova, a powerful stellar explosion which is extensively studied in modern cosmological research. Good supernova candidates can be hard to find in the enormous amounts of sky survey data, and identifying them is time consuming and challenging (Lochner et al., 2016). Machine learning has aided in this effort by enabling researchers to automatically identify potentially promising supernova candidates from the

photometric data taken during the course of extensive sky surveys reducing the need to manually check each of the identified supernovae (Lochner et al., 2016).

A similar problem arises for Fast Radio Bursts (FRBs), which are extremely brief radio pulses, typically lasting only a few milliseconds (Connor et al., 2018). Since FRBs occur for only a fraction of a second and happen rarely, they are easily lost or even confused with radio frequency interference or background noise. To address this problem, researchers have come up with a classification approach using machine learning techniques that can differentiate between genuine astrophysical signals and noise (Zhang et al., 2018).

As large-scale FRB surveys grow, the machine-learning classification approach has become the standard for processing data received from these surveys (Qiang et al., 2024).

AI is also being applied to SETI (Search for Extraterrestrial Intelligence) research, where the aim is to analyze large amounts of radio telescope data in search of signals that may be of extraterrestrial origin. Since the potentially meaningful signals are rare and hard to find amidst the noise and interference, machine learning models are especially useful in detecting unusual patterns, assisting researchers in identifying signals that require more careful, manual examination (Wang et al., 2025).

This use of AI for real-time signal detection reflects a growing trend in time-domain astronomy where continuous time streams demand systems capable of detecting events as they happen instead of after they have occurred (Wang et al., 2025).

METHODOLOGY

The study includes a qualitative review of available literature from multiple sources (including peer-reviewed publications, agency reports, and trustworthy online sites). This information is used for a comparative case study to show how Artificial Intelligence (AI) has been employed to advance astronomical research using information collected through telescopes, satellites, and astronomical surveys; specifically, the datasets created by these methods.

This research paper will begin with a brief discussion of AI principles and provide some background information on how machine learning systems may be applied to analyze this volume of data. The researcher will discuss astronomical data generated from multiple sources including the challenges associated with managing it as well as describing AI technologies like

neural networks, image recognition, and classification algorithms that astronomers use to process data more efficiently.

To illustrate the above, four examples will be compared using the case study approach to highlight how AI is being used in real-world applications.

Four case studies were chosen, including: AI-assisted finding of exoplanets from Kepler data, Galaxy Zoo's AI-based galaxy classification, AI detection of supernovae in the Dark Energy Survey, and AI detection of fast radio bursts using radio telescope data. Each of the four case studies will be reviewed according to the same categories: background, application of AI, outcomes, limitations and significance. The paper will also compare the use of AI in different areas of astronomy and assess its overall contribution to scientific research.

RESULTS

AI Discovery of Exoplanets Using Kepler Data (2017–2018)

Background

NASA's Kepler mission is one of the most important examples of the practical application of AI in astronomy. Kepler is a spacecraft designed to detect planets by measuring the tiny dimming in a star's brightness as a planet passes in front of it, a method known as the transit method. During its mission, Kepler observed more than 150,000 stars and returned over 10,000 possible transit signals leading to the discovery of thousands of exoplanet candidates (NASA, 2017). This yielded a lot of useful information, but also a problem: many of the faintest signals from smaller planets, or planets further away, would be difficult to detect in the manual review and researchers wondered whether more planets were lying hidden in the archive.

AI Application

To cope with that, researchers Christopher Shallue and Andrew Vanderburg built a deep neural network that was inspired by the arrangement of neurons in the human brain. It was able to identify the subtle details of a true planetary transit in Kepler's light-curve data (Shallue & Vanderburg 2017). Light curves record the dip in brightness of a star's light over time and are used to identify the small dips caused by planets passing in front of the star (NASA, 2017). The model was trained on data from thousands of previously confirmed planets and false positive signals. This helped the model identify real transits rather than noise and instrumental artifacts, without requiring astronomers to look at each signal individually (Shallue & Vanderburg, 2017).

Outcomes

This proved to be successful in December 2017, when the network spotted a weak and previously overlooked signal that was later confirmed to be the eighth planet orbiting Kepler-90, namely Kepler-90i (NASA, 2017). This discovery made the Kepler-90 system the first known planetary system outside our solar system to have eight confirmed planets orbiting a single star, matching the number of planets in our solar system (NASA, 2017). The same neural network discovered another previously unknown planet, Kepler-80g, in another system, demonstrating the method's ability to detect hidden planets in different solar systems (Shallue & Vanderburg, 2017).

Significance

These findings were important not only because two new planets were discovered but also because of the impact they could have on the field of planetary science. It showed that machine learning could uncover important signals that traditional ways of analyzing data had missed, and that there was still the possibility of finding hidden discoveries in previously studied data (Shallue & Vanderburg, 2017). The neural network came to be viewed as an intelligent screening tool that could assist astronomers in focusing on potentially promising candidates (Shallue & Vanderburg, 2017). These discoveries also encouraged researchers to revisit older datasets using AI technology to uncover information that might have been previously overlooked. Building on this work, NASA developed the ExoMiner classifier a few years later. It is a more advanced deep learning system based on many of the same concepts, and also takes into account how human experts review a transit signal. ExoMiner was then used to validate 301 more exoplanets from the Kepler archive, and can also be adapted for future missions like TESS (Valizadegan et al., 2022).

Limitations

This method, however, has its drawbacks. Neural networks are dependent on high quality, well labeled, and complete training datasets. Incorrect detections are always a possibility if a model encounters signals that are dissimilar to what it encountered during training (Shallue & Vanderburg, 2017). That is the reason why detections based on AI, such as Kepler-90i, need follow up and verification by human experts. Despite these limitations, the Kepler mission remains among the earliest and most cited examples of AI-assisted scientific discovery in astronomy and demonstrates the meaningful contribution machine learning can make to this field.

AI-Assisted Galaxy Classification through Galaxy Zoo

Background

The classification of galaxies according to their shape is one of the most basic and fundamental tasks in astronomy. A galaxy's morphology provides important clues about its formation, interactions and evolution over time (Walmsley et al., 2021). Traditionally, astronomers classified galaxies into spirals, ellipticals, and irregulars manually. However, this approach became increasingly unfeasible as sky surveys began producing millions of galaxy images which was far more than what research teams could realistically examine manually.

AI Application

To address this challenge, the Galaxy Zoo project was launched in 2007 as a citizen-science initiative, inviting the public to classify galaxies through an easy-to-use website. It proved to be an exceptionally successful crowdsourcing effort. By the time the Galaxy Zoo project added images from the Hubble Space Telescope, volunteers had classified over 120,000 galaxies according to their morphology (Willett et al., 2016). The work done by these thousands of volunteers created a large and well-labeled database that would later prove to be very useful for training AI systems (Willett et al., 2016). As newer sky surveys produced even larger volumes of data, it became obvious that citizen science alone would not be able to keep up with the pace. This is when the use of AI was considered. Scientists used the volunteer classifications gathered by Galaxy Zoo to train deep learning models to identify galaxy shapes in the same manner as the human volunteers had done. These deep learning models achieved a galaxy morphology classification accuracy similar to that of human volunteers, while completing the task in a fraction of the time (Walmsley et al., 2021). In another similar study, researchers compared traditional machine learning with deep learning techniques for classifying galaxies. Both methods were found to be equally accurate in distinguishing between elliptical and spiral galaxies, achieving an accuracy of more than 94.5% on a catalog of approximately 670,000 galaxies (Barchi et al., 2019).

Outcomes

The partnership between citizen scientists and AI systems has significantly boosted both the speed and scale of galaxy classification. Tasks that typically took years of volunteer work can now be done automatically on much larger datasets in a fraction of the time. This has enabled

astronomers to study the evolution of galaxies using much larger, and more varied samples, providing a better picture of how galaxies form and evolve with time (Walmsley et al., 2021).

Significance

Galaxy Zoo demonstrates how AI can complement rather than replace human expertise. The classifications provided by thousands of volunteers formed the basis for training reliable AI models, making Galaxy Zoo one of the best examples of human expertise working in conjunction with machine learning to advance research in galaxy formation and evolution (Walmsley et al., 2021).

Limitations

However, there are some drawbacks to this approach. AI models are trained on current galaxy classifications and therefore may struggle to accurately classify rare, unusual galaxies that do not closely match the examples in their training data. They may incorrectly classify any galaxy with a less distinct shape, such as transitional galaxies. As a result, human review remains necessary for verifying uncertain or ambiguous classifications (Walmsley et al., 2021).

AI Detection of Supernovae in the Dark Energy Survey

Background

The purpose of the Dark Energy Survey (DES) is to investigate the nature of dark energy by observing millions of astronomical objects including a massive sample of Type Ia supernovae, which are well-established “standard candles” used to measure cosmic distances and the rate of cosmic expansion. During the initial five years of the survey, DES collected a final sample of 1,499 high-quality Type Ia supernovae for cosmological analysis (Dark Energy Survey Collaboration, 2024). Many of these were at high redshift, which means that they were extremely distant and their light had travelled a long distance before reaching the Earth. The detection and confirmation of such events need to be done quickly, as supernovae brighten and eventually fade over time. This becomes increasingly difficult as the number of observations increases, and large amounts of nightly survey data need to be analyzed rapidly.

AI Application

To keep up with the large volume of survey data, DES researchers decided to use machine-learning classification instead of spectroscopic confirmation of every individual supernova. Automated algorithms were trained to analyze their light curves, detect likely supernova

candidates and distinguish them from other types of astronomical events (Lochner et al., 2016). The survey was able to classify supernovae using only photometric data, which measures changes in the brightness of an object over time. This helped researchers filter out false detections and focus valuable telescope observing time on the most promising candidates (Lochner et al., 2016).

Outcomes

By following this approach, DES was able to greatly reduce the number of candidates requiring human investigation and enable researchers to focus their observation time on the most promising candidates (Lochner et al., 2016). The classification, which leveraged machine learning, contributed to the development of one of the largest and most well-constrained high-redshift supernova samples used for cosmological studies (Dark Energy Survey Collaboration, 2024).

Significance

The successful use of AI to assist in classification for DES highlighted the practical use of machine learning in astronomy to speed up the classification of astronomical objects, especially when dealing with short-lived events that need to be identified and observed quickly (Moller et al., 2022). It also showed that machine learning could help astronomers study a much larger number of supernovae without needing spectroscopic confirmation for every individual candidate. Studying a larger sample also helped researchers make better measurements of how the universe is expanding and learn more about the nature of dark energy (Fermilab, 2024).

Limitations

Although this approach has several benefits, there are some shortcomings to machine-learning classification of supernovae. False positives and classification uncertainties can occur especially when astronomical events have similar light-curve patterns or when the system comes across transients that have not been classified before and are therefore different from those in its training data (Lochner et al., 2016). The level of reliability of these classifications also depends on the quality of the observational data used, and human verification may still be needed for many uncertain events identified by automated systems (Lochner et al., 2016).

AI Detection of fast Radio Bursts (2018–Present)

Background

Fast Radio Bursts (FRBs) are one of the most mysterious phenomena in contemporary astronomy, with bursts lasting only a few milliseconds, but producing extremely bright radio signals (Connor et al., 2018). FRBs are also useful in astronomy because their signals can help astronomers study matter and magnetic fields in the space between galaxies (Bailes, 2022). These signals may be hard to detect because of their very short duration and may sometimes be mistaken for radio frequency interference or background noise from human-made technology and instrumentation. Large radio telescope surveys, such as the Canadian Hydrogen Intensity Mapping Experiment (CHIME) survey, generate huge amounts of radio data containing possible FRB signals that need to be rapidly and accurately filtered (Qiang et al., 2024).

AI Application

To overcome this challenge, deep-learning and unsupervised machine-learning methods have been used to detect and classify FRBs (Connor et al., 2018; Qiang et al., 2024). Deep learning models can analyze incoming radio data in near real time, as they are trained to recognize the ‘signature’ or patterns of a true fast radio burst in the face of large amounts of ‘noise’ and interference. Unsupervised methods have also been applied separately to existing FRB catalogs such as the CHIME catalog to identify patterns and groups within the FRB population without relying on previously labeled examples (Qiang et al., 2024).

Outcomes

Such AI-based methods have enabled researchers to detect the FRB signals that could otherwise be lost among noise and interference (Zhang et al., 2018). One important example came from observations of the repeating FRB 121102. A machine-learning-based search identified 72 additional bursts that had not been detected in the original analysis of the data (Zhang et al., 2018).

The use of machine learning on large catalogs like CHIME has also helped researchers in the identification of patterns and groupings that are not immediately apparent through manual analysis. This provides more information about the different characteristics of FRBs and helps identify groups that need to be studied further (Qiang et al., 2024).

Significance

The contributions of AI to FRB detection have been significant in enhancing our understanding of these short-lived radio signals, not just by helping detect more bursts, but also by shedding light on the structure of the overall FRB population (Qiang et al., 2024). This case study shows how machine learning can be a key contributor in an area of astronomy where signals can last only for milliseconds and a large volume of radio data, marked by noise and interference, needs to be examined quickly. It also shows that AI can uncover or detect signals that may have been missed earlier, as was seen by the additional bursts detected from FRB 121102 (Zhang et al., 2018).

Limitations

Despite these advances, AI-based FRB detection still has several limitations. It can be difficult to tell the difference between real bursts and noise or interference in radio data, as both can generate short and irregular signals. As is the case with many machine-learning tools, these models are also heavily dependent on the representativeness and quality of their training data. Most importantly, although AI can help identify and classify FRBs with greater speed and accuracy, it cannot by itself explain the physical origin of these mysterious signals. Further astronomical observations coupled with human analysis are therefore still required to understand their origins.

DISCUSSION

Cross-Case Analysis

All four case studies analyzed in this paper show a similar challenge: astronomers are dealing with far more data than can be realistically analyzed manually (Djorgovski et al., 2022). The Kepler exoplanet search generated tens of thousands of transit signals, Galaxy Zoo needed to classify large numbers of galaxy images, the Dark Energy Survey monitored nightly observations for fading supernovae producing thousands of images every night while CHIME produced large catalogs of Fast Radio Bursts that needed to be separated from noise and interference. In each case, AI was adopted because the sheer scale of data meant that automated analysis was becoming a necessity rather than simply a useful tool.

The case studies also demonstrate that AI was used in a different way in each case study depending on what astronomers were seeking to detect or classify. The nature of the data

governed the use of AI in each case. In the Kepler case, neural networks were used to search light-curve data and look for small dips in a star's brightness that could indicate a planet. For Galaxy Zoo, AI analyzed millions of images to classify galaxies according to their shape. In the Dark Energy Survey, astronomers made use of machine learning to identify possible supernovae by analyzing how their brightness changed over time. In the FRB case, AI models searched through radio data to identify extremely short signals lasting only a few milliseconds while filtering out noise and interference. AI was therefore applied to very different forms of astronomical data, including light curves, images, transient events, and radio signals (Wang et al., 2025).

The scale and nature of the final outcome also differed across the four cases. In the Kepler case, the use of AI led to specific individual discoveries such as the Kepler-90i, while in Galaxy Zoo AI classified a large number of galaxies. In the DES and FRB cases, machine learning was used to continuously identify and classify large numbers of short-lived events and signals rather than being centered on a single discovery. Despite these differences, all four cases show how AI can speed up the analysis of astronomical data and allow researchers to work with much larger datasets than would be possible through manual analysis alone.

The four case studies also differed in the level and type of human involvement. Galaxy Zoo provides a particularly clear example of human-AI collaboration because its deep-learning models were trained using classifications made by thousands of human volunteers (Walmsley et al., 2021). The other three cases relied more heavily on automated analysis to identify or classify possible signals, with researchers becoming particularly important in reviewing and verifying the results. Despite these differences, human involvement remained necessary across the cases, whether confirming an exoplanet detection, reviewing supernova candidates, checking unusual galaxy classifications, or examining possible FRB signals. This shows that AI generally worked as a tool to support astronomers rather than replacing their scientific judgement (Djorgovski et al., 2022).

Lastly, several common limitations emerged across the four cases. False positives, classification uncertainty, and dependence on the quality of training data were recurring concerns. These appeared in different ways, whether determining if a planetary signal was a real exoplanet or noise, classifying unusual galaxies, identifying supernova candidates, or separating real FRBs from interference. Although the applications were different, the cases therefore show a similar

trade-off: AI greatly increases the speed and scale of astronomical analysis, but its results still depend on the quality of the data and often require human verification. Table 1 compares the four case studies and highlights the key challenges, AI methods, and outcomes in each case.

Table 1. Cross-Case Comparison of AI Applications in Astronomy

Case	Key Challenge	AI / Tech Method	Main Outcome	Maturity Score	Citation
Kepler Exoplanets	Detecting weak transit signals in noisy light curves	Deep Neural Networks	Discovered Kepler-90i and Kepler-80g	5/5	Shallue & Vanderburg (2017)
Galaxy Zoo	Classifying millions of galaxy images	Deep Learning trained using volunteer classifications	Deep Learning predictions produced for 314,000 galaxies	4/5	Walmsley et al. (2021)
Dark Energy Survey	Real-time filtering of nightly transient alerts	Machine Learning classification of light curves	Sub-minute supernova alert screening	4/5	Dark Energy Survey Collaboration (2024)
Fast Radio Burst Detection	Isolating very short FRB pulses from noise and interference	Machine Learning/Deep Learning	Detected 72 additional bursts from FRB 121102 that had been missed in the original analysis	3/5	Zhang et al. (2018)

Note. Created by the author using information from Shallue and Vanderburg (2017), Walmsley et al. (2021), Dark Energy Survey Collaboration (2024), and Zhang et al. (2018).

Importance of AI in Astronomy

The four case studies show several important advantages of using AI in astronomy. Speed is perhaps the most obvious advantage of using AI. AI has the ability to process large amounts of data much faster than traditional manual analysis. For example, AI can quickly analyze thousands of light curves in search of possible exoplanet signals or look through large amounts of nightly survey data for possible supernovae (Djorgovski et al., 2022). In addition to speed, machine learning can also improve the efficiency and accuracy of detecting and classifying

astronomical objects from various types of data including images, light curves and radio signals (Wang et al., 2025).

AI-based tools may also be better at identifying subtle patterns or detecting signals within large amounts of data as compared to human researchers. For example, in the Kepler case, a neural network identified the Kepler-90i signal in existing Kepler data (Shallue & Vanderburg, 2017). What makes this example noteworthy is that the weak signal was overlooked in the manual analysis (Valizadegan et al., 2022). It also reveals another potential use of AI: to re-examine existing astronomical data and look for information that could have been overlooked during earlier analysis.

The Galaxy Zoo case showcases the potential of human-AI collaboration. It also strengthens the viewpoint that AI can be an able assistant to human judgement and AI can work alongside humans rather than replacing them. In this case, the classifications made by thousands of human volunteers were used as training datasets for machine learning models. These models were then used to analyze much larger quantities of data (Walmsley et al., 2021).

Challenges and Limitations

While the case studies demonstrate that AI-based tools can be very useful in astronomy, they come with their own set of limitations. Most of these limitations are not specific to astronomy but are common across the various fields in which AI is used. The accuracy of their predictions is heavily dependent on the quality of the data on which they are trained. If there are problems in the training data like inadequate, biased or incomplete information, this can impact the accuracy of the results produced by the model (Buchner & Fotopoulou, 2025). This point becomes particularly important in the case of rare or unusual astronomical objects which may not be adequately represented in the training data. In such cases, the AI models may have difficulty in detecting and classifying objects which are very different from those in their training data (Buchner & Fotopoulou, 2025). However, machine-learning models can be retrained using new data, which may help improve their performance.

Lack of transparency is another challenge faced by some deep learning systems. As these models become more complex, it can be difficult for researchers to understand exactly the reasoning behind a particular classification or prediction (Buchner & Fotopoulou, 2025). Therefore, researchers may not fully trust the results and may seek to validate them. There is also the risk of

overdependence on automatically generated results at the cost of human understanding and analysis.

In light of these limitations, human involvement remains important. AI can identify possible planets, classify galaxies, detect supernovae and find FRB signals, but new and important findings still need to be reviewed and validated by researchers.

Figure 3 gives an overview of the key factors that contribute to the reliable use of AI in astronomical research.

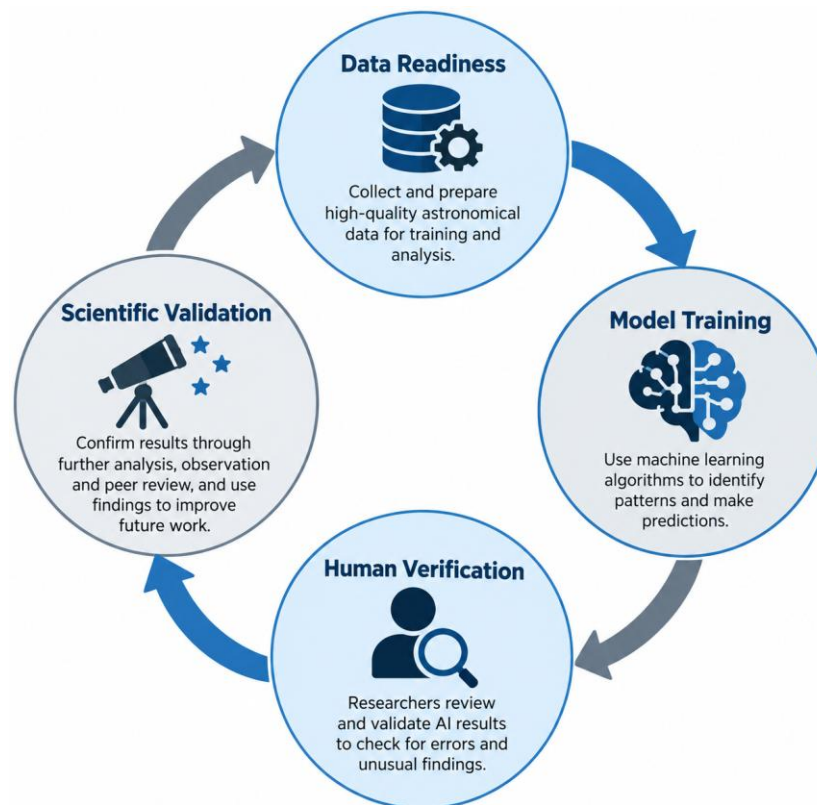


Figure 3. *AI-Driven Astronomical Research Cycle*

Future Directions

The role of AI in astronomy is only likely to grow with next-generation observatories and more advanced versions of telescopes producing even larger amounts of data in the future. Researchers may be inundated with data as future surveys may produce information on millions of astronomical objects and events. They may find it difficult to examine all this data using traditional methods, increasing the need for AI-based tools which may be significantly faster and more efficient than the traditional options (Wang et al., 2025). They could be especially useful

for events that appear and disappear in an instant, where astronomers are required to make real-time decisions on which events need follow-up observations and closer examination.

The future may also see machine-learning models that are more accurate, transparent and better at dealing with unusual or unfamiliar data (Buchner & Fotopoulou, 2025). This may increase reliability which is essential for building the confidence and trust of both the astronomers and the general public. Advanced future systems may also allow astronomers to combine information from different telescopes and observatories to get a more comprehensive understanding of astronomical events.

The future is likely to see greater collaboration between astronomers and AI systems rather than the replacement of human judgement with automated research. While AI can assist with labor-intensive tasks like searching enormous datasets and identifying possible patterns or discoveries, human researchers can analyze and interpret these findings, question unusual results and decide what areas require follow-up investigation.

CONCLUSION

Each of the four case studies showcased a very different use of AI in astronomy. AI was used in discovering exoplanets, classifying galaxies, and detecting supernovae and fast radio bursts.

Together they show that AI is not limited to any one area of astronomy, rather it has become a valuable tool across several areas of astronomy related research. It can not only quickly analyze enormous amounts of data and identify patterns, but it can also support researchers in analyzing data and interpreting results and even uncover signals that may have been missed in previous research.

However, as is the case with AI in all fields, its effectiveness and accuracy are heavily dependent on the quality of data on which it is trained. There may be difficulty in identifying rare events or unfamiliar objects which may lead to false or inconsistent findings. Some complex models may lack the transparency to show how the results were arrived at, causing trust issues among researchers (Buchner & Fotopoulou, 2025). Therefore, human judgement and verification remain extremely important both in determining appropriate training datasets and in reviewing results produced by AI systems.

Ultimately, AI should be viewed as a very able assistant to the effort of human researchers. As astronomical data progressively becomes larger and machine-learning techniques continue to

improve, AI can take on more of the time-consuming work, leaving humans to focus on areas that require greater judgment and discretion, including interpreting unusual findings, questioning AI-based conclusions and pinpointing observations which need to be investigated further (Wang et al., 2025).

REFERENCES

- Bailes, M. (2022). The discovery and scientific potential of fast radio bursts. *Science*, 378(6620), abj3043. <https://arxiv.org/abs/2211.06048>
- Barchi, P. H., et al. (2019). Machine and deep learning applied to galaxy morphology. arXiv. <https://arxiv.org/abs/1901.07047>
- Baron, D. (2019). Machine learning in astronomy: A practical overview. arXiv. <https://arxiv.org/abs/1904.07248>
- Buchner, J., & Fotopoulou, S. (2025). How to set up your first machine learning project in astronomy. arXiv. <https://arxiv.org/abs/2502.08222>
- Cavanagh, M. K., Bekki, K., & Groves, B. A. (2021). Morphological classification of galaxies with deep learning: Comparing 3-way and 4-way CNNs. *Monthly Notices of the Royal Astronomical Society*, 506(1), 659–676. <https://arxiv.org/abs/2106.01571>
- Connor, L., et al. (2018). Applying deep learning to fast radio burst classification. arXiv. <https://arxiv.org/abs/1803.03084>
- Dark Energy Survey Collaboration. (2024). Cosmology results using the full 5-year dataset. arXiv. <https://arxiv.org/abs/2401.02929>
- Djorgovski, S. G., et al. (2022). Applications of artificial intelligence in astronomy. arXiv. <https://arxiv.org/abs/2212.01493>
- Fermilab. (2024). Final supernova results from Dark Energy Survey offer unique insights into the expansion of the universe. <https://news.fnal.gov/2024/01/final-supernova-results-from-dark-energy-survey-offer-unique-insights-into-the-expansion-of-the-universe/>
- Fluke, C. J., & Jacobs, C. (2020). Surveying the reach and maturity of machine learning and artificial intelligence in astronomy. *WIREs Data Mining and Knowledge Discovery*, 10(2), e1349. <https://arxiv.org/abs/1912.02934>
- Fotopoulou, S. (2024). A review of unsupervised learning in astronomy. arXiv. <https://arxiv.org/abs/2406.17316>

- Lochner, M., et al. (2016). Photometric supernova classification with machine learning. arXiv. <https://arxiv.org/abs/1603.00882>
- Moller, A., et al. (2022). The Dark Energy Survey supernova sample. arXiv. <https://arxiv.org/abs/2201.11142>
- National Aeronautics and Space Administration. (2017). Artificial intelligence, NASA data used to discover eighth planet circling distant star. <https://www.nasa.gov/news-release/artificial-intelligence-nasa-data-used-to-discover-eighth-planet-circling-distant-star/>
- National Aeronautics and Space Administration. (2025). AI, astrobiology, and exoplanetary science. <https://www.nasa.gov/a-i-astrobiology-exoplanetary-science/>
- Qiang, D.-C., et al. (2024). Unsupervised machine learning for classifying CHIME fast radio bursts. arXiv. <https://arxiv.org/abs/2411.14040>
- Shallue, C. J., & Vanderburg, A. (2017). Identifying exoplanets with deep learning. arXiv. <https://arxiv.org/abs/1712.05044>
- Smith, M. J., & Geach, J. E. (2022). Astronomia ex machina: A history, primer, and outlook on neural networks in astronomy. arXiv. <https://arxiv.org/abs/2211.03796>
- Valizadegan, H., et al. (2022). ExoMiner: A highly accurate and explainable deep learning classifier that validates 301 new exoplanets. *The Astrophysical Journal*, 926(2), 120. <https://arxiv.org/abs/2111.10009>
- Walmsley, M., et al. (2021). Galaxy Zoo DECaLS: Detailed visual morphology measurements from volunteers and deep learning for 314,000 galaxies. *Monthly Notices of the Royal Astronomical Society*. <https://arxiv.org/abs/2102.08414>
- Wang, Z.-N., Qiang, D.-C., & Yang, S. (2025). Artificial intelligence revolutionizing time-domain astronomy. *Universe*, 11(11), 355. <https://www.mdpi.com/2218-1997/11/11/355>
- Willett, K. W., et al. (2016). Galaxy Zoo: Morphological classifications for 120,000 galaxies in HST legacy imaging. arXiv. <https://arxiv.org/abs/1610.03068>
- Yu, L., et al. (2019). Automated triage and vetting of TESS candidates. arXiv. <https://arxiv.org/abs/1904.02726>
- Zhang, Y. G., et al. (2018). Fast radio burst detection using machine learning. arXiv. <https://arxiv.org/abs/1809.03043>