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Exploring the Potential of Machine Learning in Space Exploration

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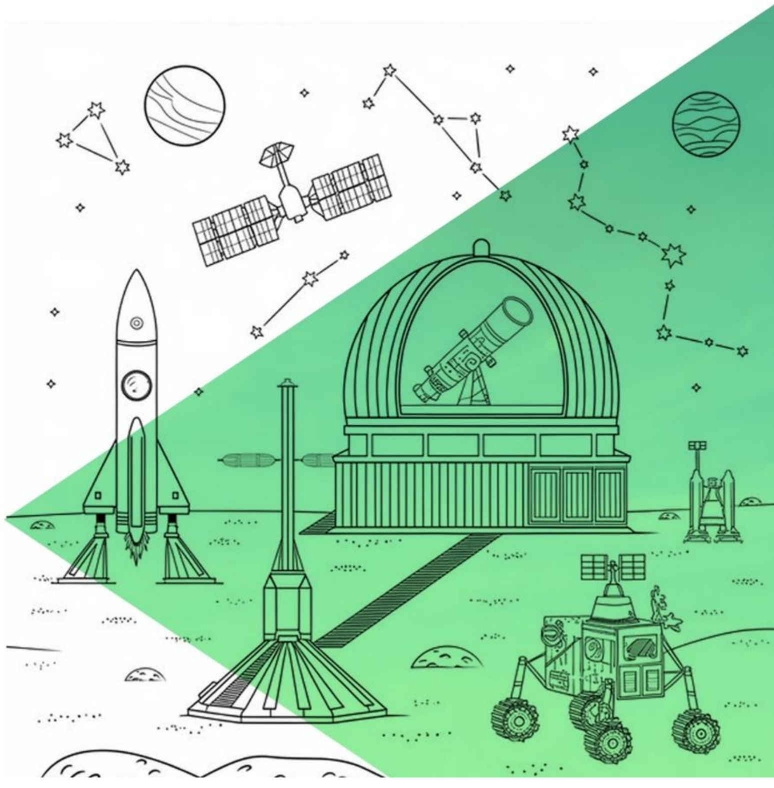

Working Paper

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Abstract

Space-based capabilities have become one of the central themes in the technological discourse. Rapid proliferation of these capabilities has increased the significance of space exploration. As various space agencies and private entities expedite their ingress towards space, Machine Learning (ML) is becoming more relevant to ensure efficiency, safety and mission success. This paper examines the interplay between ML and space exploration, focusing on its key applications across three levels: near-Earth, solar system, and interstellar. The findings of this paper indicate that ML has major implications across all three levels of space exploration. In near-Earth applications, ML facilitates data collection and analysis, autonomous navigation, and development of Robonauts. At the solar system level, it plays a crucial role in planetary exploration, space weather forecasting, space debris identification, and asteroid trajectory prediction. Similarly, at the interstellar level, ML contributes to exoplanet detection, analysis of diffuse interstellar bands, and advancements in interstellar travel. However, while ML-driven applications offer substantial benefits, their implementation is hindered by various challenges arising from the inherent complexity of the space domain, necessitating targeted solutions for optimal utilisation.

Keywords: Machine Learning, Space Exploration, Near-Earth Applications, Solar System, Interstellar Level, Autonomous Navigation, Planetary Exploration, Space Weather Forecasting, Exoplanet Detection, Artificial Intelligence in Space.

Introduction

The space industry is growing at a tremendous pace. Over the last thirty years, miniaturisation, enhanced sensor performance and advanced connectivity have led to numerous applications, unfolding new potentials and unprecedented advantages at a meteoric speed.[1] Moreover, the space economy is expected to reach USD 1.8 trillion by the year 2035.[2] Amongst a comprehensive list of applications, key sectors range from earth observation, agriculture, communication, surveillance & reconnaissance, navigation, planetary sciences to the health sector.[3] Given increasing employment of space-based applications, space exploration has become considerably important and over time, more complex. The increasing accessibility of space, growing frequency of missions, ambitious objectives, advancements in technology, and emergence of new actors have introduced new dimensions to space exploration.[4] These developments necessitate the full integration of cross-cutting technologies to enhance exploration efforts and maximise benefits, especially as humanity continues to extend its reach beyond Earth's gravitational pull.[5]

The technological advancements in quantum computing, cyber, big data and Artificial Intelligence (AI) impact how we approach space exploration.[6] Amongst these technologies, machine learning (ML) – a subset of AI stands as an important factor that has given rise to numerous expectations across different sectors.[7]

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1 Antonio Carlo and Paola Breda, "Impact of Space Systems Capabilities and their Role as Critical Infrastructure," *International Journal of Critical Infrastructure Protection* 45, (2024): 100680, https://www.sciencedirect.com/science/article/abs/pii/S1874548224000210?via%3Dihub.

2 Jeremy Jurgens and Ryan Brukardt, *Space: The $1.8 Trillion Opportunity for Global Economic Growth,* report (Geneva: World Economic Forum, 2024), 9, https://www3.weforum.org/docs/WEF_Space_2024.pdf.

3 International Space Exploration Coordination Group (ISECG), *Benefits Stemming from Space Exploration*, report (International Space Exploration Coordination Group, September, 2013), 2, https://www.nasa.gov/wp-content/uploads/2015/01/benefits-stemming-from-space-exploration-2013-tagged.pdf.

4 Francisco Del Canto Viterale, "Transitioning to a New Space Age in the 21st Century: A Systemic-Level Approach," *Systems* 11, no.5 (2023):232-270, https://www.mdpi.com/2079-8954/11/5/232.

5 Sisay Tadesse Arzo, Dimitrios Sikeridis, Michael Devetsikiotis, Fabrizio Granelli, Rafael Fierro and Mona Esmaeili, "Essential Technologies and Concepts for Massive Space Exploration: Challenges and Opportunities," *Transactions on Aerospace and Electronic Systems* 59, no. 1 (2023): 3-29, https://ieeexplore.ieee.org/abstract/document/9761732.

6 Antonio Carlo and Lucille Roux, "Emerging Technologies and Space," (paper presented at 4949th International Conference, Prague, October 20-21, 2022).

7 Koosha Sharifani and Mahyar Amini, "Machine Learning and Deep Learning: A Review of Methods and Applications," *World Information Technology and Engineering Journal* 10, no.7 (2023): 3897-3904.

ML is defined as 'Machine learning (ML) is a branch of Artificial Intelligence (AI) and computer science that focuses on using data and algorithms to enable AI to imitate the way that humans learn, gradually improving its accuracy.'[8]

The phenomenon has garnered substantial attention, driving technological advancements and enhancing efficiency across various domains.[9] Its capabilities, particularly in processing and analysing vast datasets and making precise predictions, present substantial advantages for space exploration. As the field continues to evolve, ML is expected to play a pivotal role in fostering innovation, expanding the technological landscape, and unlocking new opportunities at the frontier of exploration.[10] Notably, various forms of AI have been utilised in space applications over time.[11] However, recent advancements in ML necessitate a focused examination of its interplay with space exploration, especially in light of emerging developments. This research paper examines the interplay between machine learning (ML) and space exploration, focusing on its applications to enhance space missions.

Methodology

The study follows qualitative research design, using secondary data collection methods. Sources include books, book chapters, journal articles, conference papers, websites, magazines, and opinion articles. Relevant journal articles were identified through databases such as Web of Science, Scopus, and Google Scholar, using keywords like 'Space Exploration', 'Space Applications', and 'Machine Learning', both individually and in combination.

For the literature review, abstracts of 80 research articles were initially consulted, with 57 selected for in-depth analysis. To ensure the study remains current and forward-looking, the majority of the selected articles were published between 2022 and 2024. Thematic analysis was employed to analyse the data, using a coding tree to categorise and label key themes. Recurring ideas were grouped into broader categories and their

8 International Business Machines, "What is Machine Learning (ML)?", https://www.ibm.com/topics/machine-learning [Accessed 22 July 2024].

9 Mohsen Soori, Behrooz Arezoo and Roza Dastres, "Artificial Intelligence, Machine Learning and Deep Learning in Advanced Robotics, A Review," *Cognitive Robotics* 3 (2023): 54-70, https://www.sciencedirect.com/science/article/pii/S2667241323000113.

10 Varun Shah, "Next-Generation Space Exploration: AI-Enhanced Autonomous Navigation Systems," *Journal Environmental Sciences and Technology* 3, no.1 (2024): 47-64, https://zenodo.org/records/10779068.

11 Manas Biswal, "A Short Review on Machine Learning in Space Science and Exploration," *Acceleron Aerospace Journal* 1, no.4 (2023): 84-87, https://acceleron.org.in/index.php/aaj/article/view/AAJ.11.2106-2317.

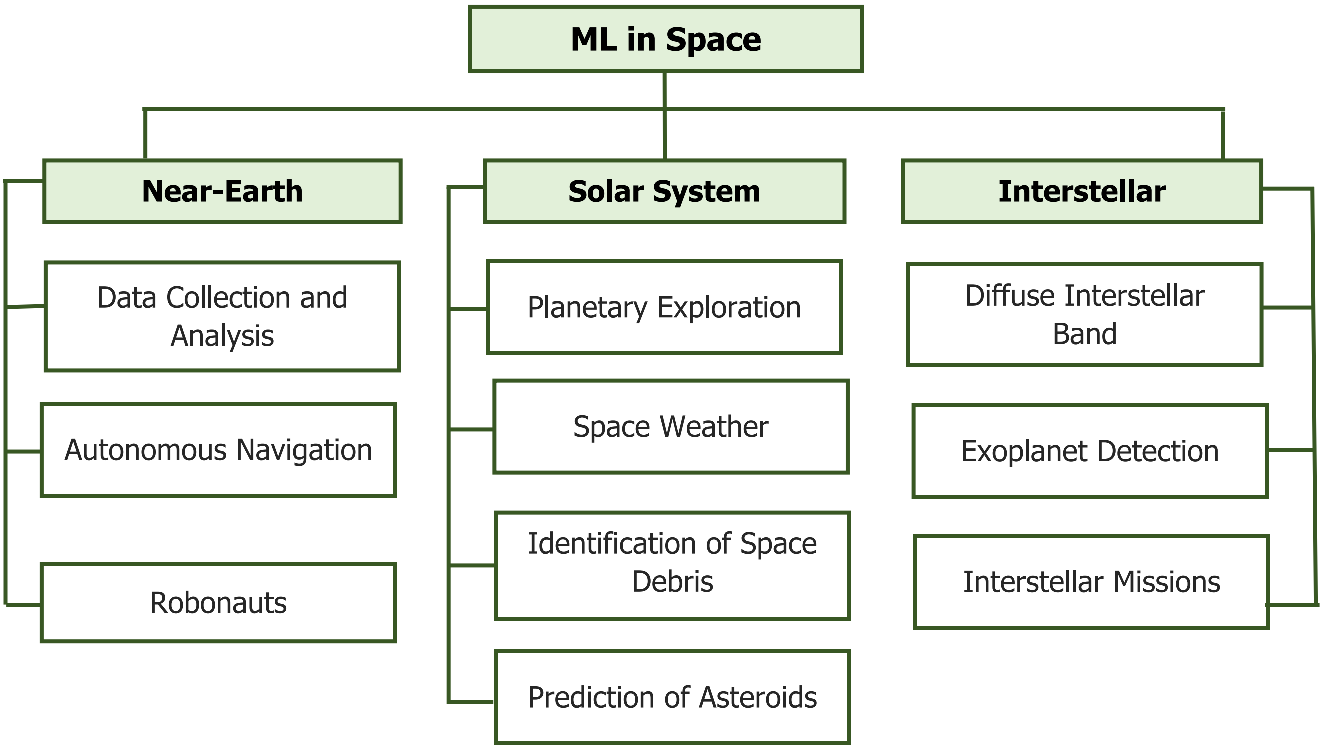
corresponding sub-themes. A key limitation of the study is that it does not investigate the technical intricacies of ML in space exploration. To maintain focus, it also does not provide a historical overview of ML's application in space but instead adopts a forward-looking perspective.

Machine Learning Applications in Space Exploration

There are several applications of ML in space exploration. The following section of the paper will shed light on the potential applications of ML in space exploration. The applications are studied in three categories or levels:

1. Near-Earth
2. Solar System
3. Interstellar

Figure 1: Coding Tree - ML in Space Exploration



Source: Author's own.

Near-Earth

The first category focuses on the applications that are relatively proximal to the Earth and typically within the orbits comprising satellites, International Space Station (ISS) and proximal spacecraft.

Data Collection and Analysis

In the vast realm of space exploration, effectively managing data has always been a considerable challenge.[12] For instance, the ISS orbits the Earth at a speed of 28,000 km per hour, capturing abundant amounts of data.[13] The sheer volume of the gathered data necessitates an efficient mechanism and relevant tools that streamline the process. ML enhances space missions by filtering out irrelevant information and optimizing data quality through advanced surveying and analysis.[14] In existing applications, convolutional neural networks (CNNs) process satellite imagery, uncovering hidden patterns and trends that might otherwise remain undetected by human observation.[15] This capability not only provides critical insights into space but also has applications in Earth observation, benefiting sectors such as disaster management, climate monitoring, and agriculture.

Furthermore, the application of reinforcement learning can optimise communication link efficiency by enhancing the quality and speed of data transmission from satellites or spacecraft. This improvement not only increases overall operational efficiency but also minimises the volume of unusable data, ensuring that only relevant and high-quality information is transmitted for analysis. [16] The European satellite Phi-Sat-1 is a prominent example of ML techniques improving data transmission and analysis.[17] Furthermore, while data collection and analysis have been used extensively in near-Earth applications, the technique is applicable to the other two levels as well.

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12 Tina Salvage, "Data Governance in Space - Key Challenges and Opportunities," *Chief Data Officer Magazine,* July 11, 2024, https://www.cdomagazine.tech/opinion-analysis/data-governance-in-space-key-challenges-and-opportunities.

13 Kennedy Space Centre, "The 20 Most Frequently Asked Questions about the International Space Station," October 23, 2020, https://www.kennedyspacecenter.com/blog/the-20-most-frequently-asked-questions-about-the-international-space-station.

14 Biswal, "A Short Review on Machine Learning in Space Science and Exploration."

15 Pablo Miralles, Kathiravan Thangavel, Antonio Fulvio Scannapieco and Nitya Jagadam et al. "A Critical Review on the State-of-the-Art and Future Prospects of Machine Learning for Earth Observation Operations," *Advances in Space Research* 71, no.12 (2023): 4959-4986, https://www.sciencedirect.com/science/article/abs/pii/S027311772300145X.

16 Kevin Lange, Federico Fontana, Francesco Rossi and Mattia Varile et al., "Machine Learning in Space: Surveying the Robustness of On-board ML Models to Radiation," (paper presented at University of Liechtenstein, Vadus, 2024).

17 Arindam Bhattacharyya, Shvetha M. Nambiar, Ritwik Ojha, and Amogh Gyaneshwar et al., "Machine Learning and Deep Learning Powered Satellite Communications: Enabling Technologies, Applications, Open Challenges, and Future Research Directions," *International Journal of Satellites, Communication and Networking* 41, no.6 (2023): 539-558, https://onlinelibrary.wiley.com/doi/abs/10.1002/sat.1482.

Autonomous Navigation

Autonomous navigation of satellites has been a key aspect of research in space exploration.[18] Vast distances in space, communication limitations, need for obstacle avoidance and precise landing indicates the importance of autonomous navigation in space.[19] With the advent of Distributed Satellite Systems (DSS) - where multiple spacecraft operate collaboratively toward a common objective - the demand for autonomous navigation has grown exponentially. DSS encompasses various configurations, including satellite constellations, fractionated systems, federated and modular architectures, swarms, formation flying, and hybrid missions. As the deployment of DSS increases, ensuring greater autonomy in space missions has become a critical priority. ML techniques such as supervised learning, reinforcement learning, multi-agent reinforcement learning, and CNNs can enhance autonomy across various aspects of DSS operations. Key applications of these techniques include data processing, data analysis, collision avoidance, trajectory optimisation, and path planning, all of which are essential for improving the efficiency and reliability of autonomous space systems. [20]

Robonauts - International Space Station

Space travel can be considerably challenging for human beings given the risks involved.[21] Exposure to ionising radiation, microgravity, extreme weather, rapidly changing day-night cycles, and a harsh environment pose significant risks to an astronaut's health.[22] Robotic astronauts, commonly known as 'Robonauts' can play a role in this regard, assisting astronauts in completing tasks that are deemed dangerous.[23] Such measures could help in expanding the research and development capacity of space agencies like the National Aeronautics and Space Administration (NASA). The robonaut also comes with advantages such as compact size, enhanced

18 Erdem Turan, Stefano Speretta and Eberhard Gill, "Autonomous Navigation for Deep Space Small Satellites: Scientific and Technological Advances," *Acta Astronautica* 193, no.1 (2022): 56-74, https://www.sciencedirect.com/science/article/pii/S0094576521006652.

19 Shah, "Next-Generation Space Exploration," 3.

20 Kathiravan Thangavel, Roberto Sabatini, Alessandro Gardi, Kavindu Ranasinghe et al., "Artificial Intelligence for Trusted Autonomous Satellite Operations," *Progress in Aerospace Sciences* 144 (2024): 100960, https://www.sciencedirect.com/science/article/pii/S0376042123000763.

21 National Aeronautics and Space Administration,"5 Hazards of Human Spaceflight," https://www.nasa.gov/hrp/hazards/ [Accessed 29 July 2024].

22 Editorial, "Space Missions Out of this World with AI," *Nature Machine Intelligence*, March 23, 2023, https://www.nature.com/articles/s42256-023-00643-3.

23 Venkatesh Venkataramanan, Aashi Modi and Kashish Mistry, "AI and Robots Impact on Space Exploration," *Advances in Astronautics Science and Technology* 7, no.1 (2024):1-9, https://link.springer.com/article/10.1007/s42423-023-00147-7.

sensors, and high speeds.[24] NASA's Robonaut 2, launched in 2011, is an important example in this regard.[25] The use of ML can improve productivity of robonauts by increasing their autonomy, enabling them to perform tasks outside the ISS. While currently, they are used in basic tasks onboard the International Space Station (ISS), in future, they can perform complex tasks such as exploring life on other planets, repairing satellites, and performing tasks outside the ISS.[26]

Solar System

The second category includes the solar system, which includes the Sun, its immediate planets, and other celestial bodies, all bound together by the Sun's gravitational force.[27]

Planetary Exploration

Mars exploration has been a central focus of space research, with numerous missions dedicated to investigating the planet's potential for sustaining life.[28] Over the years, various efforts have been undertaken to analyse its surface and atmospheric conditions. Notably, for the past three years, AI has been used by the 'Perseverance' rover to study the mineral composition of Martian rocks, enhancing the efficiency and accuracy of geological analysis.[29] The initiative is part of NASA's 'Mars Sample Return Program' that aims to bring samples from the red planet for the first time.[30] The Planetary Instrument for X-Ray Lithochemistry (PIXL) plays a crucial role in mapping the chemical composition of Martian rocks to determine whether past conditions were suitable for microbial life. ML enhances PIXL's functionality in two key ways.

First, ML enables precise positioning of the instrument when it approaches a rock target, ensuring optimal alignment for analysis. Once positioned, ML facilitates

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24 National Aeronautics and Space Administration, "About Robonaut," https://www.nasa.gov/robonaut2/what-is-a-robonaut/ [Accessed 24 July 2024].
25 Ibid.
26 Piyush Pant and Anand Singh Rajawat, "Study of AI and ML Based Technologies used in International Space Station," *Global Journal of Innovation and Emerging Technology* 1, (2022): 10-14, http://iet.adsrs.net/index.php/iet/article/view/3/15.
27 National Aeronautics and Space Administration, "The Solar System," https://science.nasa.gov/learn/basics-of-space-flight/chapter1-1/ [Accessed 25 July 2024].
28 National Aeronautics and Space Administration, "Mars", https://www.nasa.gov/humans-in-space/humans-to mars/ [Accessed 18 July 2024].
29 National Aeronautics and Space Administration, "Here's How AI Is Changing NASA's Mars Rover Science," July 16, 2024, https://www.nasa.gov/missions/mars-2020-perseverance/perseverance-rover/heres-how-ai-is-changing-nasas-mars-rover-science/ [Accessed 25 July 2024].
30 National Aeronautics and Space Administration, "Mars Sample Return," https://science.nasa.gov/mission/mars-sample-return/ [Accessed 25 July 2024].

targeted scanning by directing PIXL's X-ray beam to selected rock sections, systematically creating a grid of microscopic dots. Each dot contains valuable data about the rock's chemical composition. Predicting which of the hundreds of X-ray zaps will reveal specific minerals is a complex challenge. However, ML optimises this process by halting further scanning once the desired mineral is identified. At this point, PIXL initiates a process known as 'long dwell,' allowing it to gather additional data on the identified mineral, thereby improving the efficiency and precision of planetary analysis.[31] This capability is achieved through the use of previous datasets, where weight percentages are assigned to various compounds based on their significance. A predefined threshold is set for each composition of interest, triggering the long dwell process when the threshold is met. This marks a groundbreaking advancement, representing the first instance of autonomous decision-making by an exploration spacecraft through in-situ composition analysis on the surface of another planet.[32] Furthermore, research indicates that ML can greatly improve remote detection of cave entrances on Mars, a critical step in investigating potential biosignatures and past or present traces of life. By leveraging advanced pattern recognition and image processing techniques, ML can analyse planetary surface data to identify geological features that may provide shelter for microbial life, similar to cave systems on Earth.[33] Similarly, 2,300 miles away from 'Perseverance', the 'Curiosity Rover' has also been making use of ML in unique ways. The rover uses autonomous laser-zapping techniques on rocks subjected to their shape and colour.[34] Self-navigation is a prominent feature of the rover.

Hence, integration of supervised learning, computer vision, classification algorithms, and reinforcement learning significantly enhances Mars exploration. As ML continues to advance, its applications in planetary research are expected to expand further. While Mars garners more attention due to its proximity to Earth, ML-driven techniques are not limited to the red planet. The same methodologies can be adapted and applied

31 National Aeronautics and Space Administration, "Here's How AI Is Changing NASA's Mars Rover Science."

32 Peter R. Lawsona, Tanya V. Kizovskib, Michael Ticec and Benton C. Clark, "Adaptive Sampling with PIXL on the Mars Perseverance Rover," (paper, ArXiv, 2024), https://arxiv.org/pdf/2405.14471.

33 Thomas H. Watson and James U.L. Baldini, "Martian Cave Detection Via Machine Learning Coupled with Visible Light Imagery," *Icarus* 411, (2024):115952, https://www.sciencedirect.com/science/article/pii/S0019103524000101.

34 National Aeronautics and Space Administration, "Here's How AI Is Changing NASA's Mars Rover Science."

to the exploration of other planetary bodies, broadening the scope of extraterrestrial research and discovery.

Space Weather

Space weather refers to the activities on the Sun's surface, creating a specific type of weather.[35] This impact in magnetosphere, ionosphere and thermosphere can significantly impact the performance and reliability of space and ground-based technologies.[36] The disruptive effects of space weather have been observed across multiple sectors, including satellites, aviation, communication, and navigation, often resulting in economic consequences.[37] ML models, which map inputs to outputs, can uncover hidden patterns and underlying relationships that traditional methods often fail to detect.[38] Furthermore, ML provides a more cost-effective approach to forecasting space weather compared to conventional techniques, such as ionospheric scintillation monitoring receivers (ISMRs), enhancing both efficiency and predictive accuracy.[39]

The Echo State Network (ESN), an ML technique, was employed to develop a model capable of replicating complex space simulations. Through a sophisticated set of calculations, the model analysed the interaction between solar wind and Earth's gravitational field. The experiment's results demonstrated that ESN could generate real-time space weather predictions at significantly higher speeds than traditional methods. Furthermore, the model's ability to incorporate new data enables it to run additional simulations, continuously improving the accuracy of future forecasts.[40]

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35 NASA Science Space Place, "What is Space Weather?" February 14, 2024, https://spaceplace.nasa.gov/spaceweather/en/.

36 Sara-Lena Brännström, "Umeå has been Chosen to Host the European Space Weather Week in 2025", *Umeå University*, April 24, 2024, https://www.umu.se/en/news/umea-has-been-chosen-to-host-the-european-space-weather-week-in-2025_11929428.

37 Randa Natras and Michael Schmidt, "Machine Learning Model Development for Space Weather Forecasting in the Ionosphere," (paper presented at 1st Workshop on Complex Data Challenges in Earth Observation, November 1, 2021, Virtual Event, QLD, Australia).

38 Enrico Camporeale, Simon Wing and Jay R Johnson, *Machine Learning Techniques for Space Weather* (Amsterdam: Elsevier, 2018).

39 Tech Xplore, "Predicting Space Weather: Machine learning Enhances GNSS Signal Stability," June 19, 2024, https://techxplore.com/news/2024-06-space-weather-machine-gnss-stability.html.

40 Ryuho Kataoka, Aoi Nakamizo, Shinya Nakano and Shigeru Fujita, "Machine Learning-Based Emulator for the Physics-Based Simulation of Auroral Current System," *Space Weather* 22, no.1 (2024): 1-11, https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2023SW003720.

Dentification of Space Debris

Since the launch of the first satellite, the number of objects in space has increased due to rapid technological advancements and corresponding expansion of spacecraft deployments. Currently, approximately 36,000 objects larger than 10 centimetres are present in Earth's orbit, alongside millions of smaller debris fragments, posing challenges for space operations and sustainability.[41] In order to avoid dangerous collisions and formation of more orbits as a result of the collisions, it is important to determine the orbits of the concerned objects. ML can be applied for orbit estimation via a combination of three approaches including orbit determination, orbit prediction and establishing thermospheric density mass models.[42] The enhanced accuracy of these factors can improve classical algorithms and lead to increased safety for space missions.[43] Likewise, ML techniques such as deep reinforcement learning (DRL) can be applied to collision probability assessment between spacecraft and space debris, optimisation of energy consumption, and management of various operational constraints.[44] Furthermore, ML can also play an important role in estimation of debris in its reentry phase.[45] ML techniques such as 'Decision Tree' have proven to be considerably more accurate in predicting the velocity, latitude and longitude of the points where the spacecraft debris is expected to land as compared to other models. Furthermore, ML-driven approaches enable results to be obtained in significantly shorter timeframes, enhancing the real-time responsiveness of safety warnings and improving the overall effectiveness of collision avoidance measures.[46]

Prediction of Asteroids

Potentially Hazardous Asteroids (PHAs), particularly those that intersect the Earth's orbit, referred to as near-Earth Asteroids (NEAs) can have catastrophic impact, posing a considerable risk to human civilisation. Hence, it is crucial to monitor them in an

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41 Douglas Gorman, "ESA Report Shows Unsustainable Levels of Orbital Debris," *Payload*, July 23, 2024, https://payloadspace.com/esa-report-shows-unsustainable-levels-of-orbital-debris/.

42 Francisco Caldas and Cláudia Soares, "Machine Learning in Orbit Estimation: A Survey," *Acta Astronautica 220,* (2024); 97-107, https://www.sciencedirect.com/science/article/pii/S0094576524001917.

43 Ibid.

44 Chaoxu Mu, Shuo Liu, Ming Lu, Zhaoyang Liu et al., "Autonomous Spacecraft Collision Avoidance with a Variable Number of Space Debris Based on Safe Reinforcement Learning," *Aerospace Science and Technology* 149, (2024):109131, https://www.sciencedirect.com/science/article/abs/pii/S1270963824002645.

45 Hu Gaoa, Zhihui Lib, Depeng Danga, Jingfan Yanga et al., "Reentry Risk and Safety Assessment of Spacecraft Debris Based on Machine Learning," (paper, arXiv, 2023), https://arxiv.org/pdf/2302.10530

46 Ibid.

effective manner. Regression Trees can play an effective role in the categorisation of asteroids according to their level of threat.[47] Moreover, while ML techniques inducing Logistic Regression and Random Forest Classifiers have been used over time, there is a need to seek more innovative measures using ML to monitor asteroids.[48]

Interstellar

The third category is the interstellar level, referring to the region between the Sun's heliosphere and the astrospheres of other stars. ML plays a crucial role in advancing exploration within this vast and largely uncharted domain.[49] Key areas where ML can be applied in interstellar exploration include:

Study of Diffuse Interstellar Bands (DIBs)

Diffuse Interstellar Bands (DIBs) refer to observation features, existing in the optical and near-infrared spectra of stars, as their light passes the interstellar medium.[50] The study of DIBs remains a key research area in astronomy.[51] ML techniques such as random forest models can potentially allow better understanding of DIBs, usually impacted by interstellar dust and gas.[52] Further research and advancements in the study of DIBs can provide critical insights regarding different dynamics of the interstellar medium by offering insights regarding the composition and processes involved in shaping the universe.

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47 Seyed Matin Malakouti, Mohammad Bagher Menhaj and Amir Abolfazl Suratgar, "Machine Learning Techniques for Classifying Dangerous Asteroids," *MethodsX* 11, (2023): 102337, https://www.sciencedirect.com/science/article/pii/S2215016123003345.

48 Priya Pareshbhai Bhagwakar, Chirag Suryakant Thaker and Hetal A. Joshiara, "Review of Quantum Algorithms for Prediction of Hazardous Asteroids," *Computing and Artificial Intelligence* 2, no.1 (2024):1-9, https://ojs.acad-pub.com/index.php/CAI/article/view/1141/798.

49 "10 Things: Going Interstellar," *NASA Science*, July 26, 2022, https://science.nasa.gov/solar-system/10-things-going-interstellar/.

50 Mathias Schultheis, He Zhao, Tomaz Zwitter, Bailer-Jones et al., "Gaia Focused Product Release: Spatial Distribution of Two Diffuse Interstellar Bands," *Astronomy & Astrophysics* 680 (2023):1-33, https://www.aanda.org/articles/aa/abs/2023/12/aa47103-23/aa47103-23.html.

51 Martin A. Cordiner, "Diffuse Interstellar Bands," in Muriel Gargaud, William Irvine, Ricardo Amils, Philippe Claeys et al., *Encyclopedia of Astrobiology* (Berlin, Heidelberg: Springer).

52 He Zhao, Mathias Schultheis, Caixia Qu and Tomaz Zwitter, "Diffuse Interstellar Bands in Gaia DR3 RVS Spectra-New Measurements Based on Machine Learning," *Astronomy & Astrophysics* 683 (2024): 1-22, https://www.aanda.org/articles/aa/full_html/2024/03/aa48671-23/aa48671-23.html.

Exoplanet Detection

Exoplanets refer to those planets that lie beyond the solar system. The process of exoplanet detection is a remarkably challenging task.[53] ML can also be employed for exoplanet detection. An ML approach called 'Machine Learning for Cross-correlation Spectroscopy' (MLCCS) can potentially improve the process of exoplanet detection. Tested on simulated data, the use of neural networks, MLCCS was able to detect 26 times more planets as compared to the traditional signal-to-noise ratio approach. Furthermore, the use of advanced convolutional neural networks increases the rate to 77 times. There is also a remarkable increase in the sensitivity of detection, from 0.7 percent to 55.5 percent.[54]

Interstellar Missions

Once seen as a fictional concept, the hopes around interstellar concept are likely to increase in future with the help of ML.[55] The huge distances involved in interstellar journeys require efficient and autonomous spacecraft that are able to take critical decisions without human involvement. A study proposes that given the general assumption that computing power per mass is still increasing by a figure of 20.5 in the time frame of 2050 to 2090; the payload mass of the spacecraft is likely to decrease to a level that can be transported for interstellar travel by the year 2050. The size of such a spacecraft will remain comparable with the Daedalus Probe, the initial conceptual model for interstellar travel developed in the 1970s. The paper further forecasts that with computing refinements, even modest payloads weighing 1 kg can be a possibility.[56] Although interstellar travel remains a futuristic concept, it is likely that AI systems could assist in planning trajectories, allocating resources and predicting the risks involved.

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53 Michelle L. Hill, Kimberly Bott, Paul A. Dalba, Tara Fetherolf et al., "A Catalog of Habitable Zone Exoplanets," *The Astronomical Journal* 165, no.2 (2023):1-16, https://iopscience.iop.org/article/10.3847/1538-3881/aca1c0/meta.

54 Emily O. Garvin, Markus J. Bonse, Jean Hayoz, Gabriele Cugno et al., "Machine Learning for Exoplanet Detection in High-Contrast Spectroscopy," *Astronomy & Astrophysics* 2 (2024): 1-27, https://arxiv.org/pdf/2405.13469.

55 James Bird, Linda Petzold, Philip Lubin, and Julia Deacon, "Advances in Deep Space Exploration via Simulators & Deep Learning," *New Astronomy* 84 (2021): 101517, https://www.sciencedirect.com/science/article/abs/pii/S1384107620302219.

56 Andreas M. Hein and Stephen Baxter, "Artificial Intelligence for Interstellar Travel," *Journal of the British Interplanetary Society* 72, no.4 (April 2019): 125-143, https://www.bis-space.com/membership/jbis/2019/JBIS-v72-no04-April-2019-d94kwe.pdf.

Selection of Machine Learning Models in Space Exploration

Before moving to the discussion section, it is essential to examine the selection and application of different ML models. ML techniques can be broadly categorised into supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning, each offering distinct advantages and challenges. In supervised ML, labelled data is initially fed into the system, allowing the model to learn from predefined patterns.[57] Over time, the system develops the capability to classify and label new data independently, improving its accuracy and efficiency in various applications.[58] In unsupervised ML, systems rely on unlabelled data, identifying patterns and structures independently during subsequent processing. Instead of predefined labels, the model detects hidden correlations, making it particularly useful for exploratory data analysis. Semi-supervised ML combines elements of both supervised and unsupervised learning, using a mix of labelled and unlabelled data. This approach offers the limited availability of labelled datasets while improving model accuracy through autonomous pattern recognition. Finally, in reinforcement learning, systems learn through a reward and penalty mechanism, continuously optimising their actions based on feedback. This technique is particularly valuable for autonomous decision-making in space applications, such as robotic navigation and adaptive mission planning.[59]

In space exploration, the selection of the kind of ML would remain dependent on the nature of mission. In this context, missions that deal with readily available data sets would be best met by using supervised ML such as prediction of space weather or classification of minerals. Likewise, for exploratory missions – where already available datasets are scarce - would be met more optimally with unsupervised ML – for example identification of space debris and interstellar medium analysis. Similarly, interplanetary missions could employ semi-supervised ML, combining both label and unlabelled data sets. Lastly, autonomous decision-making in space exploration could be a potential

57 Iqbal H. Sarker, "Machine Learning: Algorithms, Real World Applications and Research Directions," *SN Computer Science* 2:160, (2021), https://link.springer.com/content/pdf/10.1007/s42979-021-00592-x.pdf.

58 Shaza Arif, "Adversarial Attacks on Machine Learning – An Appraisal,"(paper, Centre for Aerospace & Security Studies, Islamabad, 2022), https://casstt.com/adversarial-attacks-on-machine-learning-an-appraisal/.

59 Ibid.

area where reinforcement learning could play its part. Hence, the exact requirement of the mission would decide the specific preference vis-à-vis selection of the ML model.

Discussion: Challenges and Recommendations

The findings of this study highlight the significant potential of ML in advancing space exploration across all three levels examined. Near-Earth applications are particularly impactful, enhancing data analysis, autonomous navigation, and robotic capabilities. ML's integration into space exploration is poised to play a crucial role in future missions beyond the solar system, offering valuable insights at the interstellar level. While ML holds relevance across all three domains, its applications are most prevalent in near-Earth exploration, where real-time data availability enables more immediate and practical implementation.

The research reveals that various ML techniques have been employed to enhance space applications, with data processing and analysis emerging as the most prevalent across all three levels of exploration. Among the commonly used ML methods, supervised learning, decision trees, random forests, regression, and feature analysis have consistently appeared across different space missions. Given their widespread application, these techniques are expected to play an increasingly important role in shaping the future of space exploration.

While extensive literature exists on the applications of ML in space exploration, several challenges remain that require critical attention. These challenges primarily stem from the extreme and dynamic nature of space, particularly in terms of temperature fluctuations and radiation exposure. Space missions operate in highly volatile environments, where solar radiation, galactic cosmic rays, and the Van Allen belt pose major risks to ML models.

Radiation can directly interact with ML systems, leading to bit flips that may alter or damage their functionality. Exposure to highly charged particles can result in single-event upsets (SEUs), a phenomenon where radiation-induced disturbances cause unintended status flips in electronic devices, potentially compromising mission-critical operations. Addressing these vulnerabilities is essential for ensuring the reliability and resilience of ML-driven space technologies.[60] Such scenarios have the potential to impact hardware longevity and result in disruption of sensitive electronic components. Furthermore, there is an equal probability that performance of the ML models trained on Earth could be impaired in extreme environment and microgravity conditions. Radiation can also degrade the quality of available data, affecting critical aspects such as photographic clarity, which in turn impacts the accuracy of analysis and decision-making processes. This challenge is further aggravated by the militarisation of space technology, as smaller and more compact systems tend to have lower radiation tolerance, making them more vulnerable to damage. Given these constraints, ensuring the hardware resilience of ML-driven systems must be a priority to enhance their reliability and functionality in extreme space environments.

Similarly, while technological advancements are driving various space applications, their current capabilities may not yet align with the ambitious goals of human space exploration. For example, although ML can support colonisation efforts, achieving this objective would require the development of self-replicating space equipment to sustain long-term extraterrestrial settlements. Given the current state of space technology, such advancements remain a long-term endeavour, requiring advanced progress before they become feasible.

Interstellar applications also face challenges due to the inherent complexity and vast distances involved. While literature suggests that increasing computing power could lower spacecraft launch costs, interstellar travel depends on more than just computational advancements. It requires simultaneous progress in materials science and propulsion systems to enable ML breakthroughs in deep-space missions. Although computing power has advanced considerably and is expected to see further breakthroughs, corresponding progress in materials and propulsion technologies remains essential for realising ML-driven interstellar exploration.

Another major challenge is the collection and processing of vast datasets from space. Imbalanced datasets, where rare but highly consequential space weather events occur infrequently, can lead to biases in algorithmic learning, skewing predictive models.

60 Sari Katz, Uriel Goldvais and Colin Price, "The Connection Between Space Weather and Single Event Upsets in Polar Low Earth Orbit Satellites," *Advances in Space Research* 10, no.67 (2021): 3237-3249, https://www.sciencedirect.com/science/article/abs/pii/S0273117721001204.

The complex and dynamic interactions between the Earth and the Sun, which remain only partially understood, further complicate accurate space weather forecasting.

Other constraints arise from data collection limitations, including variable time scales, inconsistent spatial coverage, and an uneven distribution of GNSS receivers, particularly in remote regions such as the oceans and the Southern Hemisphere, which contribute to less accurate predictions for these areas. Moreover, the risk of inaccurate information remains a persistent challenge. For example, while ML applications in detecting cave entrances on Mars are being explored, current results have shown notable inaccuracies, underscoring the need for further refinement of these models.

Current limitations indicate that ML applications will continue to advance most rapidly in near-Earth exploration, where real-time data availability and technological maturity provide a solid foundation for innovation. However, solar system and interstellar applications must overcome sizeable technical and operational barriers before ML can be effectively deployed on a broader scale. Nonetheless, ongoing advancements and research initiatives suggest that major breakthroughs in space exploration are likely in the middle and later decades of the 21st Century, paving the way for more sophisticated and autonomous deep-space missions.

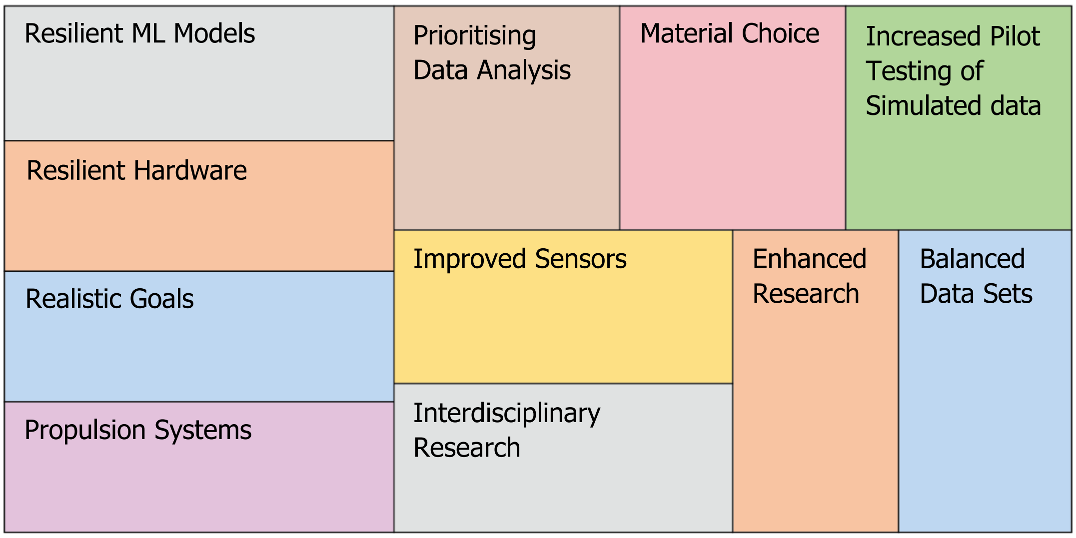
Lastly, the synergy between ML and other emerging technologies could also impact future space applications. Merging the power of quantum mechanics with ML can provide an exponentially faster speed as compared to classical computers.[61] Such synergy can optimise flight trajectories and process data more efficiently. Likewise, the combination of ML and nanotechnology can also provide innovative measures to address modern-day engineering challenges.[62] In space applications, integration of nanotechnology with ML can offer advanced solutions vis-à-vis small, lightweight spacecraft such as Cubesats or nanosatellites and advanced capabilities such as self-replication and advanced propulsion systems. Hence, in the future increasing integration of ML with emerging technologies could fuel advancements in space exploration.

61 Jun Qi, Chao-Han Huck Yan, Samuel Yen-Chi Chen and Pin-Yu Chen, "Quantum Machine Learning: An Interplay Between Quantum Computing and Machine Learning," (paper, arXiv,2024), https://arxiv.org/pdf/2411.09403.

62 Arnav Tripathy, Akshata Patne and Subhra Mohapatra, "Convergence of Nanotechnology and Machine Learning: The State of the Art, Challenges, and Perspectives," *International Journal of Molecular Sciences* 25, no.2 (2024):12368, https://www.mdpi.com/1422-0067/25/22/12368.

Hence, a targeted and strategic approach is essential for maximising the potential of machine learning (ML) in space exploration. While the path forward is broad, certain key areas must be prioritised to ensure effective implementation. Based on the findings of this paper, the following key directions can help guide the future of ML in space exploration (Figure II), as analysed using NVIVO 11:

Figure II: Way Forward



Source: Authors own using NVIVO 11.

Recommendations

Strengthening ML Applications in Space Exploration

- While efforts should continue to be invested in near-Earth applications, more research and pilot testing of simulated data are required to strengthen distant ML applications in space exploration.
- Given the expanding scope of space exploration, interdisciplinary research should be prioritised into future research vis-à-vis ML and related subjects, including astrophysics, planetary science, astrobiology, chemical composition and geology, to make better use of ML in space exploration.
- Realistic goals need to be set with pragmatic timelines to streamline the process of ML integration in space exploration.

Data Collection, Processing and Adaptability

- Data collection and processing have emerged as a prevalent theme across all three levels, suggesting its increasing importance and the need for continuous improvement in ML techniques employed in the process.
- Balanced data sets, improved sensors, and adequately distributed GNSS servers should be ensured to improve data collection methods.
- There is a need to develop ML models that can handle data in different time variations and at different geographical locations. The adaptability feature should be ensured in ML models to self-correct the errors that result out of extreme environment / radiation exposure.

Hardware Resilience and Space Environment

- Given the extreme environment in space, there is a need to develop hardware and ML models that are resilient to the space environment and capable of withstanding the intense temperatures.
- There is a need to explore techniques that can lead to the development of hardware-optimised algorithms that can overcome bitflips and the impact of radiation. Therefore, the choice of material and shielding techniques needs to be improved to protect the hardware and spacecraft.
- Material science innovations should be promoted to develop resilience against space environments. In addition, design strategies should be explored to incorporate fault-tolerant systems.

Technological Advancements and System Integration

- Technological advancements in computing power need to be synchronised proportionately with material and propulsion systems.
- Nanotechnology and self-replication need to be explored to power ML techniques in space exploration.

Standardisation and Safety Protocols

- To ensure the safety, reliability, and durability of space equipment, adherence to international standards such as NASA EEE-INST-002, NASA-STD-8739.8A, NASA-

STD-5019, ESA's ECSS-Q-ST-30-02C, ECSS-Q-ST-60-15C, ECSS-E-ST-10C, MIL-STD-883, and MIL-STD-1540 should be prioritised.

- Development and implementation of enhanced testing protocols that complement these existing standards are also essential for improving hardware performance and resilience in extreme space environments.

Conclusion

Space exploration presents a compelling domain for scholarly inquiry, given its rapid advancements and expanding significance. The evolution of space-based technologies and applications has led to an exponential increase in global reliance on them. As these applications continue to expand, the integration of machine learning (ML) offers substantial opportunities for enhancement. Similar to its transformative impact across various sectors, ML holds significant potential to advance space exploration through improved data analysis, automation, and decision-making capabilities. ML techniques such as deep learning, supervised learning, regress trees, random forests, and regression can power space exploration across near-Earth observation, solar system, and interstellar levels. In near-Earth applications, ML can enhance data collection and analysis, facilitate autonomous satellite navigation, and improve the efficiency of robotic astronauts. Similarly, within the solar system, ML can support planetary exploration, space weather forecasting, space debris identification, and asteroid trajectory prediction. At the interstellar level, ML plays a critical role in exoplanet detection, the analysis of diffuse interstellar bands, and advancement of interstellar missions, demonstrating its broad applicability across multiple domains of space exploration. While ML offers significant advantages for space exploration, several challenges hinder its optimal implementation. Factors such as extreme temperatures, radiation exposure, imbalanced datasets, and varying time scales for data collection pose substantial obstacles. Addressing these challenges requires proactive measures and targeted solutions to enhance ML's effectiveness in space applications. Therefore, prioritising this area is essential for relevant stakeholders to maximise the potential of ML in advancing space exploration.

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