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# State of Artificial Intelligence Research in Space Exploration and Its Obstacles

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## Abstract

Artificial intelligence (AI), defined as the capacity of machines to learn and behave in ways often associated with human intelligence. Artificial intelligence (AI) spans a wide range of controversial topics, including those related to society, economy, public policy, technology, law, ethics, and even national security. In the context of military operations and the battlefield, notably with the employment of drones and, more controversially, Lethal Autonomous Weapons Systems, the advancement of AI-based autonomous systems is of equal relevance. Autonomous devices with the ability to make their own decisions and more sophisticated services using extremely huge quantities of information from space are projected to have a profound effect on space operations in the not-too-distant future. Reason being, AI and ML will be crucial in these fields moving forward. Here, we'll take a look at some of the ethical and legal concerns that have arisen because of its widespread use. Existing international treaties are inadequate for finding and implementing solutions to these moral and legal challenges. Therefore, a legal strategy must be developed to permit the coupling of intelligent systems and services with an appropriate body of law. This article discusses current artificial intelligence (AI)-based legal technologies that might be utilised to make space law applicable, interoperable, and machine-readable for future compliance instruments. Due to a variety of circumstances, space-based systems' ability to view and interact with any specific spacecraft is restricted in comparison to that of ground-based systems. Among them are the availability of personnel, the speed of communications, the size of available power reserves, and the reliability of their link to the ground.Every spacecraft needs some degree of autonomy to function, but previous tests and flights have demonstrated that adding more complex autonomous mechanisms may greatly improve the efficiency of many missions.A growing number of ships are looking to artificial intelligence as a means to achieve autonomous flight. As varied as AI's potential applications are, so too is the range of AI techniques and variations now documented in the literature.

**Keywords:** Space, Artificial Intelligance,Technology

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# II.INTRODUCTION

Spacecraft have a variety of inherent limitations that make them harder to observe and manage than systems on the ground. Among them are the availability of personnel, the speed of communications, the size of available power reserves, and the reliability of their link to the ground.Incorporating more complex autonomous mechanisms has been found significantly.Common Off-The-Shelf Products' Increasing Popularity (COTS)Existing state of affairs is only possible because to the enhanced processing capacity of today's components. So, developing processes and algorithms to provide spacecraft a higher degree of autonomy and awareness is essential. This may also pave the way for missions that call for the spacecraft to make autonomous judgements under hazardous conditions and carry out its tasks with little or no input from Earth's inhabitants.However, the range of possible uses for the many AI methods and variations described in the literature is equally as broad. Sector outlines FDIR ideas for spacecraft and how AI might be used to improve system dependability considering these discoveries. Autonomous spacecraft operations are the topic of Subdivision. The study is then concluded in section 7 after section 6 provides a review of the relevant literature.

**Specifics of artificial intelligence in space and the dynamics of space environments**

The European Union, along with most of the globe, makes heavy use of space-based resources right now. Space-based services and activities are crucial to the national security and strategic interests of many countries. Europe wants to encourage cutting-edge technology development and strengthen the inventive ability and competitiveness of the space industry's enterprises by granting its people considerable autonomy in the space sector. Europe's innovative use of AI has propelled it to the forefront of the global space industry.The physical, technological, and operational domains are becoming more complicated and hard because to the "New Space" contextual quadrant, which is enhancing the application of AI in space. We will discuss current appropriate dynamics of space, as well as the qualities of space that AI considers helpful, in the following sections.

**Changing Dynamics in Spacetime**

Examples of the proactive and open attitude towards technology disruption and opportunity that characterises the modern Space 4.0 era include technological advancements in fields like AI, ML, and the IoT have played a pivotal role in ushering in this new era (IoT). By 2025, the IoT is predicted to have enabled the deployment of billions of sensors across large constellations of small satellites, leading to a gigantic data explosion (“such as Hiber, Astrocast and Keplercars”).

The advantages of space operations on Earth are amplified by the uniqueness of the products, techniques, and data input that can only be performed in space. The monitoring of land and infrastructure, security are all areas of the economy that are becoming more reliant on satellite navigation and EO systems.When we talk about "space democratisation" or "space privatisation," we're referring to the practise of making space accessible to and used by any nation with the technological wherewithal to do so, as well as non-governmental groups like privately owned legal businesses. Seventy percent of all space endeavours are currently funded by the private sector (UNOOSA, 2018). As more private enterprises see mining's potential, this figure is projected to climb.

Space exploration and mineral extraction have been given a boost by AI and the digital revolution.These forward-thinking companies are joining the space race. Between $1.1 and $2.7 trillion dollars in income is expected from the space sector by 2040.The most cutting-edge innovations in the production of tiny satellites are now dominating space trade.

Helpful Properties of the Real World for AI 2.1To fully understand how artificial intelligence (AI) in space varies from its Earthly applications, much more research is required. Some important differences and further details are provided below.Only astronauts are prepared for the extreme conditions of space. The extreme isolation, harsh conditions, and deadly atmosphere of space make AI-connected devices crucial for exploration and survival. Thirteen AI-powered decision-making tools that are robust, flexible, and able to handle unforeseen challenges.

The second consideration is how AI will affect the universe in the future. Launch operations, constellation management, and satellite health monitoring are just some of the many potential applications of AI in the space sector. A spacecraft driven by AI may see a possible threat, gather data, analyse it, devise a plan of action, put it into motion, and then broadcast its success to other satellites. It's possible that a message sent from Mars to Earth might take as long as 24 minutes to reach its destination. Because decision making takes so much time, scientists are slowly equipping space robots with the ability to reason on their own..

**Objectives**

The combination of geospatial big data with "Big Data Analytics" allows for the creation of "value" from massive datasets that are currently difficult to gather, store, manage, and analyse with simply existing technologies due to their size, velocity, variety, veracity, and value. There are several ways in which AI may be put to use in the space exploration industry, and geospatial intelligence is only one of them. Geographical information on objects on Earth, in the sky, and in between is gathered and analysed with the help of AI (AI). This technique may be used to monitor natural disasters, refugee movements, and crop yields in real time, among other things. Section 3.2 of this chapter delves further deeper into these concerns.

| “Level | Description | Functions |
|---|---|---|
| E1 | Mission execution under ground controlwith limited on-board capability for safetyissues | Ream-time control from ground fornominal operations Executionof time-tagged commands forsafety issues |
| E2 | Execution of pre-planned, ground-defined, missionoperations on-board | Capability to store time-based commands in an on-board scheduler |
| E3 | Execution of adaptive mission operations on-board | Event-based autonomous operations Execution of on-board operations controlprocedures |
| E4 | Execution of goal-oriented missionoperations on-board | Goal-oriented mission re-planning” |

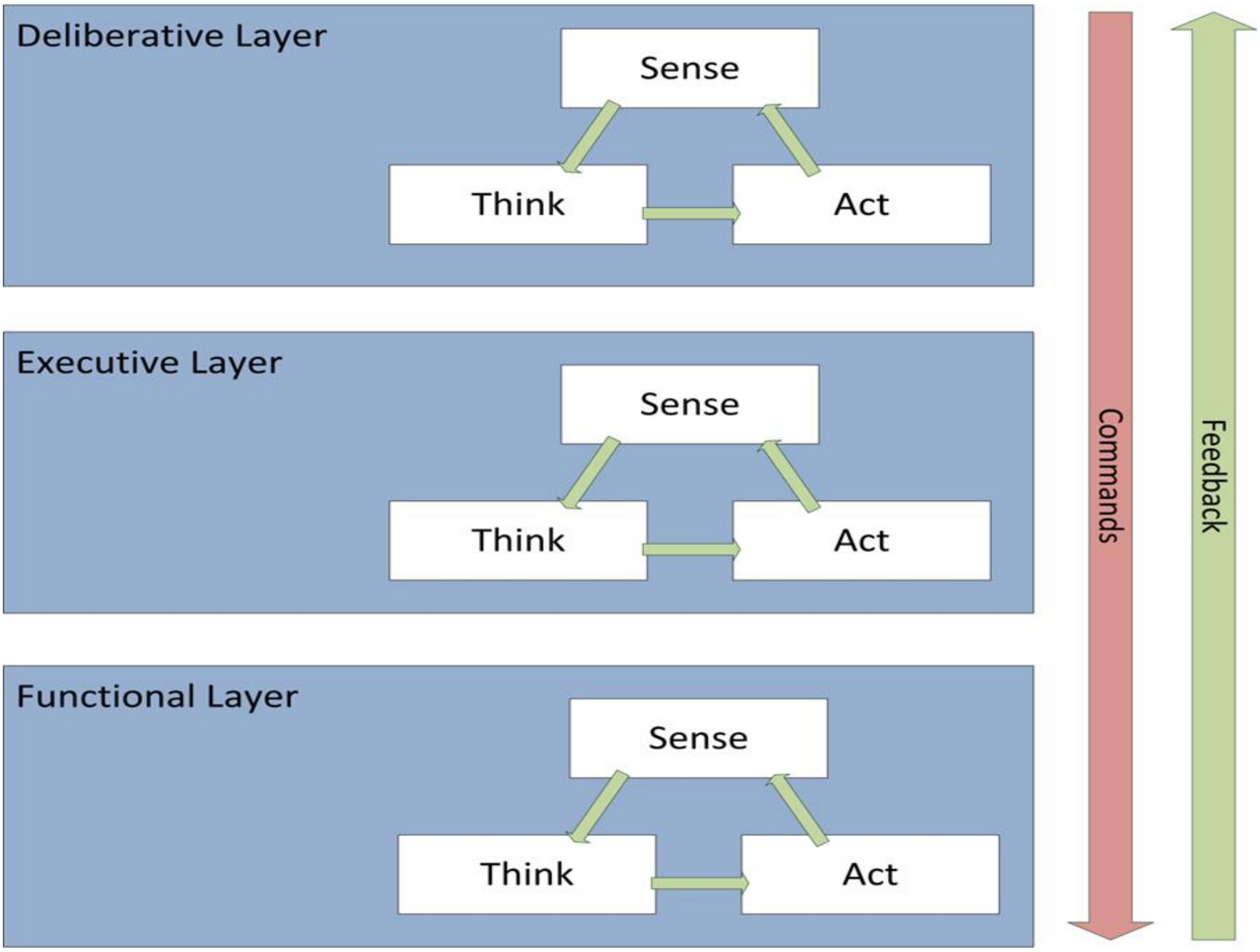
Table 1: ECSS-defined degrees of autonomy in mission execution

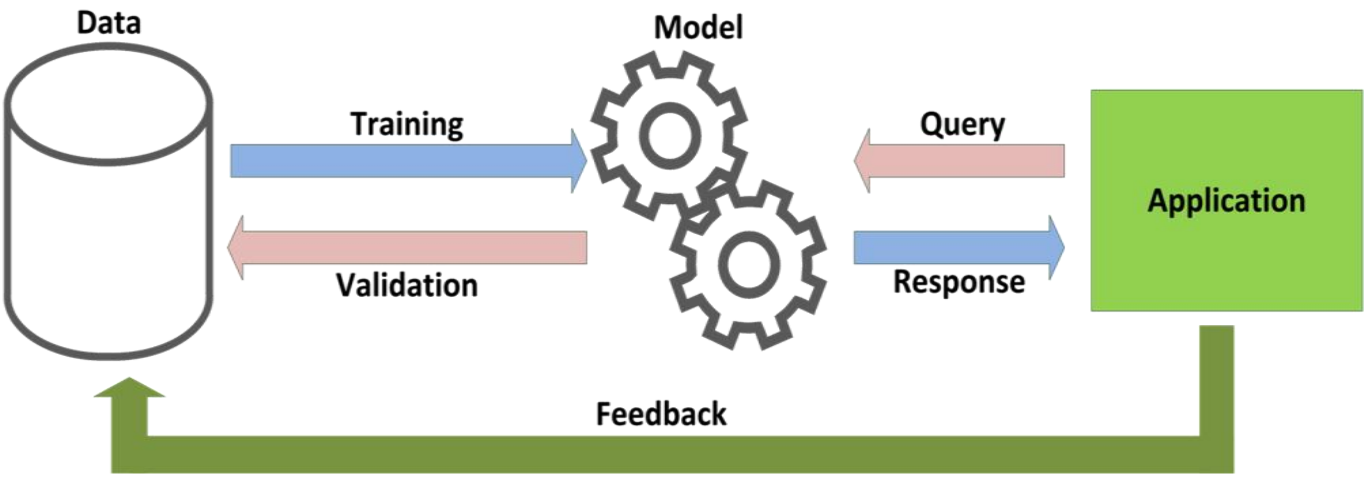
To achieve autonomy, it is best to use a tiered design that reflects the many perceptual and decision-making phases, from control-loops and other hardware operations to more abstract objectives. There are three parts to such architecture:

• The deliberative layer, also known as the planning layer, focuses on strategic choices, records high-level objectives, and creates long-term plans of action. The executive layer then receives responsibility for carrying out these sequences.

• The executive layer, also called the task sequencing layer, coordinates, and keeps tabs on ongoing projects, using its perceptual powers to determine whether to launch more fundamental projects or put them on hold. The functional layer is responsible for these fundamental operations, with the shortest reaction time possible because to its focus on executing simple activities according to established control loops or computations. These rely on data collected from sensors and instructions sent to the underlying hardware. Each of these levels has a self-referential feedback loop that continually assesses its environment, makes inferences, and puts those inferred actions into motion. The sense-think-act loop is another name for this pattern. Figure 1 shows how information travels from the top to the bottom of the system in the form of feedback and orders. This Section provides an in-depth analysis of autonomous systems used in previous and contemporary space missions.According to what has been said thus far, the term "autonomy" refers to a more abstract concept than the specific technologies used to accomplish it. Therefore, AI is only one method among several that may lead to independence. The following section provides a high-level overview of AI.

Intelligence Simulation



Separating "weak" AI from "strong" AI is essential. Imitating or even surpassing human intellect (including sentience, awareness, mind, and emotions) is at the heart of strong or general AI research. But weak or applied AI is geared on accomplishing a single goal or resolving a single issue. Weak artificial intelligence is the primary subject of this study since it is the extent of existing research in the space domain.In AI, there is a classification system that divides issue statements into five groups Information about the world (or a model of it) must be stored in a way that a computer can process it effectively, and this is the focus of knowledge representation.The capacity to make inferences about the environment based on sensory data is what we mean when we talk about perception.

As a result of applying logic and probability theory to existing information, conclusions may be drawn via the process of reasoning and problem solving.It is the job of planners and schedulers to devise and implement methods that will lead to the achievement of a target or the maximisation of a predefined utility function.The term "machine learning" refers to the process wherein a computer algorithm learns to perform better as it collects more data.Figure shows a diagram of the machine learning process. For use in applications, a model is trained from data or a knowledge base. Training the model for longer and with a larger dataset leads to better results, regardless of the quality of the initial data, the data selection, or the likelihood of overfitting. For models that need to be able to pick up new skills on the job, applications may enrich their knowledge bases with fresh information while they're running and then use that information to done their models. Figure: A High-Level View of the Machine Learning Process.Modern spaceships include all of the aforementioned characteristics in various ways. Their primary applications include pattern recognition (using either time series or multi-dimensional data, such as photographs), as well as the management of highly nonlinear systems that may need continuous tuning in response to changing conditions (i.e. learning). As available computing power increases, so does the possibility of using ANNs that are both more complex.It is easier and less labor-intensive to put them into practise.computational time and effort as compared to ANNs. Model-based A model of some part of the system is used to make inferences about how the whole system will behave. Diagnoses may infer information about the system and its surroundings from the accuracy of these forecasts. Therefore, it may be prudent to do in-flight analysis based on both data and expert knowledge.So-called anomaly detection is an essential part of autonomy and a fertile area of study for AI researchers. When applied to a stream of data, anomaly detection may pick out regularities and distinguish them from random occurrences. The capacity to identify and categorise these outliers is a crucial piece of data for decision-making systems at higher levels. Next, we'll go into a quick introduction to anomaly detection before diving into the topic in full in Segment.

**Recognizing Unusual Behaviors**

This remains crucial for spacecraft to identify out-of-the-ordinary events and take corrective action. As shown in Table the ECSS specifies two degrees of autonomy with respect to the handling of on-board data seen by the spacecraft.Storage of critical mission data, such as event reports, is covered at the D1 level. Such as images, are also analysed for anomalies in order to identify potential scientific breakthroughs or to reduce the volume of data sent down.

Perils of Artificial Intelligence in Outer Space

Space AI hastens the break from "computer-assisted human choice and human-ratified computer choice"20 by facilitating the move towards analysis, decision making, and action execution by machines. When, not if, the use of such objects violates privacy rights, breaks data protection rules, or causes injury due to a space object collision, this raises new questions for the current space law system.

| “Level | Description | Functions |
| --- | --- | --- |
| D1 | Storage on-board of essential mission data following a groundoutage or a failure situation | Storage and retrieval of event reports<br>Storage management |
| D2 | Storage on-board of all mission data, i.e. the space segmentis independent from the availability of the ground segment | As D1 plus storage and retrieval of all mission Data” |

Altitudes of mission-independent data handling are shown in Table 2.

For a comprehensive review of anomaly detection for discrete sequences, see. Techniques that may be used in the space industry are discussed in Section 3, along with a representative sample of applications in space missions, most of which involve health monitoring of spacecraft.Systematic Detection, Localization, and Resolution of Errors (FDIR)

As a prerequisite to the rest of this article, we must first agree on what constitutes a defect or failure. This might be a temperature reading that's too high or too low, or it can be a flipped bit in memory caused by something called the Single Event Effect (SEE). In terms of how the system really works, a failure is the (partial) loss of services provided by the system as a direct result of a problem. This method, known as FDIR in spaceship design, is becoming more popular. The capacity of a system to detect the occurrence of a defect is known as its fault detection capability. This is followed by fault isolation, which pinpoints the specific site of the error (in terms of subsystem, memory region, etc.). At last, the system aims to reboot into a fault-free condition of operation during the fault recovery phase. Finally, this process is often implemented in a hierarchical structure, with each layer responsible for handling errors at a different level of abstraction. A higher level of management is only engaged in the fault handling procedure if absolutely essential.The ECSS establishes two degrees of autonomy for FDIR in circumstances when a problem cannot be addressed and results in a failure. This Sector provides a comprehensive review of the current FDIR methods and how they are used in space missions.

**DIFFERENTIATION OF ANOMALY**

Adding autonomy to spacecraft means equipping them with a cognitive system that can assess its surroundings and internal status, form judgements based on their objectives, and take appropriate action without assistance from Earth.

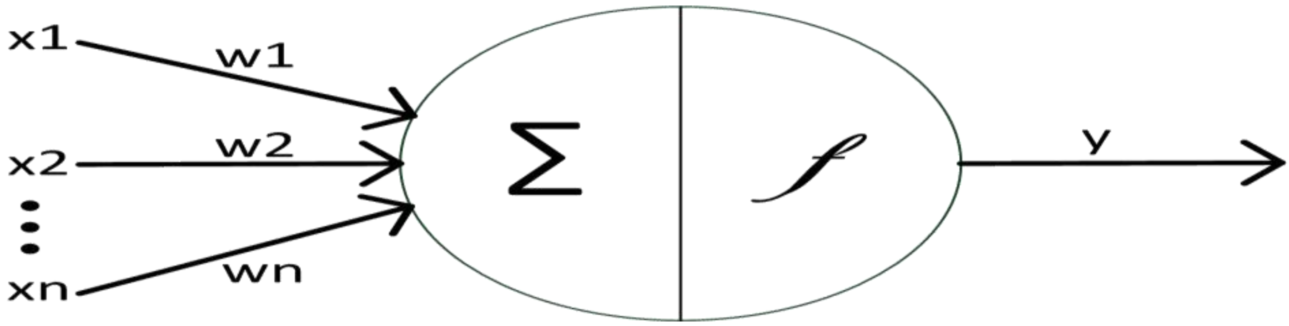
| “Level | Description | Functions |
|---|---|---|
| F1 | Establish safe space segment configuration following an on-boardfailure | Identify anomalies and report to groundsegment<br>Reconfigure on-board systems to isolate failed equipment or functions<br>Place space segment in a safe state |
| F2 | Re-establish nominal mission operations fol- lowing an on-board failure | As F1, plus reconfig-ure to a nominal oper-ation configuration<br>Resume execution ofnominal operations Resume generation ofmission products” |

the ability to spot deviations from the norm during mission operation relies heavily on the observer's familiarity with patterns and anomalies.

Consideration of the surrounding data points (context) is required before a data point may be labelled as a contextual anomaly. For instance, a daytime high temperature would not be deemed an abnormality if it were to be recorded at night. Even though individual data points may seem normal when taken in isolation, when taken as a whole, an unusual pattern emerges. The difficulty of identifying contextual and, more importantly, collective anomalies, as opposed to single-point anomalies, is self-evident.Point anomalies are often identified by performing Out-Of-Limit (OOL) tests on a range of parameters that have been given fixed upper and lower limits. In order to report occurrences at an early stage in the development of an abnormality, hard and soft boundaries are specified nowadays. Further, many constraints might be placed on the present situation (orbital period, spacecraft mode, etc.). This also includes minor discrepancies in context. These advanced OOL checks, however, are still limited in their ability to detect abnormalities since they cannot examine the underlying patterns of the data. As shown in growing friction on a Venus Express reaction wheel could only be detected by careful visual observation.One potential downside is that the system may not detect unusual behaviour the first time it occurs, if it has never seen such behaviour previously and instead considers it to be the norm. In the unsupervised setting, the system assumes that out-of-the-ordinary occurrences are very rare compared to typical behaviour. As a result, it looks for commonalities in the training data and labels outliers as such. However, if the same kind of anomalies keep cropping up, the system may mistake them for the norm.

Unique computationally besides theoretically straightforward method involves calculating the Euclidean distance between a specific time series and all previously observed time sequences by first calculating the lowest, maximum, average, and standard deviation of the sequence in question. Local Outlier Probabilities are then used to evaluate the likelihood of seeing an outlier or abnormality. When used for classification and regression, SVMs are a mathematical process that assumes the data can be linearly separated by a hyperplane and then converts the input data to higher dimensions. Kernels are used as similarity functions to achieve this goal. Standard kernels may be either linear, polynomial, or RBF. By using just a few number of training samples (support vectors), this hyperplane may be transformed into a non-linear separator during the inverse transformation. As a consequence, we have a hyperplane that is both easy to understand and very stable. As a supervised machine learning method, SVMs are a useful tool. This requires labelled training data for both typical and out-of-the-ordinary circumstances, which is a prerequisite for anomaly identification. Training an SVM in several phases with increasing numbers of data solves the issue of having a small sample size for anomalies, which are by definition uncommon relative to nominal behaviour. Based on data collected during Flight Experiment II of the Interferometry Program, the findings have been confirmed (IPEX II).In a similar vein, one option is to utilise simply nominal data, which does not need any specific domain expertise to label. The suggested method is likewise kernel-based, but it is "knowledge-free" in the sense that it does not rely on any previous expert knowledge. Here, we take input data as a time series and turn it into a series of overlapping windows. When performed, PCA yields linear combinations of the original characteristics that are independent of one another and depict patterns in the underlying data. The

PCA's principal component direction (the principal component vector) is then calculated based on this distribution. The distribution may now be compared to the main component vector of the newly obtained windows. The window is deemed abnormal if its anomaly score, calculated from its probability, is greater than some predetermined threshold. JAXA supplied simulation data of an orbital transfer vehicle's thrusts, which was used to verify the findings.




Model of a single artificial neural network neuron shown in Figure 3.

Relies on shrinking data and grouping like items together. The first step in normalising multidimensional data is to filter it for extreme values using just the th and (100 th) percentiles of the same time period. One such method to extract multi-scale frequency characteristics is using wavelet-based preprocessing . In this method, all of the mission data is unsupervisedly grouped using Euclidean distances based on these attributes. Then, a professional labels a group as "normal" if they find it in a cluster. Significant characteristics that distinguish the anomalous clusters from the nominal cluster are created. The clusters are then assigned to various nominal modes or classified as actual anomalies based on the presentation of these key traits to a trained expert. However, the presented strategy is only applicable for ground analysis since it requires access to all mission data obtained in the past. Real-world data from the Lunar Atmosphere and Dust Environment Explorer's power system confirmed the method's efficacy (LADEE).

As we go from traditional statistical approaches to neural networks, we find a wide variety of purpose-built designs. Multi-Layer Perceptron (MLP) is perhaps the most well-known. Artificial neurons are used to construct thisdesign, and they are meant to mimic the performance of real brain cells. Figure depicts this model. People have been curious in whether or not we share the cosmos with any other intelligent life forms since the dawn of civilisation. Thereare now two scenarios possible: "Either we are alone in the cosmos or we are not," Each one is just as terrible as the other. NASA has been exploring the solar system and beyond for decades, and throughout that time it has created more sophisticated instruments to answer this basic issue. Machine learning, cognitive automation, and AI can help us better manage satellite communications and other forms of space technology. Earth has thousands of satellites in orbit. There are others that capture images of Earth that are used by meteorologists in their forecasting and hurricane monitoring efforts. Cloud, ocean, land, and ice data are all gathered by satellites that gaze down at Earth. Some photograph the sun, distant galaxies, black holes, and dark matter. Gases like ozone and carbon dioxide are monitored, as is the amount of energy that Earth takes in and gives forth. Astronomers and space researchers may get valuable insight from these images. To what extent does a less intelligent satellite vary from a conventional satellite? The conventional one can do all of those things and more, but the AI satellite can do everything that regular satellites do and more since it runs AI software. We can now fix the increasingly complicated robotic systems used in space research, even if they are millions of kilometres (or even light years) from home thanks to this programme. Thousands of planets circling stars beyond our solar system have been discovered thanks to spacecraft like Kepler and TESS. To determine whether other planets, like Mars, have the potential to support life, scientists are sending out robots and satellites equipped with artificial intelligence to investigate. Less money is spent on sending a robot to space than a person. They have no need for food, sleep, or restroom Image 1.Earth Observer 1 (EO-1) breaks, robots can operate for extended periods without any interruptions. Because of their long shelf

life, they may be left in space without being brought back. More so, there are

many things that robots can accomplish that humans cannot. They are resilient enough to hold up under severe circumstances such as intense heat or radiation.Robots may be designed to do tasks that human astronauts cannot or should not attempt. To lessen our concerns, we may now send robots into space for exploratory purposes. These robots are expensive, so naturally we want them to survive as long as possible. We need them to stay still long enough to scout

out their locations and report back to us on what they find. However, human participants in a robotic mission will be unharmed if the operation fails.As an example, consider the Earth Observer 1 (EO-1) spacecraft. Figure shows how the AI algorithms on board have improved the analysis and reaction to natural disasters like floods and volcanic eruptions since the satellite was first launched in the early 2000s. The capacity of AI to sift through massive volumes of data in search of patterns will become more and more crucial to making the most of available information.

In the process of getting humans to Mars, AI has been utilised to optimise both the flight path and the cargo. It's a little ironic[4] that NASA's next rover mission to Mars, the Mars 2020 Rover, is scheduled to arrive on the red planet in early 2021, but both are crucial preflight tasks. In Fig (2). Onboard the current NASA rovers on Mars is a piece of artificial intelligence known as AEGIS. It can manage autonomous camera aiming and decide what needs to be looked at. Vehicle control, autonomous study selection aid, and dynamic scheduling and execution of scientific assignments are just a few of the tasks that the future generation of AIs will be able to handle.

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*Figure NASA already launched three Rovers*

Use of Artificial Intelligence in These Rovers

The following is a list of all targets identified by the AI system: While red targets are kept, blue ones are discarded in . The highest-priority objective is shown in green, while its nearest competitor is shown in orange. Image contrast has been adjusted for these NavCam photos. And as may be seen in Fig.NASA's Curiosity rover, equipped with artificial intelligence software, is altering the way scientists explore Mars. Because of how helpful this programme has proved to be, it will be used on NASA's future Mars 2020 mission. By way of long as there are sufficient power reserves, it is employed on almost every drive. The bulk of these applications included choosing locations to zap with Chem Cam's laser, which vaporises tiny samples of rock or dirt for further analysis.

While Curiosity's human operators are separated from the rover, the latter may make more scientific progress thanks to AEGIS. They feed it a new set of photographs and data every day, and then write it a set of orders to carry out. If the instructions include driving, the rover might be at its new location for hours before it can receive further directions. Through the use of AEGIS, it can automatically zap rocks that scientists may wish to examine in the future. The scientific team has found many new and exciting minerals with the aid of AEGIS. The discovery of increased amounts of chlorine and silica in surrounding rocks on different occasions aided the next day's scientific preparations. During periods when Chem Cam would have been idle while

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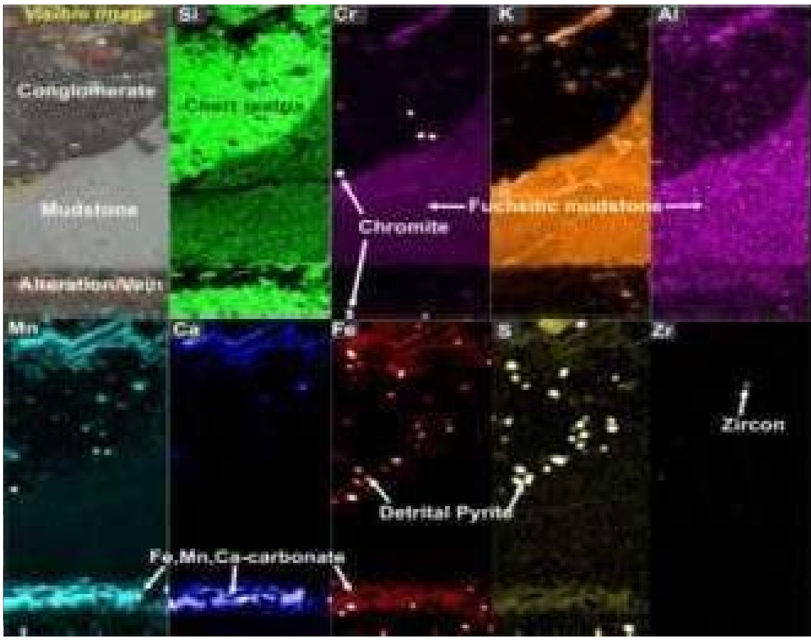
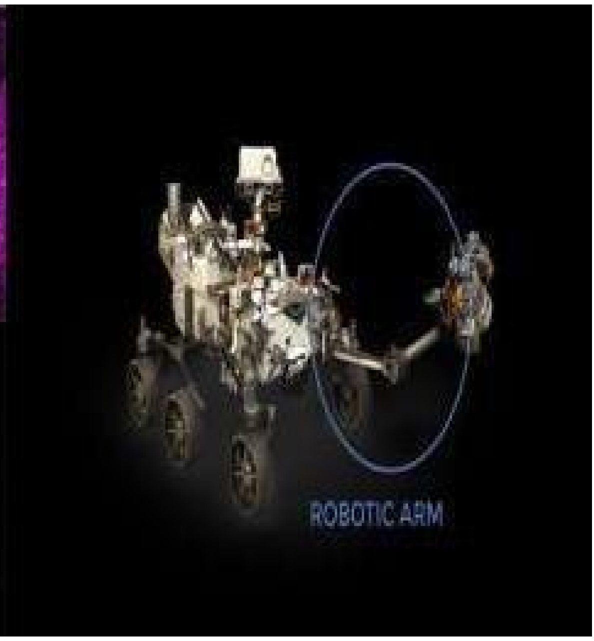


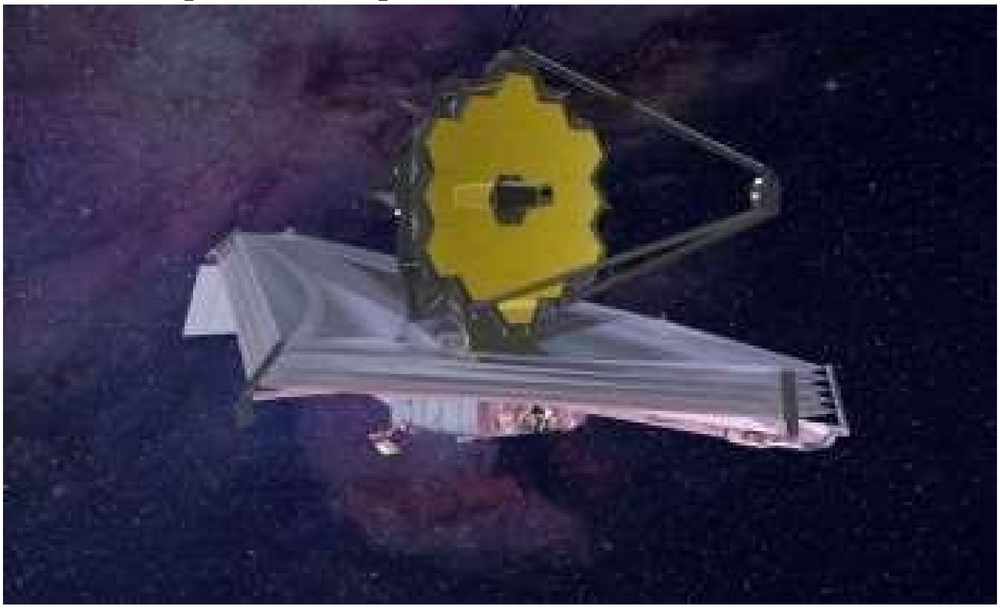




waiting for a command, AEGIS has been collecting data. As there was no way to actively look for a target, the aiming had to stick to a predetermined angle.Intelligent targeting meant that half the time it would merely strike dirt, which was still helpful but less so than the rock measurements that would be obtained. The programme utilises computer vision to scan the environment for edges; if it finds enough, it likely has an item. The programme may then sort, filter, and score the items depending on how well they match the criteria set by the scientific team. Furthermore, AEGIS may be used for pinpoint aiming. Two times in the last year, Curiosity's operators have used this feature to fine-tune the pointing because they weren't convinced that Curiosity would strike a very small vein in a rock on the first attempt. AEGIS, a component of Chem Cam's successor, Super Cam, will be incorporated in the future Mars 2020 rover. PIXL is a self-driving AI science instrument aboard the Mars 2020 Rover. The capabilities of the Mars 2020 rover's PIXL instrument will be greatly expanded in comparison to those of comparable equipment dispatched to Mars in the past. Rather of providing typical rock compositions spanning tens of centimetres, it will pinpoint exactly where each element is located inside the rock. First of its kind, PIXL will use a spatial resolution of around 300 micrometres to correlate elemental compositions with observable rock textures, marking the beginning of petrology research on Mars.

The PIXL microscope is mounted on the end of the rover's arm and has to be positioned 14 mm from the object under investigation. Many cameras mounted on the rover make this possible. Good analogy for the handover procedure and determining the precise location to position the arm. Artificial intelligence is well equipped for this task. This is where AI comes in handy, as it allows PIXL to operate autonomously all night long. And as may be seen in Fig.To Mars and Beyond!

Mars is not expected to be the last destination for AIs in space. The moons of Jupiter have always piqued the interest of astronomers. In particular, Europa, which may have an ocean under its roughly 10-kilometer-thick ice cover. If life exists somewhere in the universe, it probably does too. In 2020, NASA hopes to put the James Webb Space Telescope into an orbit around 1.5 million kilometres from Earth, so a future mission like that might still happen. The entire deployment of the telescope's 705-kilogram mirror will be monitored by AI-enhanced autonomous systems as part of the project. Supplement and expand the discoveries made by the Hubble Space Telescope by providing high-resolution images in the infrared spectrum. Coming in 2021.

The James Webb Space Telescope as an Illustration



Because of this, it is crucial that the artisans have autonomy when making choices. The Mars Rover project provides an example of how long it may take for a rover to communicate with Earth due to the immense distance involved. The time it takes to send a message during a voyage to Europa would be much higher. One of the biggest obstacles to using AI in space travel is shown by both missions, although to various degrees. The more information artificial intelligence systems have access to, the better they function. As the saying goes, "the more, the merrier." However, there is a severe lack of information that might be used to train such a system on what it could find on a voyage to Europa. Between 36% and 75% of Mars would have been covered in seas, according to various estimates. For an illustration of this, see Fig. Europa, a moon of Jupiter, with its aft half coloured about how it would be in nature. “Europa's mostly water-ice surface has a greater mineral richness in the darker parts”. In Fig.

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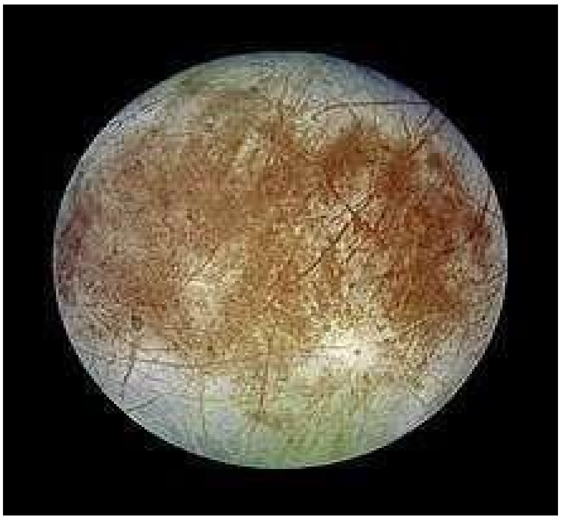

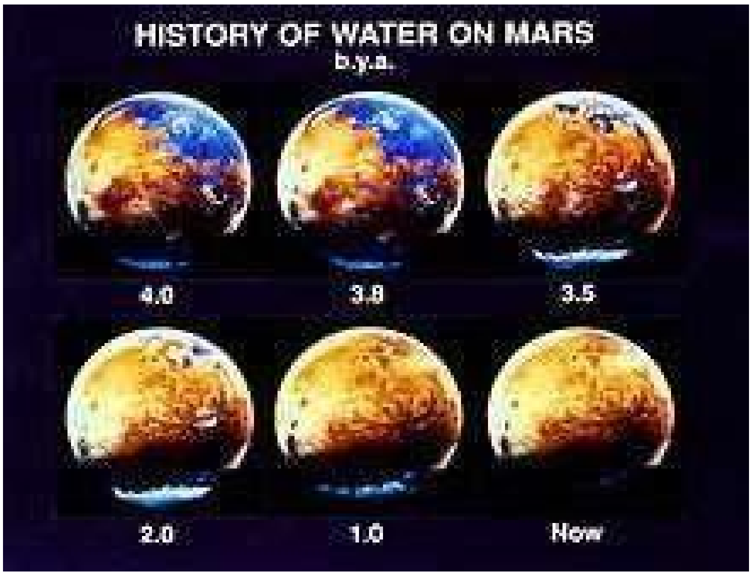


**Transformation of Our New Home's Terrain**

In the far future, we may look forward to moonshots like terraforming Mars. Without AI, it would be difficult to undertake such endeavours as bringing other worlds up to Earth standards. Terraforming by autonomous ships is already a reality on our home planet. Drones are used by Bio-Carbon Engineering to plant as many as "100,000 trees in a single day. First, drones scan and inspect the region, then an algorithm determines the best places to plant trees", and finally, a second swarm of drones actually plants the trees. There is much room for synergy and convergence, as is so frequently the case with exponential technology. Take the case of artificial intelligence and robots, or quantum computing and machine learning.

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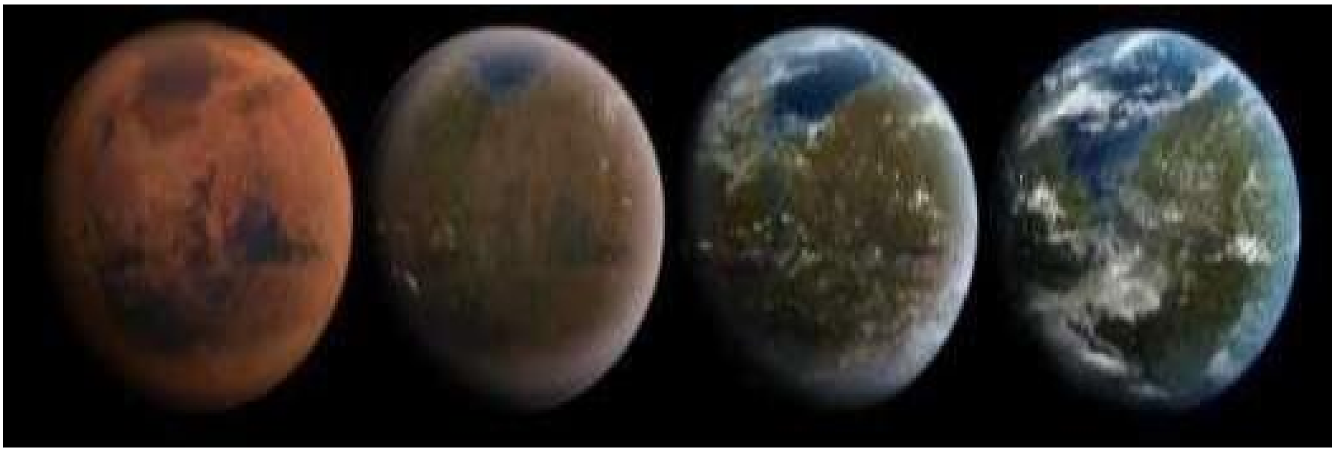

synergy and convergence, as is so frequently the case with exponential technology. Take the case of artificial intelligence and robots, or quantum computing and machine learning. Exoplanet Exploration With Artificial Intelligence

Any planet outside of our solar system is known as an exoplanet. Two telescopes, KEPLER and TESS, are now actively searching for planets.

Figure. Two Space Telescopes (KEPLER and TESS)

Former NASA space telescope Kepler was designed to find Earth-sized “planets orbiting other stars. The spacecraft, named after the scientist Johannes Kepler, was put into a heliocentric orbit” that trails the Earth on March 7, 2009. In Fig (10)

For NASA's Explorers programme, “the Transiting Exoplanet Survey Satellite (TESS) is a space telescope that will conduct transit-method exoplanet searches across an area 400 times greater than Kepler's”. SpaceX has successfully launched it. In Fig .

More than 2,900 potential planets have been identified by NASA's Kepler telescope, and this number continues to grow. The exoplanets discovered by Kepler have also allowed astronomers to begin classifying them into categories, which has aided in tracing their histories. Having discovered an eighth planet around Kepler-90, a Sun-like star 2,545 light-years from Earth, our solar system is now matched for the maximum number of planets surrounding a single star. Computers were trained to recognise planets by looking for signals from extrasolar planets (exoplanets) in the Kepler telescope's data.

Kepler-90 isn't the only promising planetary system out there. Kepler-90i, which is around 30% the size of Earth, orbits so near to its star that its surface likely reaches temperatures beyond 800 degrees Fahrenheit, which is hotter than Mercury. Kepler-90h, its furthest planet, circles its star at about the same distance that Earth orbits the Sun. To illustrate this point, consider Fig.

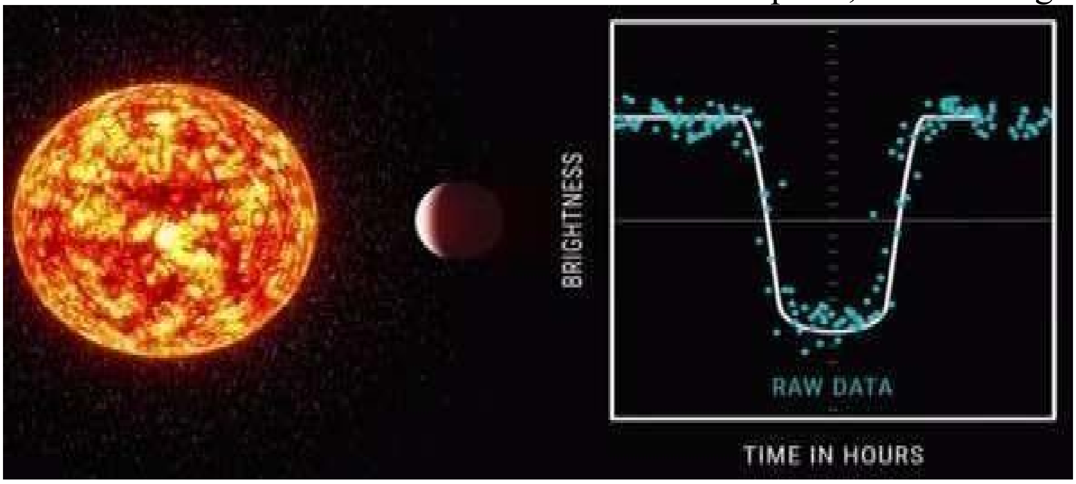


Figure. The Kepler telescope, assisted by artificial intelligence, has identified a new planet, Kepler90i.

The star system Kepler-90 may be thought of as a smaller counterpart of our own solar system. A small number of inner planets and a larger number of outer planets are packed together in a relatively tight space. The neural network was first taught to recognise transiting exoplanets using a curated sample of 15,000 signals taken from the Kepler exoplanet database. The neural network has a 96% success rate in separating genuine planets from false positives in the test set. They reasoned that planetary systems with many planets would be the most likely sites to find more exoplanets. Over the course of TESS's two-year survey of the solar neighbourhood, the spacecraft will look for dips in star brightness that might be produced by transiting planets. Discoveries made by the TESS mission demonstrate the wide range of planetary types across the Milky Way. According to astronomers' predictions. During its two-year main mission, TESS is predicted to discover some 20,000 exoplanets, including several thousand Earth-sized worlds. More than 17,000 planets bigger than Neptune will be discovered by TESS. Despite the aspirations, ambitions, and statistical

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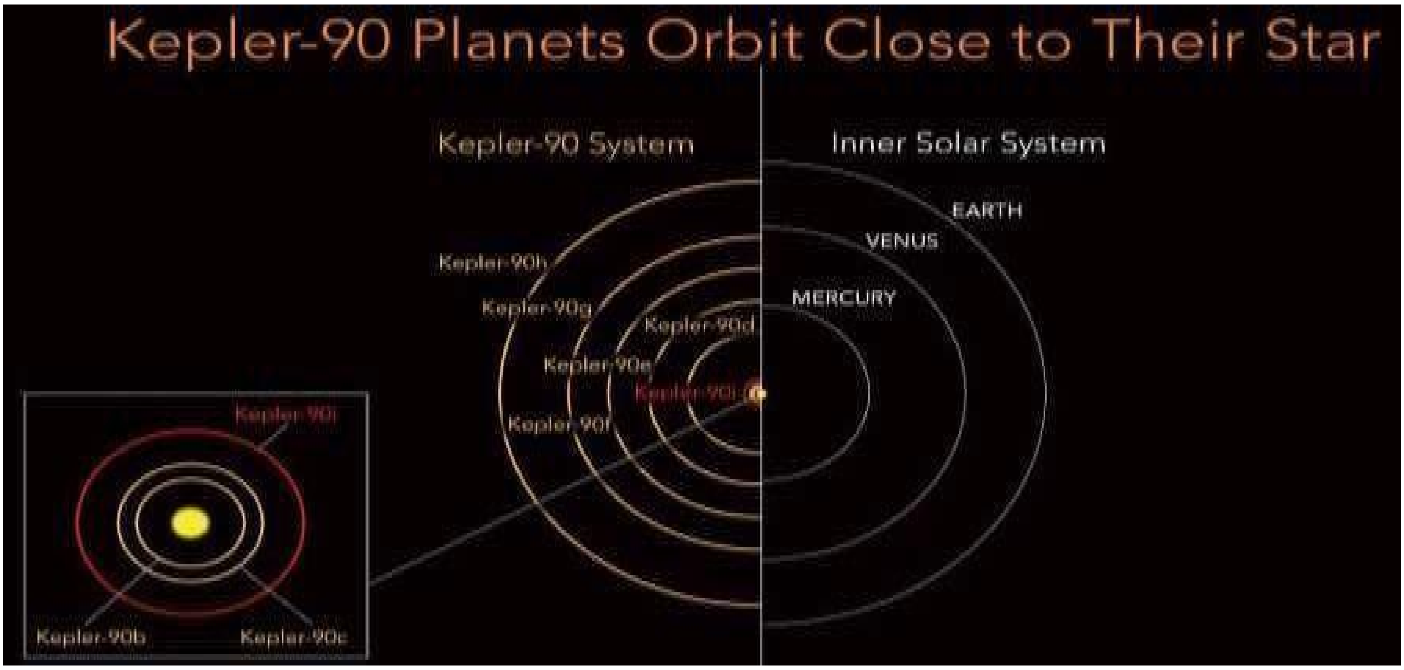
possibilities held by scientists and star-gazers, it is anyone's guess if NASA's newest space observatory, once it goes into orbit, will detect intelligent life in the cosmos. However, TESS, an abbreviation for Transiting Exoplanet Survey Satellite, will launch with a plethora of technologically advanced instruments, navigational Kepler-90 is a planetary system that has been observed to be almost identical to our own computers, cameras, and artificial intelligence (AI) capable of deciphering the data it gathers.

Astronomers may use AI to better interpret the data from TESS's telescope in several ways, including reading the sky. TESS, like Kepler, will




detect planets via a process called "transit." Because of this, Kepler and TESS's development teams need to evaluate a great deal of data, and that's where AI comes in. Figure 2 illustrates this as an example. That kind of research has the potential to increase TESS data's use in its extensive sky survey. It is likely to run out of fuel and cease operations within the next few months. However, TESS's four cameras will scan an area 400 times bigger than Kepler's. As observed from Earth, transiting extrasolar planets are the only kind of extrasolar planets known to do so. Planets that were first discovered by measuring their radial velocities fall under this group.The Functions of ML and DL in Paving the Way to AI

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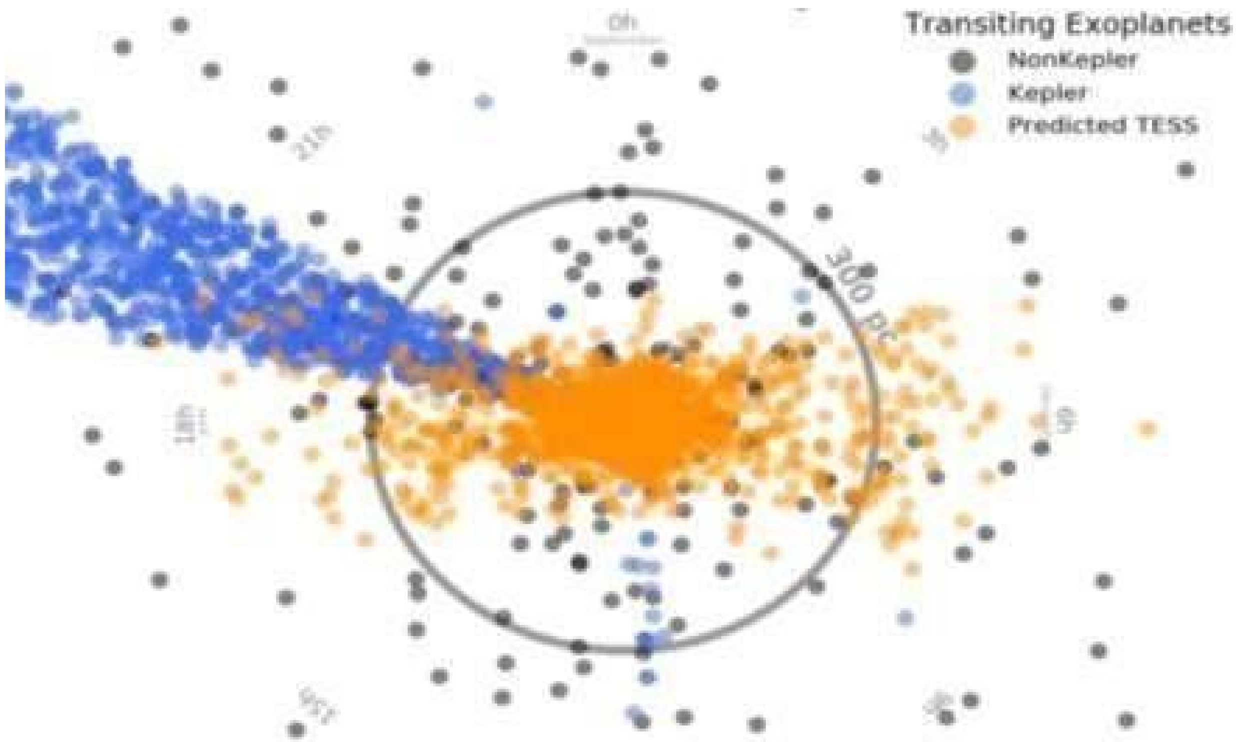
Machine learning (ML) enables AI since it trains computers to learn by themselves. ML allows a relatively simple algorithm to be "trained" to take on increasingly complicated behaviours. The system learns and improves as it is given ever more data. In ML, artificial neural networks are created to allow computers to analyse data in a manner that mimics how people do it. Since the advent of the internet, this branch of artificial intelligence has made great strides. Deep learning (DL) is a subfield of machine learning in which the computer is taught to do complicated tasks by using many artificial neural networks. Methods for doing so include supervised learning, in which the network is given examples to learn from, and unsupervised learning, in which the network is left to discover patterns on its own. And as may be seen in Fig.



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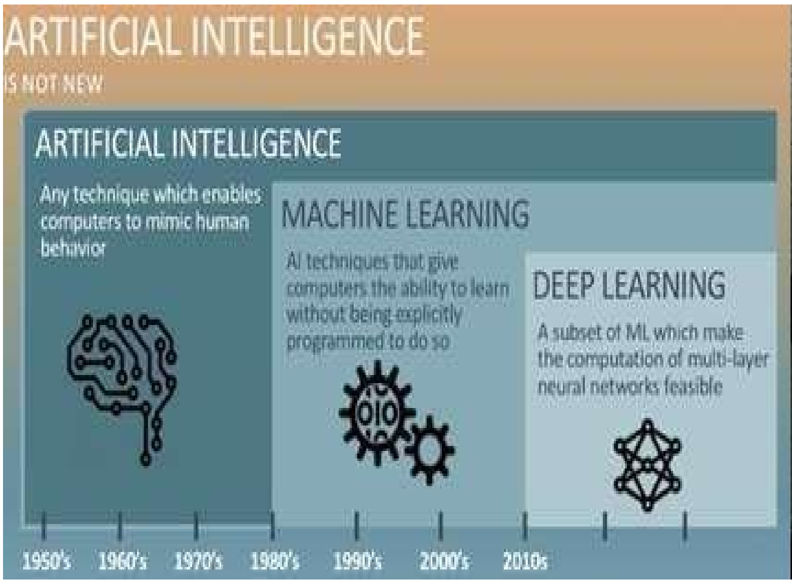
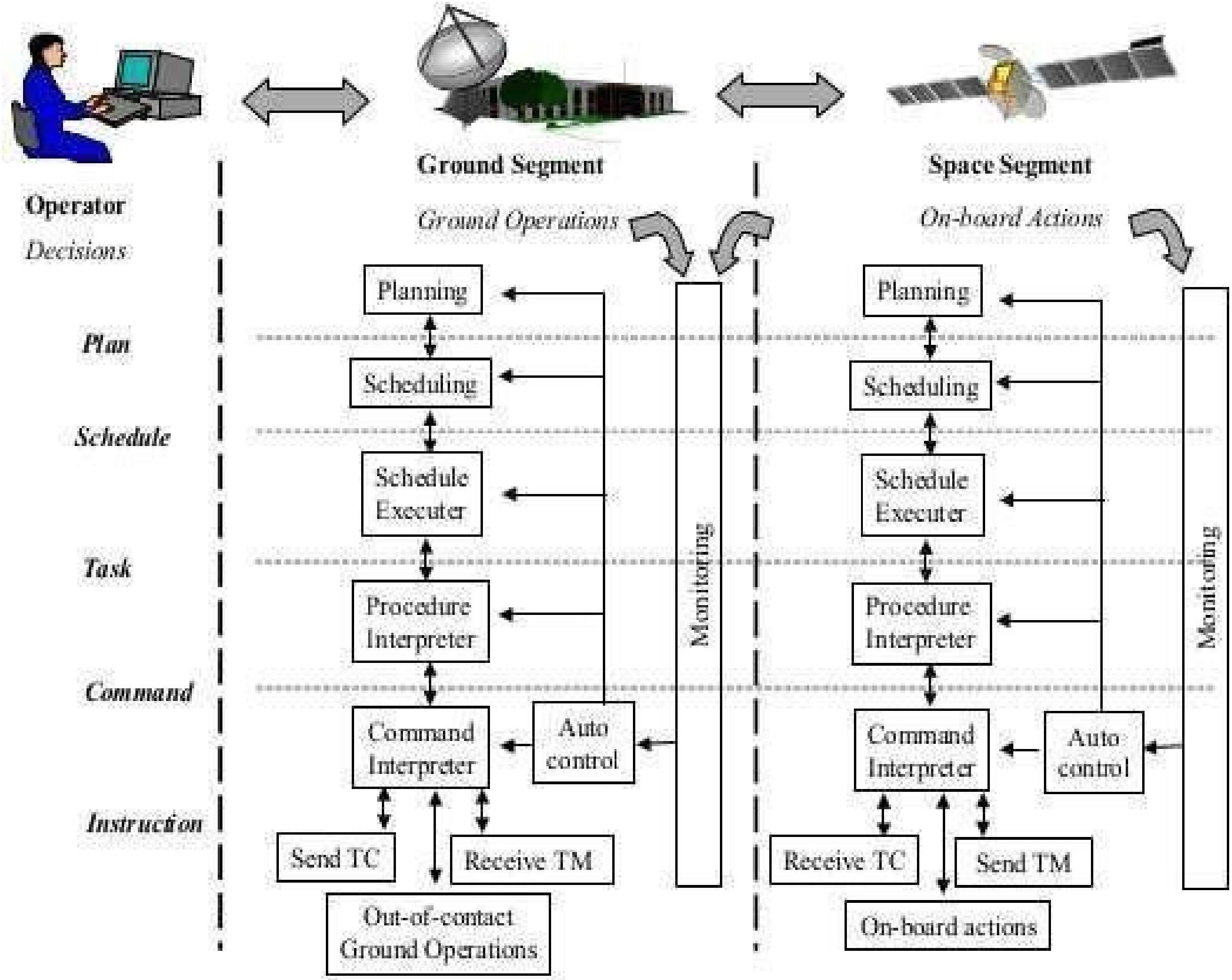



Unsupervised data feeding and reinforcement learning are the two primary methods by which deep learning systems acquire knowledge. Automatic landing, smart decision making, and completely automated systems are just a few of the numerous uses for DL. The Advanced Concepts Team (ACT) at ESA is hard at work on projects like these. In particular, evolutionary computation, which entails programming in such a manner that all evolutions are addressed, has lately been the subject of ACT research. Like in biological evolution, the more favourable outcomes are preserved while the less favourable ones are discarded. The orbital paths of the planets are only one area where this has been put to use. And as may be seen in Fig.


Investigated the use of large groups of tiny robots that communicate with one another over a network: if one robot discovers via trial and error that a specific manoeuvre is successful, the rest of the swarm would quickly pick up on this knowledge. Hive learning describes this kind of situation. Several investigations on the potential of AI in space-based contexts and spacecraft management have been conducted as part of ESA's core activities. Like in Figure 1.




Functioning Spacecraft Flowchart

Telemetry data from spacecraft and the important scientific data gathered by a spacecraft, only two examples of the vast amounts of data generated by space technology and space applications. Moreover, ML may be used to analyse all this data. One research conducted as part of ESA's Basic Activities fed previously completed missions' worth of data into ML algorithms to identify undiscovered characteristics that may be used to improve the quality assurance of telemetry, command verification, and procedure authoring in the future.

**Space exploration with AI**

Mobile robots that can explore on their ownAutonomous NASA rovers showcase the potential of AI. The rovers must make split-second decisions, navigate around obstacles, and plot the most time and energy-saving routes as they investigate the Martian surface. Autonomous rovers have produced some of the most important discoveries concerning Mars.

**Robots and mechanical aides**

The core of the work scientists are conducting to construct intelligent-based assistants that will help future space exploration voyages to the Moon, Mars, and beyond is focused on sentiment analysis, commonly known as emotion artificial intelligence (AI) or opinion mining.Sentiment analysis may be used to extract and identify opinions expressed in a wide variety of textual data sources (reviews, forums, social media postings, and so on). These aids, with their understanding of mental health and emotions, will be able to gauge the team's mood and provide appropriate assistance in a crisis.Robots might be useful for a variety of physical tasks, including docking, spacecraft navigation, and more.

**System for intelligent navigation**

While Google Maps makes use of satellite navigation systems like GPS to provide precise maps of Earth, there is currently no equivalent service for extraterrestrial places. Without GPS satellites, scientists will need to be creative if they wish to explore Mars or the Moon.A team of NASA researchers and engineers worked with Intel to develop a state-of-the-art navigation system in 2018. With the help of artificial intelligence, this planetary exploration system created its own digital map of the Moon from millions of photographs collected by different missions.

**Data processing for satellites**

With the help of satellites, Maxar Technologies, a space technology company located in Colorado, has amassed over 110 petabytes of image data, and is adding over 80 terabytes daily. Processing this kind of data in a timely and precise manner is made possible by computerised artificial intelligence systems.With the help of recent developments in machine learning, it is now possible to analyse millions of images in a matter of seconds and monitor changes as they occur in real time. Artificial intelligence (AI) automates these processes, allowing satellites to take photos without human involvement when sensors detect certain signals.Scientists at Leeds University in the United Kingdom used machine learning methods to discover almost 2,000 new protostars, or newborn stars still in the process of developing within clouds of gas and dust.Remote monitoring of satellites using AI might provide early warning of performance issues and allow for preventative maintenance.

**Preparation and execution of missions**

Space missions benefit from AI's ability to automate formerly laborious processes. The Italian firm AIKO developed the software library MiRAGE, which is essential to the success of space missions. With this, ESA hopes to further its mission of disseminating cutting-edge technology.To avoid having decisions made on Earth compromise the spacecraft's ability to accomplish its mission, this feature enables autonomous re-planning and the detection of both internal and external events.The use of AI and ML has the potential to enhance operational risk assessments and mission prioritising. Risk-reduction systems may make advantage of the massive volumes of data created by regular activities and historical results. Models may be trained to automatically analyse and classify emerging threats.

**Mission planning**

Scientists and engineers believe that AI might help in scheduling, saving time and money compared to traditional techniques. Spacecraft may be programmed to use their own judgement while carrying out directives, considering their own past experiences and the conditions in their immediate environment.

**Location of Space Debris**

It is estimated by the European Space Agency that there are 34,000 items larger than four inches that pose a risk to the current space system. One possible solution to the space debris issue is to deploy satellites in the low Erath orbit with the intention of initiating their controlled disintegration.Scientists are putting in long hours to develop methods to make space trash safer. It is possible to improve spacecraft decision-making and develop strategies for avoiding collisions using machine learning by sending trained models to satellites in orbit.Similar to how pre-trained networks aboard spacecraft might assure the safety of space travel by minimising the chances of orbital accidents and opening up new possibilities for satellite design, such networks could also be used to improve space travel safety.

**Colecting Information**

Massive data sets are collected by scientific missions like deep space probes, Earth-observing satellites, and rovers, and they may be improved with the help of AI automation. It will also be easier to assess the data's usefulness and share it with the public.Artificial intelligence (AI) deployed aboard spacecraft can automatically distinguish normal qualities, like typical weather patterns, from abnormal patterns, such smoke from volcanic activity, allowing for the creation of datasets and maps.What is unclear, however, is how to choose which datasets to make available to people. Artificial intelligence (AI) technology may filter or remove useless data to enhance network efficiency while transporting enormous amounts of data.

**The finding of extrasolar planets**

This convolutional neural network (CNN) might be used to confirm whether a signal picked up by the Kepler Telescope comes from a transiting exoplanet. Many of the primary fields of space engineering, including the construction of intelligent space agents, need significant improvements in order to meet the lofty short- and long-term objectives set out by the different national space agencies. The result has been a growing fascination in AI among aerospace experts in recent years. Still, some unresolved problems and roadblocks may be identified at the present time. In this chapter, we examine the ways in which AI has been used to space engineering and technology and we highlight the areas where more study is needed. Three specific areas distributed AI, augmented situational awareness, and decision assistance for spacecraft system design are highlighted and addressed.

**Agreements and Principles in Space Law**

Environmental preservation, spacecraft and astronaut safety, the utilisation of space resources, and the settlement of disputes are only a few of the many topics addressed by these five agreements.Each agreement stresses the importance of enhancing human well-being and fostering worldwide peace via the responsible use of space, space activities, and all advantages obtained from space.

**SPACE JURISPRUDENCE**

The abbreviation "space law" refers to the collection of rules and regulations that control human activity in outer space. Space law consists of many U.N. resolutions, treaties, conventions, and agreements between various international bodies. There are additional national laws in place at the national level that regulate space-related activity in various countries in addition to these international processes. The freedom of all countries to freely explore and exploit space surrounding them, as well as the notion of non-appropriation, are among the core ideas that regulate space activities.Mission of the Office of Space Law is to facilitate the understanding, acceptance, and implementation of international space law accords reached under United Nations auspices by providing information and assistance to governments, non-governmental organisations (NGOs), and the general public.

Principles and Standards for Space Operations, Debris Reduction, and Space Sustainability • The international space law community has shifted its focus to the development of consensus principles and standards for space operations, debris reduction, and space sustainability. In addition to drafting and shaping these five crucial international treaties, the United Nations also supervised the General Assembly's adoption of five underlying principles. Even though they are not mandated by law, important voluntary international standards may have more specific, ambitious, and aspirational goals. This section dissects the previous four pronouncements.

**Problems with Current Space Law**

As was previously said, there are now five important treaties that provide the international legal framework guiding the development of space. Unfortunately, throughout the last 40 years, the space industry and its players have experienced considerable changes, necessitating quick amendments to present legislation to account for variables like property rights and the conduct of commercial organisations. Space exploration might enter a new era if private companies do space research on par with or perhaps beyond the capabilities of large nations. Both the Virgin Galactic Space Ship Two and Bigelow Aerospace's planned commercial orbital space complex would feature modular components like those of the International Space Station (Beck 2009, pg. 4). New opportunities to use space's resources have emerged quickly, outpacing the ability of current international space policy to adapt.

The Outer Space Treaty, which has been signed by 91 different countries, is a great example of this kind of global agreement on international space law (U.S. Dept. of State). The law's vague and idealistic language reflects the drafters' faith that future generations would figure out how to deal with problems in the field of space travel (Johnson 2011, pg. 1500). Several provisions of the Outer Space Treaty are up for discussion now that private companies may commence space mining in the near future. This term may be taken in a number of ways, but it is typically understood to support the "freedom of use" of space, in which every country has the same opportunity to take part in space activities (Johnson 2011, pg. 1501). More potential for conflict exists as more nations and corporations get access to the potential riches that may be gleaned from exploiting outer space due to the Treaty's interpretation of Article One and the enormous development of space participants since its original formation. Adding extra complexity is Article 2 of the Outer Space Treaty, which forbids the sovereign acquisition of space territory. David Johnson raises many problems concerning the morality of human endeavours to extract resources from other planets in his paper “Limits on the Giant Leap for Mankind: Legal Ambiguities of Extraterrestrial Resource Extraction.” As long as everyone in space has access to the asset, making celestial bodies is fair game. The pursuit of commercial gain in space might lead to disputes if space actors are left to their own devices to interpret insufficient international space regulation.

An anarchical system for the utilisation of space resources has developed due to the current limitations of international space governance. Consistent with the Realist view of Earth's foreign policy, which holds that individual nations must take care of their own interests within a complex international system, such an approach is being taken here. It follows, according to this Realist theory's extraterrestrial application, that governments would take precautions to safeguard their economic aims in the realm of space exploitation from the interference of other states or hostile entities (Duvall et al. 2008, pg. 765). Thanks to developments in space-directed weapons, states now have the opportunity to tackle these issues head-scheduled.This section is linked to the first triad in the previous sentence. The advent of AI has provided solutions to existing problems and raised new ones regarding the enforcement of existing laws and the creation of new ones. Those that make sense in light of the judicial issues discussed up to this point in the chapter are especially important. Possible technological aids for General Data Protection Regulation (GDPR). The subject of accountability for autonomous agents remains open, as does the question of responsibility in the context of machine learning and automated decision-making. When making decisions, autonomous space agents must take into account their legal responsibilities as outlined by the law.

## II.CONCLUSION

With a particular emphasis on the space domain, this review provides a jumping off point for understanding the notion of artificial intelligence and machine learning as well as its potential, needs, and limits.We have provided a primer on AI and machine learning terminology as it relates to the space industry. Using this jargon as a foundation, we presented critical anomaly detection and FDIR algorithms applicable both in-flight and on-the-ground. Finally, we looked at current and planned space missions to see how AI has been used to demonstrate notions of (at least) autonomous mission operations. To minimise risks, save costs, and speed up responses, future missions are likely to depend heavily on AI. In addition to aiding in mission operations, planning, and scheduling, artificial intelligence and machine learning techniques offer promise in enabling novel missions that call for quick deed. This article examines the legal challenges brought forth by "intelligent" systems and services, beginning with the necessary laws, problems. For resolving lawful issues, the current international treaties do not provide adequate tools. As a result, a legal strategy is presented that might connect the right laws to the right intelligent systems and services. In addition, we provide legal informatics materials that may be used in the study of space law. Due to a variety of circumstances, space-based systems' ability to view and interact with any specific spacecraft is restricted in comparison to that of ground-based systems. Among them are the availability of personnel, the speed of communications, the size of available power reserves, and the reliability of their link to the ground. A growing number of ships are looking to artificial intelligence as a means to achieve autonomous flight. However, the range of possible uses for the many AI methods and variations described in the literature is equally as broad.

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