

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

# Applications and Challenges of Artificial Intelligence in Space Missions

Paul A. Oche<sup>1</sup>, Gideon A. Ewa<sup>1</sup>, and Nwanneka Ibekwe<sup>1</sup>

<sup>1</sup>National Space Research and Development Agency (NASRDA), Musa Ydar'adua Express Way, PMB 437, Lugbe, Abuja, Nigeria

Corresponding author: Paul A. Oche (e-mail: [oque.paul@cstd.nasrda.gov.ng](mailto:oque.paul@cstd.nasrda.gov.ng)).

This work was supported by the Centre for Satellite and Technology Development (CSTD), an agency of NASRDA

**ABSTRACT** Artificial Intelligence (AI) is increasingly finding acceptance in the space community, especially Machine Learning (ML), a subdomain of AI. ML algorithms now find numerous applications in autonomous navigation, spacecraft health monitoring and operational management of satellite constellations. However, a large number of surveys on the applications of AI in space missions can be classified into two categories. The first category suffers from the limitation of being old and not covering some crucial and recent developments in the field; such as the contributions of Deep Learning (DL) and bioinspired AI algorithms. The challenge with the second category lies in its being too detailed with respect to the development and application of specific AI techniques or algorithms. These limitations have necessitated the need to have a concise survey with a wider scope for those interested in the applications and challenges of AI in the space industry, especially those with technical backgrounds in other fields. In this paper, we surveyed the use of traditional AI techniques in various domains of space missions without delving into formal methods. Some bioinspired AI algorithms were also surveyed and their potential application areas highlighted. Unlike similar surveys that focus only on technological challenges, we also addressed some crucial legal drawbacks that emanate from the reliance and use of AI in space. Summarily, while discussing future directions we reviewed some advancements in Internet of Things (IoT) and Blockchain technologies. Our review prioritized three application domains positioned to benefit immensely from the inevitable AI-Blockchain convergence in the space community. These include the Internet of Space Things (IoST), Satellite Communication and Spacecraft Data Security.

**INDEX TERMS** Artificial Intelligence, Machine Learning, Autonomy, and Space Missions

## I. INTRODUCTION

AI has witnessed a growing interest in the space community over the last two decades. In [1] the authors presented an anatomy of AI spanning over the first 16 years of the 21<sup>st</sup> Century (2000-2015). Coincidentally, both AI and space exploration had their beginnings in the 1950s. In 1955, Newell Shaw and Simon developed Information Processing Language (IPL-11), the first AI language. On October 4, 1957, the Soviet Union launched Sputnik into space—the first human-built spacecraft. In 1958, McCarthy introduced LISP, which soon became the programming language of choice for AI applications after its publication in 1960. In the same year, precisely on January 31, the United States launched and sent into orbit her first satellite—Explorer 1 [2]. The two fields, AI and Space Exploration, continued to develop independently until 1972 when the Jet Propulsion Laboratory (JPL), belonging to the National Aeronautics and Space Administration (NASA), began AI research on her Mars rover. AI is currently being researched in the domain of satellite operations, especially in supporting the operational apparatus of vast satellite constellations and rovers [2]. Considering that it takes about twenty-two minutes for radio waves to travel between Mars and Earth, rovers like NASA's Curiosity rely heavily on AI to make decisions and navigate on their own without commands from mission control.

Computer Vision (CV) techniques applied to satellite imagery still remains one of the most promising applications of AI in the space sector.

In space robotics two key factors have contributed to making AI more applicable. First, owing to the rapid advancement in hardware, the improved computational power of smaller form-factor devices has made it possible for them to run sophisticated algorithms [3]. Furthermore, autonomy and big data are converging to solve new problems in new domains. Robots are making rapid and considerable progress in the field of perception. They are beginning to hear, see, read, and touch in ways not previously possible [4]. As a result, they need to collect far richer data sets than traditional, strictly passive, or even active (viewpoint-changing) sensors to enable them to interact with the environment [4]. Although ML is a core technology within robotics, robot learning has suffered considerable challenges due to the theoretical advancement at the boundary between optimization and ML. Currently, one of the biggest challenges facing humanity's space exploration quest is not visiting where no one has visited before, but managing the data generated from space missions. In light of the above, the paramount questions to ask are: How can AI help with the optimization of space missions? Are there technologies that we can leverage to resolve challenges with AI in space?

While multiple surveys on the applications of AI in space missions have been published, many of them are old and do not cover some crucial and recent developments in the field; such as the contributions of Deep Learning (DL) and bioinspired AI algorithms. Few others, although recent, focus on specific domains like remote sensing, Fault Detection Isolation and Recovery (FDIR), and space exploration.

The survey in [5] focused mainly on autonomous planning and scheduling of operations, Anomaly Detection (AD) and FDIR. Izzo *et al.* [6] surveyed the recent developments in the area of spacecraft guidance dynamics and control, with a focus on evolutionary optimization, tree searches and ML (including DL and RL) as the principal drivers and technologies for current and future research in the field. Similarly, in [7] Kunze *et al.* surveyed and discussed AI techniques as ‘enablers’ for long-term robot autonomy, current advancement in integrating these techniques within long-running robotic systems, and the future challenges and opportunities for AI in Long-Term Autonomy (LTA). Application of AI to remote sensing was reviewed in [8], including onboard data processing and the promise of AI techniques for improving our capability to perform automated analysis of multispectral imagery. Zhu *et al.* [9] in a more recent review underscore recent advances in remote-sensing data analysis with a main focus on analyzing the challenges of employing DL for remote-sensing data analysis. Some major DL concepts pertinent to remote-sensing were introduced in [10] and more than 200 publications in this field, most of which were published during the last two years, were reviewed and analyzed.

There exist publications with a different scope in close proximity to our work. For example, the use of AI with distinct focus on Deep Neural Networks (DNNs) onboard spacecraft was discussed by Furano *et al.* [11] and the possible benefits analyzed in terms of bandwidth downlink. Berquand *et al.* [12] demonstrated that AI could be employed at the start of the space mission life cycle via an Expert System (ES) deployed as a Design Engineering Assistant (DEA). Girimonte and Izzo [13] provided an overview of AI for space applications and discussed: distributed AI for swarm autonomy, distributed computing for enhanced situation self-awareness and for decision support in spacecraft system design. The state of the art in data mining of satellite telemetry was reviewed in [14] and a framework of necessary processes on data mining to resolving various problems in telemetry data was presented. In [15], DL in space was identified as one of the development directions for mobile and embedded ML and the role of on-device DL in significantly improving spacecraft operation was discussed.

Summarily, most studies surveying AI with respect to space applications have either been reviews concerning closely related aspects of space missions ([5], [7]) or detailed topical reviews with respect to the development and application of specific AI techniques or algorithms ([15], [11] and [16]) to a specific field ([17]).

This paper, contrastingly, surveys four unrelated application areas of space missions: Spacecraft Health Monitoring, Remote Sensing, Satellite Communications and Robotic Autonomous Systems (RAS) for space. Challenges and Future Directions were also discussed, especially with respect to the inevitable AI-Blockchain convergence in the space industry. Considering the need to have a simple but concise review, this survey focused more on communication and remote sensing satellites. Furthermore, conscious efforts were made to exclude complex mathematical formulas and abstractions.

The remainder of this paper is organized as follows; Section 2 highlights the need for AI in space missions and provides an overview of AI, ML and Autonomy. In this section we identified nine recently developed bioinspired optimization algorithms and their potential application areas in space missions. Section 3 highlights and discusses four application areas: Spacecraft Health Monitoring, Remote Sensing, Satellite Communications and RAS for space. Challenges and Future Directions are addressed in Section 4 and Section 5 respectively. Finally, Section 6 presents the Conclusion.

## II. BACKGROUND: THE NEED FOR AI



FIGURE 1. US Challenger Accident [18]

Current satellite architectures are built for missions and operations in the hostile environment of space. Usually, satellite operations post-launch are tightly constrained by an



FIGURE 2. A Russian Soyuz Rocket Failure [19]

inability to access. Except for software upgrades and telecommands from operators in ground segments, satellites' inaccessibility makes them vulnerable to failures before reaching End of Life (EOL) [20]. When the 9% failure rate of satellites during their operational lives is combined with the 4–5% failure rate of launch vehicles it can be statistically stated that approximately one out of every seven satellites launched will fail before reaching EOL [21].

On January 28, 1986, NASA space shuttle Challenger 1 as shown in Fig. 1 broke apart 73 seconds into its flight, killing all seven crew members roughly two minutes after blastoff. The accident was later attributed to the failure of two rubber O rings designed to seal a section of the rocket booster [18]. On October 11, 2018, the world witnessed a Russian Soyuz rocket failure as shown in Fig. 2, roughly two minutes after blastoff [19]. Given the ever-increasing number of sensors and actuators on modern spacecraft, manual operation scheduling and planning becomes less efficient and complicated. This challenge necessitates the introduction of sophisticated autonomy mechanisms, which have been proven to exceedingly improve the efficiency of several missions in terms of science output, reliability, and required operational effort [5]. In addition, there is a growing urge to reduce the overall cost of operating in space, and it is logical to believe that significant savings can be realized by automating maintenance and space vehicle operations [22]. Considering that AI provides one of the few possible approaches to reach autonomy, we shall briefly introduce AI and its role in achieving autonomy.

AI could be defined as the study of intelligence present in computer systems, in contrast to the natural intelligence observed in humans and other living species [23]. Meß *et al.* [5] showed five categories of problem statements in AI:

**Knowledge Representation**—is concerned with the storage of information about the world (or a model thereof) such that a computer can efficiently process it.

**Perception**—is the capacity to extrapolate aspects of the world given sensor input. Amongst others, this includes Natural Language Processing (NLP), AD, and CV.

**Reasoning**—generates conclusions from available knowledge using logic and probability theory.

**Planning and Scheduling**—finds and realizes strategies for reaching a specific goal or maximizing a given utility function.

**ML**—means the improvement of an algorithm's performance through experience.

All the above-mentioned categories find application in modern spacecraft and space missions. For example, AI is being utilized in trajectory and payload optimization to make space exploration much more efficient [24].

## B. OVERVIEW OF MACHINE LEARNING

ML is a core technique of AI and at the same time a multidisciplinary domain involving multiple disciplines such as: probability theory, optimization theory, statistics and computational theory [25]. In 1959, Arthur Samuel coined

the term ML and defined it as a field of study that provides learning capability to computers without being explicitly programmed [26, 27]. More recently, Tom Mitchell defined it as: “A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E [28]. Generally, ML can be divided into three key categories: Supervised Learning, Unsupervised Learning, and Reinforcement Learning (RL) [29]. Table 1 summarizes the three categories and provides a brief description of each. Fundamentally, an ML model has two core components: learning element and performance element. Therefore, the key objective of ML is to make agents simulate or execute human learning behaviors. With the help of ML algorithms, a machine agent is capable of learning from training data to implement different tasks such as image or speech recognition.

TABLE 1: ML Categories of Learning

ML Learning Category	Description
Supervised [30, 31]	A learning model is trained on a labeled data set and predictions are made on new inputs.
Unsupervised [32, 33]	Unsupervised learning analyzes unlabeled datasets without the need for human interference.
Semi-supervised [31, 34]	Defined as the <i>hybridization</i> of the above methods, as it operates on both labeled and unlabeled data.
Reinforcement [35, 36]	Model takes decisions and learns from its actions.

In supervised learning what a correct output looks like is already known [29]. Fundamentally, a learning algorithm is trained on a given data set, after which it generalizes to give accurate predictions to all possible inputs [37]. Popular supervised learning algorithms include but are not restricted to: ANN [38, 39] as shown in Fig. 3, Support Vector Machines (SVMs) [40] and Linear Regression [39].

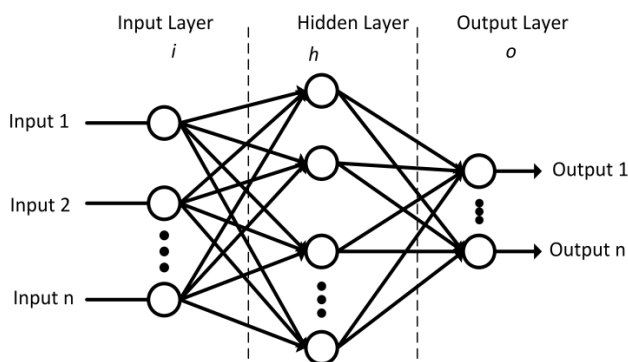


FIGURE 3. Artificial Neural Networks

Conversely, in unsupervised learning, the algorithm derives a structure from the data after identifying similarities in the inputs. What the results should look like is not known [29].

The principal goal of unsupervised learning is to discover hidden and interesting patterns in unlabeled data. Unlike supervised learning, unsupervised learning uses unlabeled, unclassified, and categorized training data [41]. Popular unsupervised learning algorithms include but are not limited to K-Means Clustering [42] and Dimensionality Reduction Algorithms [39]. In K-Means Clustering, variables in the data are grouped together based on relationships among them. An example of Dimensionality Reduction Algorithms is Principal Component Analysis (PCA) algorithm. The goal of this algorithm is minimizing the dimensionality of large data sets, by transforming a large set of variables into a smaller one while preserving as much ‘variability’ (i.e. statistical information) as possible [43].

Summarily, RL differs significantly from both supervised and unsupervised learning. An RL agent has the goal of learning the best way to accomplish a task through repeated interactions with its environment [44]. In RL, no labeled dataset is received by the machine. Instead, information is collected after interacting with the environment through different actions. The agent is rewarded after each action; hence its objective is maximizing this expected average reward where the action would become optimal [29]. The Markov Decision Process (MDP) represents a notable example of an RL model [45]. Other ML algorithms, though with less widely usage, exist [29]. They include: Naïve Bayes [39], Decision Trees [46], Bayesian Regularization [47], Kriging [48], Boosting [49] and more [39].

### C. BIOINSPIRED ALGORITHMS AND OPTIMIZATION

Optimization could be defined as the process of finding an optimal set from the set of all possible solutions for a given problem [50]. An algorithm known as the optimization algorithm is conventionally developed to find such a solution. However, many real-life problems can be characterized as multi-objective problems involving multiple conflicting objectives that should be considered simultaneously [51, 52]. They usually contain contradictory criteria, where optimization of one objective might also have negative influence on other objectives. In recent years, new Bioinspired Algorithms (BIAs) have been developed to help overcome the limitations of traditional AI algorithms, especially when it concerns the optimization of multi-objective problems [53]. These algorithms naturally tend to have a higher efficiency than the traditional AI methods; with the two most widely accepted categories being evolutionary and swarm algorithms [54, 55]. In ML, bioinspired optimization algorithms have been found to address the optimal solutions of complex problems in various science and engineering fields [55]. For example, mobile robot control (a critical aspect of rover design) is one of the main application fields of BIAs. Traditional AI algorithms are usually met with developmental constraints such as the

reliance on high-precision sensors and complex computing [54] in this field. BIAs can be also hybridized together to solve the slow convergence speed, low prediction accuracy, and trapping in local optima problems for anomaly detection of artificial satellites [14]. In our survey of BIAs we summarized in Table II eight types of BIAs and domains where they could be potentially relevant in space missions; or used to overcome the limitations of traditional AI techniques.

Ashraf in [55] noted nine recently developed optimization algorithms inspired by the biological behavior of some animals when fighting for food and mates:

- a. **Genetic Bee Colony (GBC)** algorithm [56] is a new optimization algorithm that integrates the advantages of the Genetic Algorithms (GA) and Artificial Bee Colony (ABC) for optimizing numerical problems.
- b. **Fish Swarm Algorithm (FSA)** is a novel population-based/swarm intelligent algorithm inspired by the natural schooling behavior of fish [57, 58].
- c. **Artificial Algae Algorithm (AAA)** is a population-based optimization algorithm inspired by the behavior of microalgae cells microalgae lifestyles such as the algal tendency, reproduction, and adaptation to the surrounding environments [55, 59].
- d. **Whale Optimization Algorithm (WOA)** [60] is a swarm-based meta-heuristic algorithm that emulates the bubble-net hunting maneuver technique of humpback whales.
- e. **Grey Wolf (GWO)** [61] is a new meta-heuristic that mimics the hunting technique and social leadership hierarchy of grey wolves the leadership hierarchy and hunting mechanism of grey wolves.
- f. **Chicken Swarm Optimization Algorithm (CSOA)** is a recent optimization algorithm that mimics the behaviors of the chicken swarm and their hierarchal order [55, 62].
- g. **Cat Swarm Optimization (CSO)** [63] is a Swarm Intelligence (SI) algorithm that was inspired by the natural behavior of cats.
- h. **Moth Flame Optimization (MFO)** is a novel nature-inspired optimization paradigm inspired by the navigation method of moths in nature called transverse orientation [64].
- i. **Elephant Search Algorithm (ESA)** [65], was inspired by the behavioral characteristics of elephant herds and. It divides the agents into two groups: male and female elephants.

Table II BIAs with Potential Application Areas in Space Missions

Name	Domains	Potential Application Areas in Space Missions	References
Invasive Weed Algorithm	Image clustering problem; parameter estimation problem; numerical optimization; time-modulated linear antenna array synthesis, cooperative multiple task assignment of Unmanned Aerial Vehicle (AV)	Autonomous Flight, Remote Sensing, Satellite Communication	[76-78],[79, 80]
Bacterial Foraging Algorithm	Robot path planning; Image segmentation; optimum job scheduling; optimal power flow; pattern recognition	Remote Sensing, Image Processing, Robotic and Autonomous System (RAS)	[81-86], [87]
Artificial Immune System	AD; Fault Diagnosis (FD); clustering /classification; robotics	Spacecraft Health Monitoring, FDIR, On-orbit Operations (O3)	[88],[89],[90-96]
Culture Algorithm	Pattern recognition; multi-robot coordination; fault classification; engineering design problem	Guidance, Control and Navigation (GNC), Remote Sensing	[88],[97-100],[101]
DNA Computing	Robotic control; Information security; task assignment problem; clustering problem	Robotic and Autonomous System (RAS)	[102],[103-106],[93]
Genetic Bee Algorithm	Multi-objective layout optimization; network optimization	Satellite communication, Distributed Computing	[107, 108]
Fish Swarm Algorithm	Fault identification; software testing; synchronous optimization; packet routing	Spacecraft Health Monitoring	[109, 110]
Chicken Swarm Optimization	High global optimization; feature selection; improving bit error rate performance	Re-entry trajectory optimization, Image Processing [111]	[112, 113],[111]

Despite the merits of bioinspired optimizers, solving multi-objective problems is a huge challenge as demonstrated in different application domains (e.g. robotics [66], bioinformatics [67], energy and power [68]). According to the No Free Lunch (NFL) theorem [69], the superior performance of an optimizer on a class of applications or problems cannot guarantee a similar performance on other problems. In other words, an optimization algorithm may perform well in a set of problems and fail to solve a different set of problems. For a multi-objective problem no single optimal solution exists, but rather a set of alternative solutions represent the optimal solutions [70]. These solutions are optimal when all objectives are considered and no other solutions in the search space are superior to them. These best trade-off solutions are also known as Pareto Optimal (PO) solutions [71], a concept that was first proposed by Edgeworth and Pareto [72].

It has been shown that evolutionary algorithms such as Non-Dominated Sorting Genetic Algorithm (NSGA-I) [73] and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [74], can approximate the true

PO solutions of multi-objective problems [70]. Recently Grasshopper Optimization Algorithm (GOA) was proposed and it has been proven to show very fast convergence speed toward the optimal solutions [75].

#### D. AUTONOMY

Autonomy could be defined as the ability of an agent to accomplish goals through logical decision making based on its knowledge and comprehension of the world, itself, and the situation [114]. An intelligent agent capable of autonomy must exhibit some fundamental properties such as reasoning, learning, and problem-solving [115]. Over the years, the investment in and application of autonomy has yielded significant breakthroughs in areas such as: Power Systems, Mission & Flight Operations, On-Orbit Assembly & Docking [116]. Past missions have demonstrated that using onboard autonomy to enable faster response times improves operational efficiency, optimizes costs and increases system reliability [117]. For example, by using the Autonomous Sciencecraft Experiment to automatically plan and adaptively

re-plan observations as required the EO-1 spacecraft was able to cut operational costs by \$1 M per year, with a 50% increase in science return [118]. However, as far as decisional capacity is concerned, a fundamental difference exists between automated and autonomous systems. An automated system does not make choices for itself, but relies on potentially sophisticated scripts where choices have both already been made and encoded, or they must be made externally. In contrast, an autonomous system can make informed choices on its own, even when encountering uncertainty or unanticipated events within its environment [119]. In [22], Johnson *et al.* propose the following necessary conditions for autonomy:

1) AGENCY

Autonomy embodies a range of behaviors associated with agents. Therefore, an autonomous system must possess the traditional qualities of agency, which is the ability to sense, think, and act. It must be able to sense its environment and its state; make decisions about what to do, and act on the decisions through their action. Going by this definition, the chess-playing program Deep Blue is not an autonomous system, even if it exhibits quite an impressive level of intelligence in chess-playing. Given that its range of behaviors is solely limited to the moves of a chess game, it cannot be said to meet all the requirements for agency.

TABLE III. Autonomy Levels According to ECSS [5].

Level	Descriptions	Functions
E1	Mission execution under ground control with limited onboard capability for safety issues	Real-time control from ground for nominal operations Execution of time-tagged commands for safety issues
E2	Execution of preplanned, Ground defined, mission operations onboard	Capability to store time-based commands in an onboard scheduler
E3	Execution of adaptive Mission operations onboard	Event-based autonomous operations Execution of onboard operations control procedures
E4	Execution of goal-oriented mission operations onboard	Goal-oriented mission re-planning

2) GOAL-DRIVEN

An autonomous system must be capable of achieving a set of goals by transforming the goals into sequences of actions that

accomplish each goal. Instead of just responding to its immediate environment, it should be able to make decisions to achieve a prescribed goal. Based on the above condition, a teleoperated robot would not fall under the classification of an autonomous agent, though it could exhibit a range of goal-directed behaviors. This is because it is command-driven rather than goal-driven.

3) FLEXIBILITY

Finally, an autonomous system should have the flexibility to respond to off-nominal situations by adjusting its actions to enable it to reach a goal successfully. This condition refers to a system's robustness with respect to its environment. Based on this condition, a system that is goal-directed but prone to failure in accomplishing its goals due to unpredicted changes in its immediate environment is not autonomous. Robustness, to some extent, will require the decentralization of control [22, 120].

Summarily, the architectures for autonomy consist of a planning layer, a task sequencing layer, and a reactive layer. These three layers are often referred to as deliberative, executive, and functional layers; which can be distinguished in terms of their abstraction from the hardware and their response-time requirements [120]. The European Cooperation for Space Standardization (ECSS) expounds four levels of autonomous capabilities, with level E4 being the most autonomous. The architectures and their descriptions are listed in Table III. Only systems compliant with level E4 can be regarded as genuinely autonomous, whereas levels E1 to E3 deal with manually controlled or automated systems [5]. In general, autonomy is distributed across a system in three ways: no autonomy, partial autonomy and, full autonomy.

III. APPLICATIONS

I. SPACECRAFT HEALTH MONITORING

Safety and reliability are among some of the most critical concerns to be addressed when planning space missions. In [121], Atkinson *et al.* describe briefly the spacecraft and ground systems monitoring process at the Jet Propulsion Laboratory, California Institute of Technology, and highlight some of the challenges associated with existing technology used in mission operations.

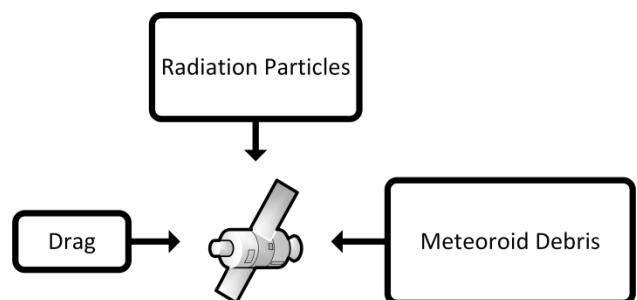


FIGURE 4. Impact of Space Environment on Spacecraft

Due to the limitations of existing technology, Spacecraft Health Automated Reasoning Prototype (SHARP), a new automated system based on AI technology was designed to automate health and status analysis for multi-mission spacecraft and ground data systems operations. By performing real-time analysis of spacecraft and ground data systems engineering telemetry, SHARP effectively detected and analyzed potential spacecraft and ground systems problems.

Recent progress in data mining techniques has also made it possible to use archived spacecraft telemetry data to produce advanced spacecraft health monitoring applications for AD and FD [122]. In his paper, Quan *et al.* introduced some conventional approaches for AD and FD before proposing feasible approaches using data mining technology. We shall be taking a look at only two of the conventional approaches.

#### A. ANOMALY DETECTION & FAULT DETECTION

In spacecraft design the technique of identifying faults and isolating them is known as FDIR [123]. Due to the harshness of space environment and the complex structure of a spacecraft it is practically impossible to utterly eliminate the possibility of anomalies or faults that might jeopardize the mission. From the deterioration of electrical circuits and solar cells as a result of high radiation particles to orbital decay due to drag, the spacecraft is also prone to collision with meteoroid debris. Fig. 4 illustrates the impact of radiation particles, drag, and meteoroid debris on a spacecraft.



FIGURE 5. NigComSat 1 (Courtesy of NASRDA)

The extreme difficulty or near impossibility of directly repairing or replacing a damaged component necessitates that serious attention is paid to FD and diagnosis. Therefore, it is not an exaggeration to state that designing and implementing FDIR techniques are among the most complex tasks in

spacecraft development. All subsystems and their modes of operations must be factored into the design process. It is also essential to factor in safety and reliability at the early stages of mission design. Unfortunately, current FDIR processes are built on the results of Failure Modes, Effects, and Criticality Analysis (FMECA) and Fault Tree Analysis (FTA) [5]. One of the drawbacks of these two approaches is that they can only be applied late in the development process, prohibiting FDIR to become an integral part of the system. [124-126] present an extensive survey of the current state of the art of FDIR approaches and emerging techniques, and how to overcome their limitations.

Failures, when not timely and adequately resolved, can result in mission jeopardy. Fig. 5 shows Nigerian Sat1, which was lost because of a failure that prevented one of the solar arrays from deploying after launch. Consequently, the amount of available solar power for recharging the batteries after an eclipse phase was limited. The failed satellite was subsequently replaced with NigComSat-1R (See Fig. 6). Given that most people tend to confuse the term fault with failure, it is pertinent for us to define what we mean by fault and failure as used within the scope of this work. A fault in simple terms is the deviation of at least one system parameter from its desired value. On the contrary, failure is the manifestation of a fault in terms of system functionality that leads to the partial loss of system services [5]. An example of a fault is when a temperature or pressure value is out of limit. In contrast, the inability of a battery charging unit to charge the spacecraft's battery is an example of a failure that could lead to the loss of power to critical subsystems; thereby resulting in the loss of one system service or more.



FIGURE 6. NigComsat Sat-1R [127]

Therefore, to guarantee system availability, reliability, and performance faults must be correctly handled so that they do not lead to failure. However, it is not enough for a system to detect a fault without taking further action. Following detection, the fault should be traced to an exact location (e.g., subsystem or memory area) and isolated, after which the

system in the recovery step tries to transfer to a safe state of execution in which the fault has been mitigated [5, 128].

## B. CONVENTIONAL APPROACHES TO ANOMALY DETECTION IN SPACECRAFT

### 1) LIMIT CHECKING

Although there have been many conventional approaches to FD and diagnosis, limit checking remains the most fundamental and widely used technique in spacecraft AD. It is used to monitor whether the various values of sensor readings such as current, voltage, and temperature are in the proper ranges, which are predefined by the spacecraft engineers and specified by lower and upper limits [122]. Given the simplicity of this technique, it can only check one sensor value at a time and might be herculean for engineers and operators to build or change the predefined ranges. Though the most significant advantage of this approach is its simplicity, it lacks flexibility and cannot check some small anomalies that occur without violating the limits on the variables [122]. To overcome these limitations Yari *et al.* proposed a new data-driven health monitoring and AD method for artificial satellites [129].

### 2) MODEL-BASED DIAGNOSIS

Given the need to overcome the limitations of limit checking techniques some rule-based expert systems and model-based reasoning methods were developed [130]. The model-based approach to automating AD encodes human knowledge into a model, which is then used to automatically detect faults [131, 132]. The core idea behind model-based diagnosis is establishing the mathematical model of the spacecraft's subsystems (e.g., thermal control model, propulsion subsystem model) and detecting the possible anomaly or fault through the comparison between the real-time telemetry data and the model output data [122]. However, one major disadvantage of this AD approach is that building models can be labour-intensive. Modeling every subsystem of a highly complex system such as a spacecraft may not be feasible [131]. It also may not be realistically possible to model all possible failure modes mathematically. Furthermore, it may not be able to recognize faults that involve relationships among large numbers of parameters. In summary, all traditional approaches of AD/FD rely heavily on prior knowledge of the system, such as the range of sensor value, mathematical model, and fault rules. With these approaches, it is challenging to acquire accurate and complete models and knowledge of the spacecraft systems beforehand.

## C. ANOMALY DETECTION AND FAULT DETECTION BASED ON DATA MINING

The traditional approaches to AD and FD are labourious, hence the need to adopt a data-driven approach that seeks to build a model for detecting anomalies directly from the data, rather than building it based on human expertise. Spacecraft telemetry data involves thousands of sensor values from different subsystems, making it difficult for human experts to

pick up faults that involve the relationships among large numbers of variables. However, with the recent advancements in data mining and ML technologies, this new intelligent monitoring approach utilizes the history telemetry data to obtain the knowledge of the system or build the system model dynamically [122, 131].

Recent developments in data mining techniques have also made it possible to use archived spacecraft system data to generate advanced system health monitoring applications. In addition to complementing existing approaches, "data-driven" applications are capable of characterizing and monitoring interactions between multiple variables to provide valuable decision support for engineers and mission controllers [131, 133].

In contrast to common individual parameter monitoring and model-based schemes, several data-driven software tools have been practically and successfully applied by NASA and JAXA to mission operations for both the Space Shuttle and the International Space Station (ISS). Orca1, a data-mining tool that searches for abnormal data points in multivariate data sets by calculating each data point's distance from adjacent points, has been applied in the shuttle. Similarly, the Inductive Monitoring System (IMS) has been deployed in the ISS. The IMS tool2 uses clustering to analyze archived spacecraft data and characterizes nominal interactions between selected parameters [122, 131, 133].

Using expert-labeled telemetry anomaly data from the Mars Science Laboratory (MSL) Curiosity rover and the Soil Moisture Active Passive (SMAP) satellite, a team of researchers at NASA demonstrated the effectiveness of Long Short-Term Memory (LSTMs) networks (a type of Recurrent Neural Network (RNN)) in overcoming issues associated with traditional AD methods for spacecraft telemetry [134].

In [122], Quan *et al.* proposed five feasible approaches using data mining technology for spacecraft AD/FD. We would look briefly at Adaptive Limit checking and Expert System (ES) based on data mining. The reader is hereby referred to Table IV for a summary of the remaining approaches.

### 1) ADAPTIVE LIMIT CHECKING

Conventional limit checking techniques require the predefinition of the lower and upper limit of sensor value, which can be quite herculean. In contrast, Fig. 7 shows a simplified workflow of the Adaptive Limit Checking method using ML techniques. This method uses ML algorithms (e.g. Gray System Theory, SVM, Rough Set Method, and GA) to dynamically and automatically produce the range limits for sensor value [122]. For training the algorithms the historical spacecraft telemetry data are used as training data. However, different algorithms will use different historical telemetry data and have different efficiency.

### 2) EXPERT SYSTEM BASED ON DATA-MINING

In an ES based on data mining as illustrated in Fig.8, the knowledge database is not static or predefined. Instead, it is



Table IV. PROPOSED ML APPROACHES TO AD/FD

S/N	Approach	Summary
1	Bayesian Belief Network (BBN)	A probabilistic graphical model employed to represent a set of arbitrary variables whose conditional independencies probabilities can be computed via a directed acyclic graph.
2	ANN	Neural networks are non-linear statistical data modeling tools; which can be used to model the complex associations between inputs and outputs or to find patterns in data.
3	Distance-Based Diagnosis	Distance computed according to the real-time telemetry, and the historical data can be used to determine whether there is some fault in the spacecraft in distance-based diagnosis method.
4	Expert System (ES) Based on Data-Mining	In the ES based on data mining, the knowledge database is dynamic and not predefined or static. Given that the data mining application has its learning algorithm it can produce new rules without operator interference, and knowledge can always be added to the database.
5	Adaptive-Limit Checking	Adaptive limit checking techniques utilize some ML algorithms like SVM and GA to produce the range limits for sensor value dynamically and automatically. Compared with the solid limit it produces more accuracy and reduces misinformation.

produced by the data mining application and dynamically added to the database [122]. At the core of this procedure is a learning algorithm used to extract useful rules for the diagnosis expert system. Though the authors of [122] acknowledge that a diagnostic method based on data mining can maximize the use of the historical data to enhance the conventional diagnosis approach, they fear many problems still need to be solved before they are used in the actual engineering practice. One of such challenges includes the building of the status vector.

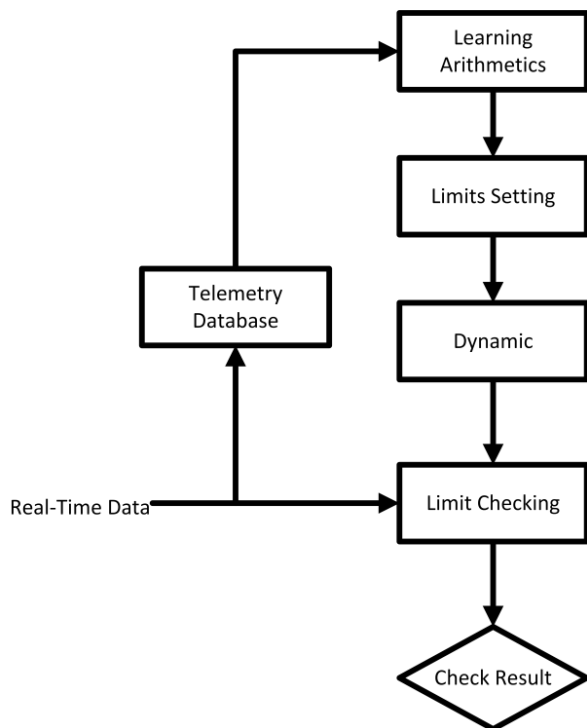


FIGURE 7. Adaptive Limit Checking using ML Techniques [122]

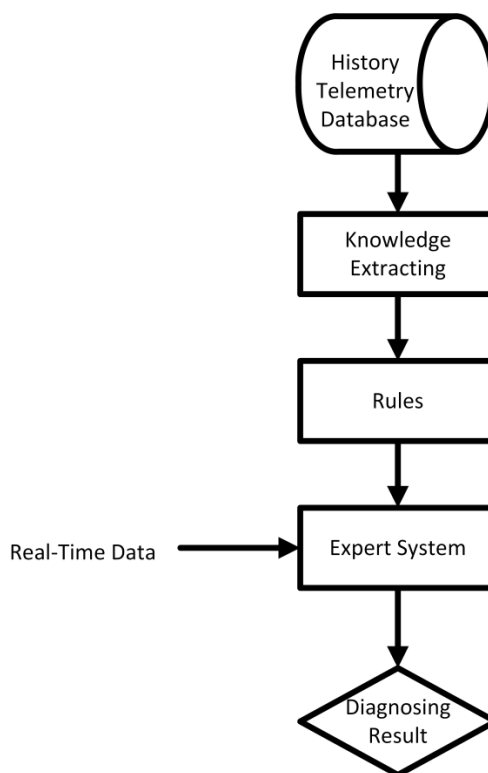


FIGURE 8. Expert System Based on Data Mining [122]

In [128], Gao *et al.* presented a new FD and diagnosis approach hinged on PCA and SVM as illustrated in Fig. 9. The framework of their approach is divided into two phases: the training phase and the real-time detection phase. First, in order to reduce the dimensionality and complexity of the input data PCA is used to extract feature vectors from input data. This is followed by the use of binary SVM to detect fault. After the FD, a multi-class SVM is used to identify fault type.

Summarily, in the training phase, a training dataset that can either be obtained from archived telemetry data or simulation data was used to calculate the PCA matrix and train SVMs. In the real-time detection phase, the real-time telemetry data of the spacecraft system is processed. The approach first transforms the input data to a low dimensional feature space using PCA matrix to obtain feature vectors. These feature vectors then pass through the Binary SVM to detect whether there is a fault or not. If the fault is detected, a multi-class SVM is used to identify the fault type. From experimental results, the authors showed that the method was efficient and practical for FD and diagnosis of a spacecraft system.

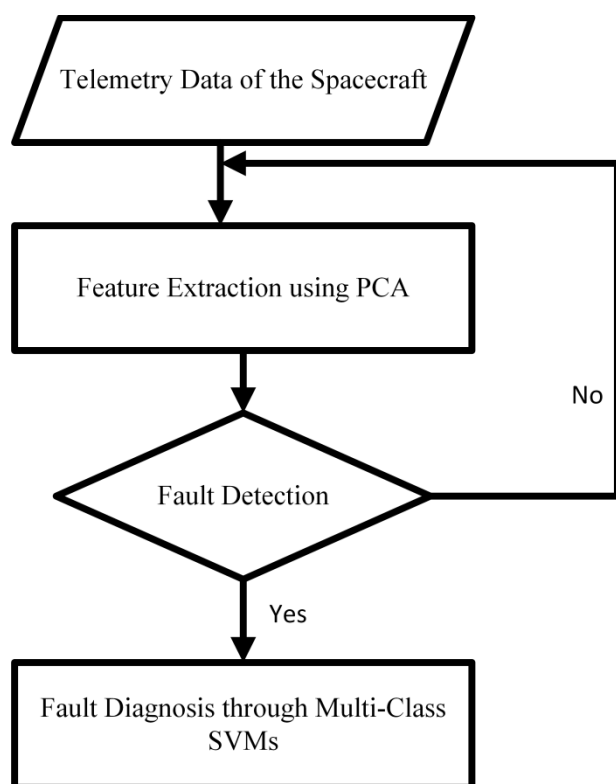


FIGURE 9. PCA and SVM-based Fault Detection and Isolation [128]

#### D. LIMITATIONS OF PROPOSED APPROACHES TO ANOMALY DETECTION AND FAULT DETECTION

Challenges central to AD in multivariate time series data also apply to spacecraft telemetry. This implies that a lack of labeled anomalies necessitates the use of unsupervised or semi-supervised approaches [134]. Having analysed the proposed approaches to AD/FD in [122] it was gathered that the limitations of each approach will emanate from the limitation(s) of the algorithm(s) used for the data-mining. For example, the adaptive limit checking approach used ML algorithms like SVM, Rough Set Method, and GA to dynamically and automatically produce the range limits for sensor value. Each algorithm utilized different historical telemetry data and produced different efficiency. Generally, SVM has some significant weaknesses, among which are:

algorithmic complexity that affects the training time of the classifier in large data sets, development of optimal classifiers for multi-class problems and the performance of SVMs in unbalanced data sets [135].

In spite of its weaknesses, SVM has demonstrated highly competitive performance in many real-world applications. However, for large data sets the training kernel matrix grows in quadratic form with the size of the data set, thus making the training of SVM on large data sets a very slow process [135]. This is expected to be the case for spacecraft telemetry data, considering that they are usually highly complex, highly dimensional and multi-dimensional [122].

Gao *et al.* in [128] used binary SVM to detect anomalies. However, SVM is designed for the classification of two classes, which makes it unsuitable for fault diagnosis. Considering that practical fault diagnosis has to deal with multi-type faults that involve relationships among a large number of parameters, they proposed two approaches for constructing a multi-class SVM: combining several binary SVMs and implementing multi-class classification. Their approach was implemented using telemetry data from an actual in-orbit satellite and simulated by Matlab/Simulink [136] [128]. Using 25000 points of data the accuracy of their approach was verified using two case scenarios. In Case 1, all 25000 points of data were used as training data, after which the same was used as test data to gauge the performance. In Case 2, the 25000 points of data were divided into two sets by cross-extraction. The first set was used for training while the second was used as test data.

The results show a classification accuracy of 99.2% and 97.4% for Case 1 and Case 2 respectively, thus demonstrating that the method is efficient and practically suitable for a spacecraft system's FD and diagnosis. Table V compares Multi-class SVM approach with ANN. From the table, it can be seen that for Case 1 the accuracy of SVM and ANN are quite close. However, for Case 2 SVM performed better than ANN because of SVM's extraordinary generalization capability, along with its optimal solution and discriminative power; especially when the number of input data is small [135].

Table V. COMPARISON BETWEEN SVM AND ANN [128]

		Case 1	Case 2
SVM	Classification Accuracy	99.2%	97.4%
	Training Time (s)	36.2	19.5
	Test Time (S)	11.2	5.8
Neural Network	Classification Accuracy	99.13%	92.6%
	Training Time (s)	39.5	18.2
	Test Time (S)	10.3	6.5

In addition, SVM has a better performance when the training and test data are not the same [128]. Notwithstanding the dividends, a key challenge of this

approach is the use of PCA, a linear dimension-reduction technique not suited for nonlinear systems. Given that some components of the spacecraft system are nonlinear, the authors acknowledged the need of a nonlinear PCA (e.g. KPCA) to be used in extracting features from input data in their future work [128].

## II. REMOTE SENSING

Remote sensing refers to the science of identification of earth surface features and estimation of their geo-bio-physical properties using electromagnetic radiation as the medium of interaction [137]. Images acquired remotely over long distances are usually affected by noise and other environmental conditions like cloud coverage; which makes them differ widely in terms of colour variations and textural contrasts [138]. Furthermore, captured data needs to be transmitted to the ground station for aggregation and analysis, which can be expensive. However, a satellite can reduce the amount of data transmitted by employing DL for on-board pre-processing. Parts of the image of no interest (e.g. those occluded by clouds) can be discarded so as to drastically reduce the amount of data transmitted [139],[15]. Fig. 10 shows a diagram illustrating six satellite image processing methods, out of which we shall treat the first two.

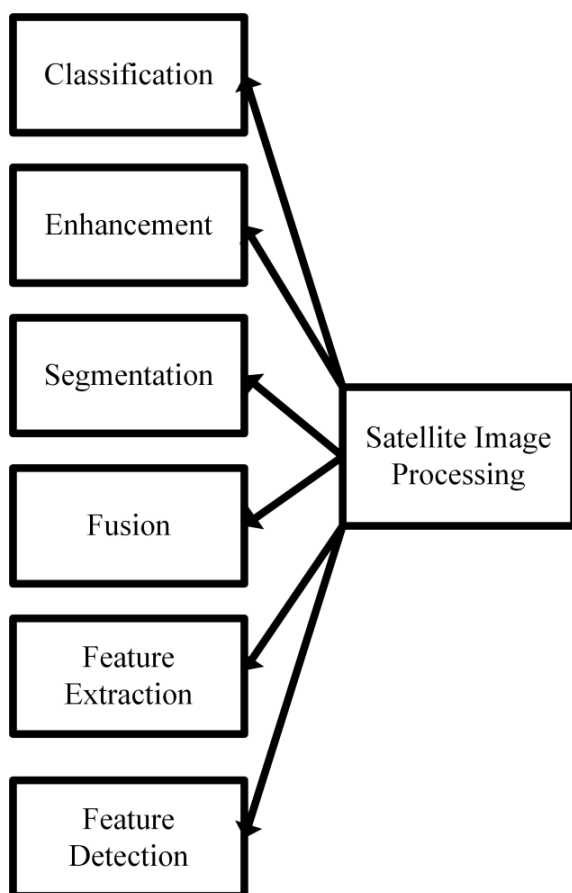


FIGURE 10. Satellite Image Processing Methods

## A. ML-BASED IMAGE PROCESSING TECHNIQUES

### 1) ENHANCEMENT

Enhancement methods applied to preprocessed data rely on metaheuristic-based algorithms to manipulate the digital pixel values for effective visual interpretation of images. Two algorithms employed in image enhancements are Particle Swarm Optimization (PSO) and GA. However, among the evolutionary algorithms GA and PSO suffer from the limitation of getting trapped in local minima [138]. One way to overcome such limitation is by combining various optimization techniques. Combining Cuckoo Search (CS) algorithm with PSO has shown better results in terms of closeness to optimal solution when compared to PSO or GA individually [71], [138]. In [140] Suresh *et al.* proposed a new method—Modified Differential Evolution (MDE) algorithm for contrast and brightness enhancement.

### 2) CLASSIFICATION

In a general sense, image classification can be defined as “the process of categorizing all pixels in an image or raw remotely sensed satellite data to obtain a given set of labels or land cover themes [141]. In supervised classification, available known pixels are used by the analyst to generate representative parameters for each class of interest. Contrastingly, in unsupervised classification pixels are grouped according to the reflectance properties of pixels. These groupings are called clusters. Two popular clustering algorithms are K-means and Expectation Maximization.

One key advantage of the unsupervised classification technique is that it can be used when no sample sites exist. Although image classification is dependent on the type of satellite image used, classification followed by other stages such as de-noising and segmentation can lead to better processing of the image [138]. Commonly used image classification algorithms include fuzzy algorithms, ANN and ES. The main advantage of Radial Basis Function Neural Network (RBFNN) is its immunity to noise signals; perhaps due to its large number of tunable parameters [142].

## B. CHALLENGES WITH REMOTE SENSING

Common challenges associated with satellite image processing methods have been reported in literature and include the following: image complexity, large image sizes, presence of unwanted artifacts and background information. In addition, satellite sensor variations (such as radiometric resolution, spatial, and spectra) and a change of viewpoint bring tremendous diversities into satellite image representations [143]. Images of the above said different variations could be integrated by fusion techniques to enrich the chosen study area's available information.

### 1) VOLUME

The volume of data generated from satellites is already far more than human imagery analysts can effectively analyze. It is growing exponentially, thus necessitating the need for CV techniques applied to satellite imagery. Recent breakthroughs in DL have also improved to the point where DL now

outperforms humans in some tasks like classifying objects in images. However, current open-source AI tools are not optimized for satellite imagery [144].

At present, even though a wide range of techniques are available for image processing, it is extremely difficult to settle for a technique which can be generally applied to all types of satellite images. Owing to the different color and textural variations and the limitations of traditional remote sensing using optical sensors, Synthetic Aperture Radar (SAR) imaging, an alternate form of remote sensing, permits the observation of large target areas during day or night under almost any weather condition [145], [146]. Although SAR has shown significant benefits over traditional remote sensing techniques, it comes with additional complexities [147]. Researchers have begun to employ advanced ML techniques (DL) to SAR data to cope with these challenges adequately.

TABLE VI. Statistical Models for Satellite Image Analysis

Author	Method	Advantage
Liu Haijiang <i>et al.</i> , 2007 [148]	Monitoring Land cover change for the desertification of an island using Maximum Likelihood Classifier	Simple mode of classification.
J.Tian <i>et al.</i> , 2007 [149].	Studied the significance of validating the correlation of satellite-derived and gauge measurements.	Experiments are analyzed with different seasons.
Francis Padula <i>et al.</i> , 2010 [150].	Land cover change detection using PCA	Fused Landsat and MODIS data are used for better data resolution.
Brian P. Salmon <i>et al.</i> , 2011 [151].	Unsupervised Land cover change detection in MODIS data using Sequential Time Series Analysis.	Lesser training time than supervised learning methods.
Deepti Sharma <i>et al.</i> , 2011 [152].	Investigated dust storm effects using aerosol products acquired from both satellite-derived and ground measurements.	Both ground-based and atmospheric parameters considered.
Biswadip Gharai <i>et al.</i> , 2013 [153].	Fusion of MODIS and CALIPSO (LIDAR) Data to study the dust storm effects.	The use of LIDAR data favors studying the vertical uplift of dust in the air.

Yionel *et al.* [154] introduced a DL framework for inverse problems in imaging and demonstrated the advantages and applicability of this approach in passive SAR image reconstruction. As a preliminary study, Chen and Wang in [155] used a single layer of Convolutional Neural Network (CNN) to learn features from SAR images automatically. DL is nowadays being frequently utilised in SAR data applications by leading companies like Orbital Insight and Descartes Labs specializing in satellite earth observation analytics [156].

## 2) COMPLEXITY

Traditional satellite image models are predominantly based on statistical methods like: Linear Discriminant Analysis (LDA); Maximum Likelihood Estimation (MLE); PCA; and other regression-based models. Unfortunately, most traditional algorithms are plagued with a lack of logical reasoning. With ML techniques vibrant progress has been made in incorporating human-level reasoning into these traditional models [157]. Despite the merits of ML methods, supervised ML techniques suffer from excessive computational complexity due to demanding training processes and insufficient ground truth data for labeling. To overcome these challenges, the training phase must be limited. This can be achieved through an unsupervised mode of learning. Furthermore, the accuracy of classification, either in supervised or unsupervised mode, can be improved using hybridization. Parallel processing of data could also be used to improve the issues with the speed of computation through higher-level Graphical Processing Unit (GPU) architectures. However, the development of this method is still in progress [157].

Table VI shows a few statistical models utilized in satellite image analysis. The performance of K-means clustering and neural network with back-propagation for successful image segmentation and classification in satellite images employing dense count values of the pixel intensities were compared in [158]. However, using more advanced intelligence schemes like DNN in satellite image analysis could improve the level of reasoning with a reduction in training complexities [159]. Complexities associated with the training of deep networks with a vast number of hidden layers can be resolved to a greater extent by employing a greedy learning-based algorithm [157]. Greedy algorithm or search is an efficient tool that is usually employed in optimization problems, especially when dealing with large sets of data [160].

## 3) INEFFICIENCY

A fundamental challenge with statistical models is that they are inefficient in prediction due to the irregularly varying patterns of voluminous data [161]. Thus, ML techniques are better in deriving prediction models as it learns through experience during the training phase. In [162], two ML techniques (SVM and CNN) were developed to extract human settlements from Very High Resolution (VHR) satellite images of 3 provinces in Afghanistan.

TABLE VII. Hybrid ML Approaches for Satellite Image Analysis

Author	Method	Advantage
Rubia et al., 2009 [163].	Integrated Fuzzy Inference System (FIS) and Genetic Algorithm (GA)	Both spatial and temporal analysis over forest land cover.
Zhiding Yu et al., 2010 [164].	Combined Ant Colony algorithm and FCM	Enhanced FCM's limit on sensitive to noisy data and random initialization of parameters.
Mohammad Awad et al., 2010 [165].	Integrated dissimilar threshold functions with Traditional Self Organizing Maps (SOM)	Overcome the under and over-segmentation issues of SOM.
Ashish Ghosh et al., 2011 [166].	Achieved unsupervised clustering and then combined with GA and Simulated annealing.	Improved random initialization problems on clustering.
Xiang Yang Wang et al., 2012 [167].	Combined FCMFCM and SVM.	Increased segmentation quality and reduced time complexity.

By comparing the results with analyst-verified reference data information (LandScan Settlement Layer), the authors demonstrated that in terms of overall pixel cells the CNN technique yielded more accurate results overall while based on derived statistics against the reference data the SVM technique performed more accurately in omission.

Given the merits of ML techniques in deriving prediction models, the hybridization of different ML methods as shown in Table VII and the integration of statistical and ML methods could acquire more efficient results. In [157], Giorgio Giacinto *et al.* proposed an approach with a combination of neural and statistical algorithms in a simple design phase to disclose that every algorithm is significant in solving a particular issue, and no single algorithm is proved to be perfect. Castellana *et al.* [168] performed the combination of both supervised and unsupervised modes of change detection and on a pixel-based method to achieve better classification of remote sensing images. In [169], Pabitra Mitra *et al.* combined an active learning method with SVM and advanced an active SVM with reduced labeled data for classification [157].

### C. PERFORMANCE EVALUATION OF IMAGE PROCESSING ALGORITHMS

Performance evaluation in a universal sense refers to the degree of some required behavior of an algorithm, whether it is attainable accuracy, adaptability, or robustness. It allows the innate characteristics of an algorithm to be emphasized, as well as the evaluation of its advantages and limitations [170]. The justification for evaluating an algorithm is to understand its behavior in dealing with different categories of

images, and/or help in estimating the best parameters for different applications [171]. Although a wide range of techniques exist for image processing it is immensely cumbersome to arrive at a technique which can be commonly applied to all types of satellite images. This is due to the different color and textural variations of the images.

Assessing the performance of any algorithm in image processing is demanding because performance depends on several factors, as surmised by Heath *et al.* [172]:

- (a) the algorithm itself,
  - (b) the algorithm parameters used in the evaluation,
  - (c) the method used for evaluating the algorithm,
  - (d) the nature of images used to measure the performance of the algorithm.
- In [138] the authors analysed different metrics for evaluating the overall performance of the discussed image processing techniques. However, for the qualitative evaluation of a proposed technique some parameters need to be computed to enable its comparison with available techniques; in addition to evaluating its suitability and reliability over other techniques. Four computable parameters were analysed: Feature Similarity Index (FSIM), Structural Similarity Index (SSIM), Precision and Recall. However, only the first two shall be treated. In a nutshell, FSIM denotes the measure of similarity of features between the input image and the final image. It is computed using equation (1):

$$FSIM = \frac{\sum_{x \in X} SL(x) PC_m(x)}{\sum_{x \in X} PC_m(x)} \quad (1)$$

where the whole image is represented by X, SL(x) represents the similarity in the two images and PC<sub>m</sub> is the phase congruency map. Structural Similarity Index (SSIM) indicates the structural similarity between the input image and the final image. It is calculated using equation (2):

$$SSIM = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (2)$$

Where  $\mu_x$  and  $\mu_y$  represent the sample means of  $x$  and  $y$  respectively;  $\sigma_x$  and  $\sigma_y$  give the sample variances of  $x$  and  $y$ , respectively; and  $\sigma_{xy}$  shows the sample correlation coefficient between  $x$  and  $y$ , where  $x$  and  $y$  are local windows in the input images. The calculated SSIM index is always a decimal value with range between -1 and 1. A value of 1 indicates perfect structural similarity while 0 indicates no structural similarity. 1 is only attainable in the case of two identical sets of data. Summarily, performance evaluation ought to rely on the use of performance indicators that convey the *qualities* of an algorithm. Considering the above suggestion, six typical performance indicators as surmised by Wirth *et al* in [173] include:

- (1) *sensitivity*: an algorithm's response to small changes in features;
- (2) *robustness*: an algorithm's capacity for tolerating various conditions;

- (3) *accuracy*: how well the algorithm has performed with respect to some reference;
- (4) *adaptability*: how the algorithm deals with variability in images;
- (5) *reliability*: the extent to which an algorithm, when repeated using the same stable data, yields the same result;
- (6) *efficiency*: the practical viability of an algorithm (time and space).

### III. SATELLITE COMMUNICATION

In the near future (2020-2025), it is expected that satellite communication systems provide capacities close to 1 Terabit/s [174]. This would require the deployment of the next generation broadband infrastructure, including fixed and mobile internet access (5G) such as the KONNECT VHTS by EUTELSAT, expected to be launched in 2021. Therefore, to meet the requirement of capacity increment there is a trend towards the use of larger, more powerful Geosynchronous Equatorial Orbit (GEO) satellites, and/or flexible payloads.

Very high throughput satellite (VHTS) aim at achieving 1 Terabit/s per satellite in the near future and will play a key role in supporting future 5G and broadcast terrestrial networks [175]. Currently, VHTS systems provide uniform throughput over the entire service area based on multi-spot coverage with frequency and polarization reuse schemes using larger bandwidths in the feeder link in the frequency Q/V bands or by optic links. However, traffic demands are expected to be unevenly distributed over the service area since the user distribution is not uniform within the coverage. This results in a system where some beams lack the required capacity, i.e., not meeting the traffic demands, whereas other beams overcome the required capacity or, simply, wasting resources [176-178]. This challenge is addressed using flexible payload architectures to enable the allocation of payload resources in a flexible manner to meet the traffic demand of each beam. New propositions for flexible payloads systems must take into account the analysis of novel efficient cost function to optimize resources allocation and the analysis of the payload architecture and its adaptive allocation methods for new traffic demand scenarios [179].

Notwithstanding the merits of Dynamic Resource Management (DRM) approaches derivable from flexible payload architectures, DRM adds significant complexity to VHTS systems. The authors in [177] analyzed and proposed the use of CNNs to manage the resources available in flexible payload architectures for DRM. A comparison between different payload architectures in terms of DRM response is carried out and the CNN algorithm performance is compared with three other algorithms, previously suggested in the literature to demonstrate the effectiveness of the suggested approach and to examine all the challenges involved.

Optimizing the data return from space missions requires planning, design, standards, and operations coordinated from formulation and development stages throughout the mission. Autonomy, enhanced by cognition and ML, are potential methods for optimizing data return, reducing operational

costs, and managing the complexity of automated systems [180]. By 2020–2025 it is envisaged that there will be more than 100 high throughput satellite (HTS) systems in GEO and mega constellations of Low Earth Orbit (LEO) satellites, delivering terabits per second of capacity across the world. These evolved satellite systems will provide Radio Access Networks (RANs), called satellite RANs, which will be integrated into the 5G system together with other wireless technologies, including cellular systems, Wi-Fi, and so on [175]. Considering the ever-increasing traffic distribution on earth the authors in [181] developed an Extreme Learning Machine (ELM) Distributed Routing (ELMDR) strategy. ELM, a fast and efficient ML algorithm, was adopted to forecast the traffic at satellite node. Simulation results demonstrate that in comparison to the conventional ACO algorithm ELMDR not only sufficiently uses underutilized link, but also reduces delay.

### IV. ROBOTIC AUTONOMOUS SYSTEMS FOR SPACE

Robots designed for space missions operate in increasingly complex environments. This includes all types of robotic agents designed to explore a planet's surface and those deployed in orbit around extraterrestrial bodies. For those operating in completely known and static environments, the challenge of LTA shrinks down to one of robustness. Similarly, for autonomous agents operating in an unstructured environment, the operational environment could change over the lifetime of the agent [7].

Categorically, space robots can be broadly classified into two groups: Orbital and planetary. Orbital robots find application in the assembly of large space telescopes, satellite repair, and deployment of assets for scientific investigations on platforms such as the ISS. In contrast, planetary robots (e.g., Curiosity and Opportunity) are used for the survey, observation, and close examination of extraterrestrial surfaces like the planets (e.g., Mars).

The rest of this section surveys systems and approaches that address the challenges of LTA using AI techniques. Although AI may have witnessed a growing interest in the space industry over the last two decades staying current on ML advancements and knowing how to best leverage available technologies can be complicated. For instance, by introducing dexterous manipulators to traditional satellite platforms the spacecraft design becomes increasingly complex. Stemming from the high level of interconnectedness between the manipulator and its floating base, the manipulator becomes an intrinsic part of the overall spacecraft design [182]. Fundamentally, the whole satellite turns in into a 'space robot.'

Depending on its application, a space robot is generally required to possess two functional attributes: locomotion and autonomy. Locomotion or mobility impacts it with the ability to manipulate or interact with a sample. Though autonomy may vary from semi-autonomous to fully autonomous, the nature of the mission and distance from the Earth determines to a great extent the level of autonomy designed into the system. With time it is envisaged that future robots would

evolve a higher level of autonomy to meet the increasingly challenging goals of space missions. Regardless of the category of autonomy, specific action plans are needed for a robot to complete its tasks. This requires optimization to ensure the conservation of resources such as energy and communication bandwidth [183].

It is worth stressing that advancements in general AI techniques are vital for improvement in many aspects of the autonomous functions of space robots. For instance, ML is often applied to sensing, perception (e.g., machine vision) tasks. It has also been applied to locomotion, such as in the improvement of locomotion strategies or policies and navigation. Planning, system-wide autonomy, scheduling, and resource allocation are also areas of continuing work for ML.

Considering the above scenarios, the consolidation of AI methods in space engineering is undoubtedly an enabling factor for improving the autonomy of space robots [13]. Irrespective of the domain LTA systems need to combine different AI abilities to cope with challenging environments and tasks. Inherently, the combination of abilities such as navigation & mapping, perception, and Knowledge Representation (KR) presents a functional integration challenge [7, 184]. The challenge becomes even more significant when other AI abilities like planning, interaction, and learning are thrown into the mix. The following highlight three core subdomains of RAS where AI finds application.

1) NAVIGATION AND PLANNING

interest in autonomous navigation and planning models for robots, especially the challenge of Simultaneous Localisation and Mapping (SLAM) [187]. When cameras are employed as the only exteroceptive sensor, it is called *visual SLAM* [188]. The challenge with autonomous navigation of mobile robots is categorized into three principal areas: localization, mapping, and path planning [189]. Localisation entails determining exactly the current pose of a robot in an environment, whereas mapping blends the fragmented observations of the surroundings into a single congruous model (What does the world look like?). Path planning concerns itself with determining the best route in the map to navigate through the environment (How can I reach a given location?) [188].

Motion planning is extension of path planning. Although the terms appear to be the same a few differences exist. Path planning seeks to find the path between origin and destination in workspace by strategies like shortest distance or shortest time. Contrastingly, motion planning focuses on generating interactive trajectories in workspace when robots interact with dynamic environment. As a result, motion planning needs to consider kinetics features, velocities and poses of robots and dynamic objects nearby. therefore path is planned from topological level [190]. In 1986, Smith *et al.* [191] introduced the concept of implementing spatial uncertainty estimation, which gave birth to the pre-development of SLAM technique. This was followed in 1991 by Leonard *et al.* in [192] developing a SLAM

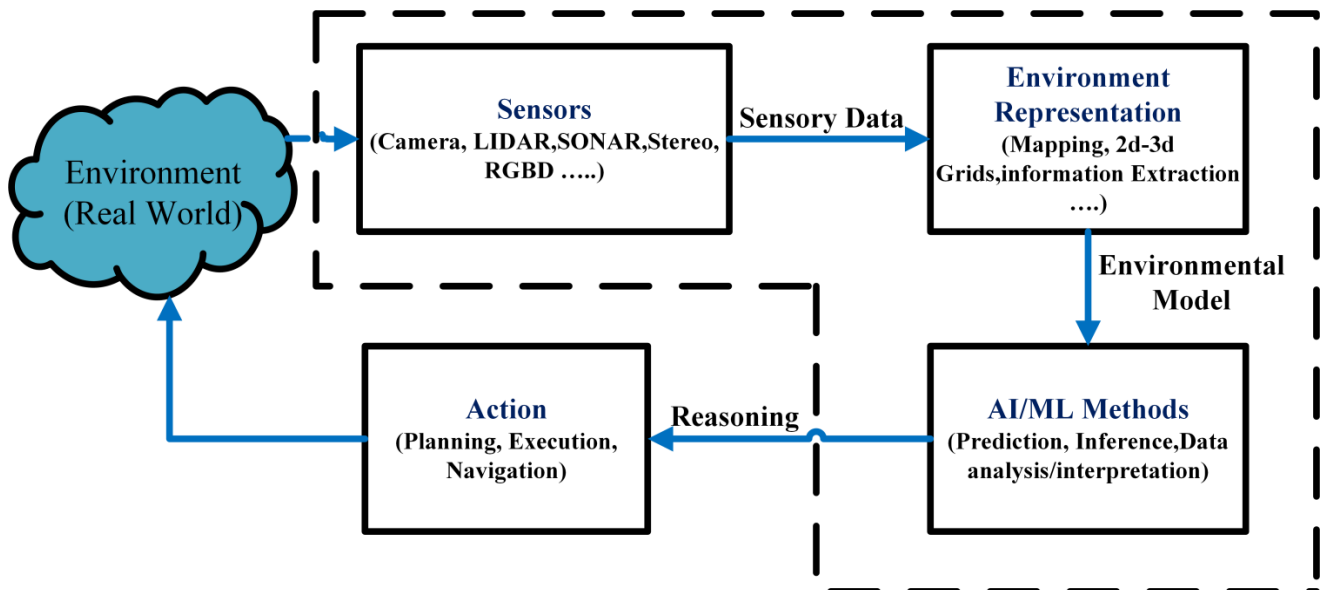


FIGURE 11. Key Modules of a Typical Robotic Perception System [185]

Robots have contributed immensely in helping humankind explore space, thereby contributing to expanding the frontier of scientific knowledge and our access to the extraterrestrial world. In 1970, the former Soviet Union built the first robot (Lunokhod) that traveled on the surface of an extraterrestrial body. It was remotely operated from Earth and traversed more than 10.5 km on the moon [186]. Within the past four decades, the AI community has witnessed a resurgence of

technique based on [191], which used a probabilistic approach in solving the SLAM problem. This gave birth to the implementation of the Extended Kalman Filter (EKF) method, which laid the foundation for the first SLAM algorithm known as the EKF-SLAM [193]. In 2001, [194] described the substantial implementation of the SLAM algorithm on a vehicle operating in an outdoor environment using Millimeter-Wave (MMW) radar to provide relative map observations.

In real environments with many landmarks present Kalman filter-based algorithms require time quadratic in the number of landmarks to incorporate each sensor observation. In light of this drawback Montemerlo *et al.* [195] introduced FastSLAM, an algorithm that recursively approximates the entire posterior distribution over robot pose and landmark locations, yet scales exponentially with the number of landmarks on the map. FastSLAM uses a hybrid technique that integrates Particle Filter and EKF approach, making it popular for its higher data accuracy [193, 195]. FastSLAM evolved to FastSLAM 2.0 a year later with a conceptually simple modification. In FastSLAM, when proposing a new robot pose, the proposal distribution relies only on the motion estimate. In contrast, in FastSLAM 2.0 it relies on both the motion estimate and the most recent sensor measurement. This approach was found to be less wasteful with its samples than the original FastSLAM algorithm, especially in circumstances where the noise in motion is high relative to the measurement noise [196].

Many modifications have been made to SLAM algorithms over the years. These include the Squared Root Smoothing and Mapping (SAM) method proposed in 2006 [197] for improving the mapping process of mobile robots; the UFastSLAM proposed in 2007 [198] to improve the FastSLAM method by using unscented transformation algorithm and the Differential Evolution technique proposed in 2009 [199].

Research in motion planning is currently witnessing a lot of attention as a result of advancements in DL and RL. This is due to their better performance in coping with non-linear and complex problems. Basically, motion planning algorithms can be divided into two broad groups: traditional algorithms and ML-based algorithms according to their principles and the era they were invented [190]. They are further categorized as shown in Table VIII.

TABLE VIII Classification of Planning Algorithms

Planning Algorithms		
Traditional Algorithms		
Graph Search-based Algorithm [200, 201].	Sampling-based Algorithm [202, 203].	Interpolating Curve Algorithm [204, 205].
ML-Based Algorithms		
Supervised Learning [206] [207, 208].	Optimal Value RL [209, 210].	Policy Gradient RL [211, 212].

Traditional algorithms can be classified into three categories (graph search algorithms, sampling-based algorithms and interpolating curve algorithms) while ML-based planning algorithms are based on ML techniques that include supervised learning (e.g. SVM, optimal value RL and policy gradient RL).

## 2) PERCEPTION

For deep space missions that suffer from lags and gaps in communication, onboard DL systems would bring a much needed degree of autonomy and robustness to GNC. In terms of LTA and performance in space environments, robotic perception is critical for planetary and orbital robots to make decisions, plan, and operate in real-world environments, utilizing functionalities ranging from occupancy grid mapping to object detection. These days, most robotic perception systems rely on ML techniques, ranging from classical to DL approaches where the learning can be in the form of unsupervised learning or supervised classifiers using handcrafted features, or DL neural networks [185].

As depicted in Fig. 11, the fundamental components of any AI perception system are sensory data processing, data representation (environment modeling), and ML-based algorithms. However, in the majority of applications, the fundamental role of environment mapping is to model data from exteroceptive sensors mounted onboard the robot to facilitate reasoning, and inference regarding the robot's real-world environment [185].



FIGURE 12. MER (Courtesy of NASA/JPL) [186]

The Mars Exploration Rover (MER) shown in Fig. 12 is equipped with two stereo imaging systems on a camera mount on the bar of the rover mast: Panoramic (Pancam) and Navigation camera (Navcam). The panoramic camera is dedicated to the mapping of medium-to-far objects in panoramic images, while the other is a navigation camera with the best focus at 1 m with a field of view (FoV) of  $45^{\circ}$  [186, 213]. Early approaches to mapping of dynamic environments were object-centric methods that identified and removed moving objects from the maps [214] or used them as moving landmarks for self-localisation [215]. Nevertheless, not all dynamic objects really move at the instance of mapping, necessitating that their identification requires long-term observations. Ambrus *et al.* [216] addressed this challenge by processing several 3D point clouds of the same environment recorded in several weeks to



identify and separate movable objects and refine the static environment structure simultaneously.

### 3) LEARNING AND INTERACTION

Learning is critical for any robotic system deployed in open or dynamic worlds where autonomy is needed to maintain reliability, robustness, and cut operational cost. However, some of the most challenging application domains for long-term running robots, such as the MER, involve interacting autonomously with a diverse range of objects, which implies that being able to learn and adapt from experience is crucial to the success of the mission. Robots or systems that need to interact *autonomously* with their environment through sensory-motor capabilities must possess the capacity to *act deliberately* to fulfill their mission [184], especially in environments requiring LTA. Techniques which allow robots to continually learn from experience such as reinforcement learning, or focus on particular experiences (e.g., failures, novelty) such as learning from demonstration should allow online improvement of capabilities [98].

Considering the interest in these research fields in Robotics and AI communities, there are several publications and survey papers that review state of the art for a few focused deliberation functions such as planning, goal reasoning, monitoring, and recognition of actions and plans [184, 217].



FIGURE 13. Dextre the ISS Robot [218]

Robotic perception, as observed by Sünderhauf *et al.* [219] differs from traditional CV perception. In robotics, the expected outputs of a perception system will result in decisions and actions in the real world. In contrast, most CV applications take images and translate the outputs into information. This shows that perception plays a critical role in the learning and interaction of any goal-driven robotic system.

Like localization and navigation, robot perception functions depend on the robot's operational environment [185]. For artificial agents like robots to interact with their real-world environment, perception and manipulation must complement each other. Once a robot is (self) localized, it

can proceed with the execution of its task by taking deliberate action, or a set of interactive actions. In the case of autonomous mobile manipulators in a typical open/dynamic setup, this involves navigating to the region of interest, observing the current scene to build a 3D map for collision-free grasp planning, and localising target objects in the operating environment and grasping them [185].

The technical feasibility of robotic servicing has been sufficiently demonstrated on the Hubble Space Telescope and the ISS where robots carry out in-orbit activities like inspection, component assembly, and docking [20, 220]. Fig. 13 shows Dextre, a two-armed robot or telemanipulator that is part of the Mobile Servicing System on the ISS. Equally known as Special Purpose Dexterous Manipulator (SPDM), Dextre performs repairs that would have otherwise require spacewalks [221]. However, to achieve the vision of on-orbit servicing for satellites, developing a new design and operation paradigms of satellite architectures is necessary [20]. In [17], Nanjangud *et al.* provide an overview of the RASs technologies that enable O3 on smallsat platforms. Robotic O3 involves a robotic agent (or chaser) operating on a client spacecraft (also called a target), which can be further classified as cooperative or non-cooperative targets.

## IV. CHALLENGES AND LIMITATIONS

Despite the risks posed to humans and robotic explorers operating in space's extremely challenging environment, humankind has not given up on the desire to conquer space and other planets. In 2017, seven nations attempted a total of 90 known orbital launch attempts from spaceports in eight different countries. As shown in Fig. 14, the United States ranks on top for the first time since 2003 after sharing it with China in 2016 [222]. Using AI techniques in space missions,

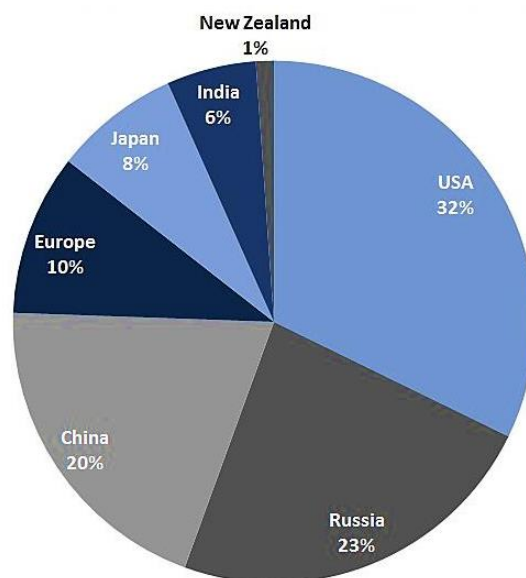


FIGURE 14. Orbital Launch Attempts by Countries in 2017 [222]

we can increase the levels of autonomy and automation, thereby freeing humans to focus on tasks for which they are better suited [223]. However, there are still challenges that

stand in the way of achieving full-scale autonomy and automation. To combat these, we would require advances in robotic sensing and perception, mobility and manipulation, rendezvous and docking, onboard and ground-based autonomous capabilities. For the next foreseeable future, it appears we would still need human-robot integration and suite of other data analysis tools to explore space. Although ML, a subdomain of AI, can be used to enable LTA in spacecraft and improve the science return of space missions, the requirements of the missions alone severely limit the use of many current ML approaches [117].

### A. AUTONOMY

Space robots are often designed to possess mobility (or locomotion) to manipulate by gripping, roving, drilling, and sampling. To a large extent, these functionalities are influenced by the operational environments (either orbital or planetary). Depending on the type of mission and distance from the Earth, these robots are expected to possess a varying autonomy level, ranging from teleoperation to fully autonomous operation [114]. In most cases, the onboard autonomy deployed in spacecraft consists of the use of a planner. For example, the autonomous capabilities of NASA's Opportunity rover came from MAPGEN, a mixed-initiative task planner and an autonomous navigation system. It was used to create daily mission schedules automatically, which were then refined by terrestrial scientists [224].

There are already several known factors that frustrate the realization of fully autonomous operation in space and limit the use of many current ML approaches. First, space missions have an extremely high cost of failure with little or no opportunity for external aid or repair. Frequent failures of GEO satellites result in high economic costs for governments and private companies, thereby resulting in the continuous increase of GEO debris and crowding of the GEO orbit [225]. Stemming from the limitations of the traditional satellite architecture paradigm and the dearth of a maintenance industry for satellites, Saleh *et al.* [226] propose O3 to provide flexibility to decision-makers in satellite design and operations in the industry. Any autonomy derived from O3 and provided for by AI techniques must be proved to be reliable, robust, and constrained from posing any threat to the spacecraft's core operations, station-keeping and health. In [225], Liang *et al.* proposed a universal O3 in GEO, consisting of a 7-DOF redundant manipulator (with replaceable end-effectors), a 2-DOF docking mechanism, a set of stereo vision and general subsystems of a traditional spacecraft platform.

In contrast to a classic payload, which is usually detached from the platform, a robotic device attached to a satellite becomes an integral part of the spacecraft itself. By introducing dexterous manipulators to traditional satellite platforms, Jaekel *et al.* [182] argue that the spacecraft design becomes increasingly sophisticated and complex. The high interdependencies between the manipulator and its floating base automatically turn the whole satellite into a 'space

robot.' Consequently, a sophisticated combination of traditional concepts and AI will be needed for system FDIR. When dealing with FDIR equipping a spacecraft with an onboard data analysis system can enable the detection of and reaction to dynamic events. For example, a satellite's timely reaction to an asteroid on a collision path would be possible if the event was detected onboard and the spacecraft equipped to react. In contrast, with ground-based analysis, such real-time reactions are not possible.

Although the integration of AI techniques at the system level is essential for the functional realization of LTA, there is little research to no standard on combining modules from different areas of AI. With the help of robotic software development [227] and robotic middleware such as the Robot Operating System (ROS) [228], researchers and roboticists have been provided with methods to integrate their software components and other people's components in a structured way, thus improving software maintainability and reusability. Examples of such middleware on which frameworks can be built upon include (STRANDS [229]) for long-term navigation planning & task scheduling; (ROSPlan [230]) for planning and execution and (RoboSherlock [231]) for knowledge-enabled perception.

Having a framework to build on makes it easier for integration and the use of different AI methods. However, our extensive survey reveals that there is still a lack of understanding and research in the domain of system-level integration. Although the space robotics market size in 2018 crossed USD 2 billion and the industry is growing rapidly, we believe that system-level integration of AI methods and their evaluation in autonomous systems research is still a significant challenge in academia and industry [232].

### B. RADIATION

The high levels of radiation that occur in space can precipitate various problems for sensitive electronic components like solid-state memory, microprocessors, and network interfaces. Adverse effects of radiation on unprotected board computation could range from complete burnout to the occasional bit flips in memory that can corrupt some data. In a study of the effect of radiation-corrupted RAM on different clustering algorithms [233], a method was developed to simulate radiation-induced bit flips and quantitatively assess the sensitivity of clustering and classification algorithms likely to be deployed onboard spacecraft. The findings surmised that the k-means algorithm could withstand radiation in the Earth orbit environment without the need for radiation-hardened memory. It also found out that simpler algorithms (regular k-means clustering and linear SVM) have less sensitivity (more tolerance) than more complex versions (kd-k-means, Gaussian SVM [117, 233]).

Kd-k-means, a faster version of the clustering algorithm that stores the data set as a kd-tree in memory, was discovered to be much more sensitive to radiation and not recommendable for onboard use on spacecraft. As a result, a

kd-tree variant was subsequently developed and restructured to increase its robustness to radiation [234].

### C. COMPUTATIONAL CONSTRAINT

A significant challenge arising directly from the high-radiation environment is the computational constraints under which remote spacecraft are forced to operate. A few reasons contribute to this problem. First, processors and memory chips used in space need to pass extremely rigorous testing to certify them fit for operation in the harsh environment of space. Unfortunately, the amount of testing and preparation spacecraft systems designers require to get a system ready for spaceflight often takes years. As a result, engineers, designers, and quality assurance experts prefer to rely on legacy processors and components that have been flown and used in older spacecraft. This implies that even more recent spacecraft run on processors and memory that lag a decade behind the desktop state of the art [235].

Since most modern electronic components were not manufactured to operate in high-radiation environments, those meant for use in space must undergo a mandatory radiation hardening process, thereby increasing their cost. For example, the RAD750 processor used by Deep Impact, Mars Reconnaissance Orbiter, the Kepler space telescope, and other current missions and instruments runs at only 133 MHz and costs ~\$200,000 [117]. Alternatively, there are specially shielded packaging of electronic parts to keep radiation at bay. However, this approach is expensive and can lead to an increase in the weight of the spacecraft, which could adversely influence launch costs. Two other ways of dealing with space radiation include using redundant subsystems and selective shielding [236].

### D. NATURE OF TELEMETRY DATA

Satellite telemetry data are largely heterogeneous and multimodal, made up of hundreds to thousands of variables and attributes. In addition, telemetry data is usually collected from different sensors in various subsystems with different output formats and operating modes that must be changed from one mode to another over time ([122] [129], [237]). According to Yairi *et al.* [14] there has been little work done in artificial satellite telemetry data mining, even though in the last few years the applications of SI in data mining have become increasingly implemented in different fields like bioinformatics and forensic analytics. However, in the research community of ML, some researchers are becoming interested in applying data mining techniques to the health monitoring problems for space missions.

Notwithstanding that some SI algorithms have shown favourable and effective results in many application areas, they still suffer from defects such as weak generalization ability, low classification accuracy and slow convergence among others. Furthermore, evolutionary algorithms require some randomness to proceed [238], all problems to which Chaos theory can be applied to improve the performance of the evolutionary algorithm. In [239], Darwish *et al.* proposed the hybridization of SI and evolutionary computing

algorithms for DL and how these integration solve some problems in satellite health monitoring based on ML data mining. Gehad *et al.* [238] presented a novel Chaotic WOA (CWOA) to overcome these problems. The performance of CWOA was compared with WOA and ten other optimization algorithms, after which experimental results showed that circle chaotic map was the best chaotic map that significantly boosted the performance of WOA [240].

### D. DEEP LEARNING TECHNIQUES

Space systems can be quite expensive to develop and launch into outer space. Due to the gradual degradation of system components and/or devices, it is highly recommended to have an on-board fault-diagnosis system capable of detecting, isolating, identifying or classifying faults in the spacecraft [123]. Historically the majority of the automated control and navigation maneuvering operations were directed by a human, which is burdensome and only attainable for near Earth missions [15].

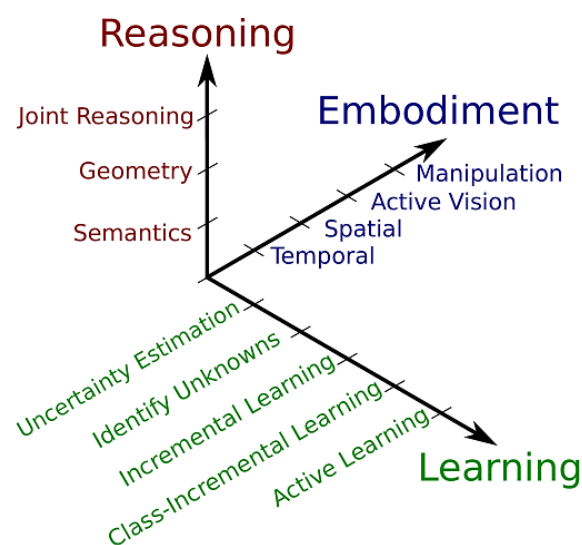


FIGURE 15. Challenges for Deep Learning in Robotic Vision [219].

Considering the need to introduce higher levels of autonomy and automation using AI, DL will continue to play a critical role in developing mission-defined RAS that are capable of surviving the hostile environment of space. However, there is often the temptation among mainstream ML communities to assume that the challenges with DL in domains like CV and Natural Language Processing (NLP) are the same for robotics [219]. Unfortunately, this is not true. Sunderhauf *et al.* [219] discussed a number of robotics-specific challenges for DL. As shown in Fig. 15, these problems were categorized into three conceptually orthogonal axes: learning, embodiment, and reasoning. For instance, under the learning axis, “Identifying Unknowns” is a key challenge because of the common assumption in DL that trained models will be deployed under closed-set conditions [241]. However, robots are often deployed in ever-changing, uncontrolled real-world environments, and are bound to come into contact with environmental conditions that were not covered by the

training data, including instances of classes, scenarios and textures [219].

In open-set conditions [242],[243] it is critical to identify the unknowns. The robot's perception system must not assign high-confidence scores to unknown objects, or falsely recognize them as one of the known classes. For instance, if a robot's vision system (object detection) is fooled by data outside of its training data distribution [244], the consequences of acting on false but high-confidence detections can be disastrous.

### E. LEGAL CHALLENGES

The current space treaties do not address the use and regulation of AI in space. The legal challenges emanating from the reliance and use of AI in space necessitates ascertaining the existence of linkage between space systems and services using AI to a system of governing rules and guiding legal principles [245]. Harnessing AI and ML technologies in the exploration of outer space will in all likelihood span a broad array of intended and unintended consequences such as privacy and liability issues. These consequences require consideration of a broad range of legal and regulatory concerns that the space industry alone cannot answer. The following are three core topics worthy of interest.

#### 1) LIABILITY OF INTELLIGENT SPACE OBJECTS

The growing delegation of decision making to AI will have repercussions on many areas of law for which *mens rea*, or intention, is required for a crime to have been committed. As machines increasingly take on tasks and decisions traditionally performed by humans, should we consider giving AI systems 'personhood' and moral or legal agency? [246]. In the legal arena, the term "person" generally refers to an entity which is subject to legal rights and duties. Generally, we think of a person as a human being [247]. However, the legal rights and duties imposed on inanimate objects and artificial entities emanate from actions or conduct engaged in by human beings. This is undoubtedly not the case for actions or conduct taken based on AI. Although a machine can learn independently from human input and make decisions based on its learning and available information, that ability does not necessarily equate with natural or legal personhood [245].

Liability under the space law treaty regime is grounded in Outer Space Treaty (OST) Article VIII, which is the genesis of the Liability Convention [245]. The Liability Convention establishes a restricted framework for assessing international liability which only applies to a launching State [248]. As noted, decisions and conduct of legal persons are ultimately decisions made by a human being. Ultimately, since fault liability under the Liability Convention Article III is premised on the fault of a state or the faults of persons, a decision by an intelligent space object will, in all likelihood, not be the "fault of persons" [245].

Existing liability models may be inadequate to address the future role of AI in criminal activities [249]. For example, while autonomous agents can carry out the criminal act or

omission, the voluntary aspect of *actus reus* would not be met, since the idea that an autonomous agent can act voluntarily is debatable. This implies that agents, artificial or otherwise, could potentially perform criminal acts or omissions without satisfying the conditions of liability for that particular criminal offence [246]. In the event that criminal liability is fault-based, it also requires *mens rea* (a guilty mind). The *mens rea* may comprise an intention to commit the *actus reus* using an AI-based application, or knowledge that deploying an autonomous agent will or could cause it to perform a criminal action or omission [250].

#### 2) DATA PROTECTION AND ETHICAL CHALLENGES

AI also raises important ethical and privacy concerns that could erode trust in emerging technologies if not addressed thoughtfully. AI requires access to vast amounts of data, but poorly drawn laws and government policies can hinder beneficial access without reducing the risk of AI activities [251]. The fear that satellite imagery can be used to discern car plates, individuals, and "manholes and mailboxes" is not fictional. In 2013, police in Oregon, used Google Earth satellite image depicting marijuana growing illegally on a man's property. In January, 2020, the United States imposed an immediate interim export controls regulating the dissemination of AI technology software that possesses the ability to automatically scan aerial images to recognize anomalies or identify objects of interest, such as vehicles, houses, and other structures [252]. Employing AI in satellite imaging presents ethical issues relating to loss of control over one's personal information and activities, which encompasses the right of individuals to move in their own home (yards and gardens) and/or other non-public places without being identified, tracked or monitored [253]. Nevertheless, a larger influx of data, observation capabilities and high-quality imagery from EO satellites is expected to become more widely available on a timely basis [254].

#### 3) LIMITATIONS OF SPACE LAW

There are no international or space treaties that address or regulate the use of AI in space. This simply implies that domestic legislation must serve as the principal source for the substantive law relating to the use of AI in space [245]. Furthermore, the dearth of international regulation of AI poses potential complex problems relating to the applicable substantive law in disputes involving the use of AI in space. It is not yet clear how ethical and legal concerns, especially around responsibility and analysis of decisions made by AI-based systems can be solved. Adequate policies, regulations, ethical guidance and a legal framework to prevent the misuse of AI in space need to be developed and enforced by regulators [245, 255, 256].

### V. FUTURE DIRECTIONS

AI and blockchain are among the key disruptive drivers behind innovation today [257]. While AI has its fair share of issues with trustworthiness, explainability, and privacy, blockchain on the other hand suffers from shortcomings such as scalability, security and efficiency. By leveraging advances in AI and blockchain platforms we can demonstrate

the capabilities of a new framework to collect vast amounts of data. The integration or marriage of these two technologies seems inevitable; especially since they have the potential to complement each other and revolutionize the next digital generation [257, 258].

Regardless of the undisputed challenges with AI, several developments in algorithmic improvements have boosted the performance of DL methods and their models' accuracy. However, the large datasets required for trainings tend to be generally proprietary, highly centralized and expensive to re-create. Furthermore, published models soon become obsolete and in need of retraining with new data. In view of the above challenges there seems to be a push towards finding ways to collaboratively improve ML models hosted on public blockchains. Blockchain will bring trustlessness, privacy, and explainability to AI while will in turn help build an ML system on blockchain for better security, scalability, and more effective personalization and governance [257].

Researchers at Microsoft [258] proposed a new framework for collaboratively building a dataset and using smart contracts to host a continuously updated model. A free and open-source implementation of this framework for the Ethereum blockchain is provided at <https://github.com/microsoft/0xDeCA10B>. Similarly, the space industry has begun experimenting with blockchain technology across its entire supply chain to address some of the challenges faced by agencies like ESA and NASA. Going forward, we shall discuss three domains that stand to benefit the most from the inevitable AI-Blockchain convergence in the space community. They include the Internet of Space Things (IoST), Satellite Communications, and Spacecraft Data Security.

### 1. INTERNET OF SPACE THINGS (IoST)

The growing popularity of CubeSats has given rise to the practicability of ubiquitous cyber-physical systems known as the IoST/CubeSats [259]. Given the already mentioned challenges associated with the development and launch of traditional satellites CubeSats have become a viable alternative for building global satellite networks [260, 261]. The concept of Internet of Space Things (IoST) utilizes Low Earth Orbit (LEO) satellites as part of a ubiquitous cyber-physical system for implementing true global connectivity. The system leverages Software-Defined Networking (SDN) and Network Function Virtualization (NFV) to integrate on-the-ground data and satellite information. Over the last couple of years research interest in the use of AI and SDR to manage networks and communication systems has gained momentum [262].

In [259] Kak *et al.* introduced a highly customizable large-scale optimal constellation design framework for IoST with the aim of achieving global coverage and robust connectivity. Fortunately, the use of CubeSats offers several advantages. First, they make extensive use of Commercial-Off-The-Shelf (COTS) components which helps bring costs down. Secondly, through the use of sequential redundancy, CubeSats have much shorter development and deployment

cycles. Furthermore, CubeSat constellations are more resilient to satellite failures due to the larger number of CubeSats in use. Notwithstanding the many use cases for IoST that focus on on-Earth or near-Earth applications, it is worth stating that IoST can also find application in deep space exploration through interplanetary data relaying, sensing and monitoring of asteroids, Mars, and Moon [260, 263].

For example, NASA aims to establish a human colony on Mars by 2025, which will require connectivity beyond Earth. The IoST, consisting of deep-space CubeSats, is expected to play a crucial role in providing such intra-galactic connectivity [264]. Currently, the utmost goal of IoST is to enable global connectivity beyond planet earth and provide sensing capabilities at a low cost [263]. Remote locations such as Mars that have little satellite coverage and connectivity can benefit from data sharing. Just as Earth's self-driving cars collectively share information about obstacle detection on a road, satellites or rovers could provide relative navigational information to each other and thus improve the accuracy of their space-based positioning and navigation.

### 2. SOFTWARE-DEFINED RADIO (SDR) AND SATELLITE COMMUNICATIONS

LEO satellite network plays a critical role in future space-terrestrial integrated network because of its unique advantages. Notwithstanding, the effective and reliable routing for LEO satellite network is a difficult task due to time-varying topology, imbalanced communication load and frequent link handover [181]. This is where automation enhanced by cognition and ML can help with optimizing data return from space missions, reducing costs of operations and managing the complexity of communication systems. Although autonomous control systems without humans in the loop already exist for ground station network management, adding ML and cognitive algorithms will open up entire new fields of research with the potential to reduce complexity, enhance performance, and undoubtedly minimize the cost of space operations [181] [180].

NASA is currently on the verge of defining and developing future space and ground architecture for optimizing the data return from space missions. In [180] the authors discussed the potential role of ML in the link-to-link aspect of the communication systems. For the first time the advantages and disadvantages of applying ML to space links in actual flight environment was demonstrated in an experiment using NASA's Space Communication and Navigation Testbed onboard the ISS and the ground station located at NASA John H. Glenn Research Center.

Given the successful result, SDR has been identified as a key technology that provides the needed flexibility and configurability for NASA's future cognitive communication systems. Cognitive communication architectures will undoubtedly play a critical role in future space missions, providing seamless internetworking services for communication and navigation from within Earth's orbit out

through Mars and other planetary exploration in deep space. However, achieving the above objectives might require integrating future 5G communication frameworks with different radio access technologies and AI-based Dynamic Spectrum Management (DSM) mechanisms. AI-based DSM mechanisms such as spectrum sensing, signal classification and dynamic spectrum access have been proven to achieve superior performance and robustness than conventional schemes. These mechanisms, enabled by Cognitive Radio (CR), Blockchain and AI, also provide more flexible and efficient means of implementing DSM. In the future, the combination of AI techniques and the DSM mechanisms would become a novel and promising research direction [175], [25, 180].

### 3. SPACECRAFT DATA SECURITY AND THE BLOCKCHAIN FRAMEWORK

Considering that both AI and Blockchain deal with data to create value, the AI-Blockchain convergence is absolutely inevitable in the space industry. While data is central to AI's efficacy blockchain enables collaborative and secure data sharing. Therefore, tokenizing space resources such as satellites, telescopes and orbits in the form of blockchain-based digital tokens will open up new research areas and possibilities. Currently, Space Assets Management, Space Financing and Secure Satellite Communication represent some of the key areas that can hugely benefit from blockchain.

In 2017, NASA awarded a \$330,000 grant to Dr. Jin Wei Kocsis of the University of Akron to support the development of an autonomous blockchain-based spacecraft system. The new system, called the Resilient Networking and Computing Paradigm (RNCP), relies on blockchain and represents NASA's first step toward blockchain adoption in space applications [265, 266]. The authors in [266] also investigated the adoption of blockchain theory based on the *space digital token* concept and proposed a new conceptual blockchain space industry framework to address some major challenges facing the space industry.

Ant-inspired algorithms, when applied to the routing problem in wireless communication networks between satellites or planetary sensors achieved great efficiency [267]. However, communication security still remains a major challenge among spacecraft/satellites. Spacecraft and ground-based systems that control them are at risk of both active hacking and denial-of-service attacks. For most existing spacecraft communication security was insufficiently implemented, thus leaving significant attack vectors related to spacecraft control [268].

Blockchain can therefore be employed to help in securing satellites swarms' communications, managing and authenticating space transactions between those swarms and ground stations [269]. In order to understand how blockchain can be employed in this regard it is first necessary to understand possible communication patterns between satellites and blockchain system. In [270] these patterns are

classified as four communication models and enumerated as follows:

1. A Satellite/spacecraft works as a blockchain node within the blockchain network;
- 2) A Satellite/spacecraft works as a validator (i.e. a miner) node within the blockchain network;
- 3) A satellite/spacecraft read from the blockchain;
- 4) A satellite requests a specific transactional data to be written to the blockchain.

With respect to the enumerated models above, Multi-Factor Authentication (MFA) can be used to verify a satellite's identity, ground station's identity, or communication pattern validity by requiring multiple security proofs [266]. For example, satellite A and Satellite B in a satellite swarm can use a code to authenticate a satellite's membership in the swarm. Take for instance a scenario where Satellite A requests a specific connection with satellite B. A sends the last block's *Nonce code* in the blockchain, which is verified by B before establishing the communication link. After terminating the connection a new block with a new Nonce code is provided, and then the new block is verified by all the miners in the blockchain network. Verification by miners (e.g. satellites and ground stations) proves the validity of connection and adds the new block to the blockchain system [266].

Data-sharing enabled by blockchain could also be used to address distrust by creating virtual trusted space zones in which rovers or satellites in swarms identify and update each other in a trustless network environment. For instance, when a specific satellite in its orbit is endangered with a space debris collision, it will update all satellites in the same swarm (i.e. in the same orbit) with the new information; the update being distributed as a digital token.

## VI. CONCLUSION

As spacecraft systems become larger and exceedingly complex, AI techniques are needed to help with control, operations, and communications. For instance, the application of ML algorithms to various aspects of remote sensing, spacecraft health monitoring and communication offers the potential to improve throughput and data return to Earth from space missions. In this survey we analyzed the applications of AI in Spacecraft Health Monitoring, Remote Sensing, Satellite Communications, and RAS. Some BIAs were also surveyed and their potential application areas in space missions highlighted.

Regardless of the benefits derivable from the use of AI in space missions, there are still lots of challenges and open issues to be addressed. These hurdles need not to be seen as unassailable obstacles, but opportunities that point the way to where technological advancements are needed. For example, there seems to be a push towards finding ways to collaboratively improve ML models by hosting them on public blockchains. Similarly, SDR has been identified as a

key technology that provides the needed flexibility and configurability for future cognitive communication systems. We encourage researchers to look into mathematical methods such as quantum computing and chaotic theory; and hybridizing them with bio-inspired computing to overcome some of the limitations associated with BAIs. Unlike similar surveys focused only on technological challenges, we thought that it was important to also address some of the key legal challenges that emanate from the reliance and use of AI in space.

Summarily, our paper outlined the need for advanced ML methods for space applications. ML has the potential to greatly increase these missions' capabilities, as well as enabling ambitious new autonomy possibilities in almost all fields of spacecraft operations. However, the combination of blockchain technology and AI will revolutionize space missions altogether as never before witnessed. This convergence has the potential to utilize data in ways never before thought possible. Given that data is the key ingredient for the development and enhancement of AI algorithms, blockchain holds the promise of securing this data and allowing us to audit all the transitional steps that these algorithms take to infer conclusions from the data.



**PAUL A. ALLEN** received the B.Eng. degree in electronic engineering from the University of Nigeria, Nsukka in 2008, and the M.Sc. degree in embedded systems from the University of Greenwich, London in 2013.

From 2014 to 2017, he was a Research & Development (R&D) engineer with Namek Solutions and holds two patents. From 2011 to 2013, he was also a contributing technology writer at Tekedia, a division of First Atlantic Semiconductors and microelectronics. He is currently an engineer with the Center for Satellite and Technology Development (CSTD), an R&D center under the National Space Research and Development Agency (NASRDA). His research interest includes embedded systems, ML, and RAS.



**GIDEON EWA** received the B.Eng. degree in computer engineering from the University of Uyo, Nigeria, in 2011 and the M.Sc. degree in mobile and satellite communication from the University of Surrey, U.K., in 2016. He is currently an engineer with the Center for Satellite and Technology Development (CSTD), an R&D center under the National Space Research and Development (NASRDA). His research interest includes wireless communication, Internet of Things, smart cities, and ML.



**ENGR (MRS) NWANNEKA IBEKWE** received the B.Eng. degree in electrical and electronics engineering from the University of Maiduguri, Borno State, Nigeria in 2002 and the M.Eng. degree in electronics and communication engineering from the Nigerian Defence Academy, Kaduna, Nigeria in 2017. She is currently pursuing the Ph.D. degree in electronics and communication engineering at the University of Abuja, Nigeria. From 2008 to 2009, she participated in the Surrey Satellite Technology

Limited (SSTL) Know-How Transfer and Training programme for the development and launch of Nigeria-Sat 2 and Nigeria-Sat X Spacecraft with

specialized training in Ground Station and Operations in the UK. She is currently the Unit Head, Spacecraft Control, and Monitoring, NASRDA. Her research interest includes space robots and AI.

Engr. (Mrs.) Nwanneka Ibekwe is a member of the International Association of Engineers (IAENG).

## References

- [1] J. Liu *et al.*, "Artificial Intelligence in the 21st Century," *IEEE Access*, vol. PP, pp. 1-1, 03/26 2018, doi: 10.1109/ACCESS.2018.2819688.
- [2] J. Straub, "A review of spacecraft AI control systems," *WMSCI 2011 - The 15th World Multi-Conference on Systemics, Cybernetics and Informatics, Proceedings*, vol. 2, pp. 20-25, 01/01 2011.
- [3] K. Rajan and A. Saffiotti, "Towards a science of integrated AI and Robotics," *Artificial Intelligence*, 03/01 2017, doi: 10.1016/j.artint.2017.03.003.
- [4] J. Bohg, M. Ciocarlie, J. Civera, and L. Kavraki, "Big Data on Robotics," *Big Data*, vol. 4, pp. 195-196, 12/01 2016, doi: 10.1089/big.2016.29013.rob.
- [5] J.-G. Meß, F. Dannemann, and F. Greif, *Techniques of Artificial Intelligence for Space Applications - A Survey*. 2019.
- [6] D. Izzo, M. Märten, and B. Pan, "A survey on artificial intelligence trends in spacecraft guidance dynamics and control," *Astrodynamics*, 07/31 2019, doi: 10.1007/s42064-018-0053-6.
- [7] L. Kunze, N. Hawes, T. Duckett, M. Hanheide, and T. Krajník, "Artificial Intelligence for Long-Term Robot Autonomy: A Survey," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 4023-4030, 2018, doi: 10.1109/LRA.2018.2860628.
- [8] J. E. Estes, C. Sailer, and L. R. Tinney, "Applications of artificial intelligence techniques to remote sensing," *The Professional Geographer*, vol. 38, no. 2, pp. 133-141, 1986.
- [9] X. X. Zhu *et al.*, "Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources," *IEEE Geoscience and Remote Sensing Magazine*, vol. 5, no. 4, pp. 8-36, 2017, doi: 10.1109/MGRS.2017.2762307.
- [10] L. Ma, Y. Liu, X. Zhang, Y. Ye, G. Yin, and B. A. Johnson, "Deep learning in remote sensing applications: A meta-analysis and review," *ISPRS journal of photogrammetry and remote sensing*, vol. 152, pp. 166-177, 2019.
- [11] G. Furano *et al.*, "Towards the Use of Artificial Intelligence on the Edge in Space Systems: Challenges and Opportunities," *IEEE Aerospace and Electronic Systems Magazine*, vol. 35, no. 12, pp. 44-56, 2020, doi: 10.1109/MAES.2020.3008468.
- [12] A. Berquand *et al.*, "Artificial Intelligence for the Early Design Phases of Space Missions," in *2019 IEEE Aerospace Conference*, 2-9 March 2019 2019, pp. 1-20, doi: 10.1109/AERO.2019.8742082.
- [13] D. Girimonte and D. Izzo, "12 Artificial Intelligence for Space Applications," *Intelligent Computing Everywhere*, 01/01 2007, doi: 10.1007/978-1-84628-943-9\_12.
- [14] A. E. Hassanien, A. Darwish, and S. Abdelghafar, "Machine learning in telemetry data mining of space mission: basics, challenging and future directions," *Artificial Intelligence Review*, vol. 53, no. 5, pp. 3201-3230, 2020/06/01 2020, doi: 10.1007/s10462-019-09760-1.
- [15] V. Kothari, E. Liberis, and N. D. Lane, "The Final Frontier: Deep Learning in Space," *arXiv*, p. arXiv: 2001.10362, 2020.
- [16] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, and A. G. Kanatas, "A survey on machine-learning techniques for UAV-based communications," *Sensors*, vol. 19, no. 23, p. 5170, 2019.
- [17] A. Nanjangud, P. Blacker, S. Bandyopadhyay, and Y. Gao, "Robotics and AI-Enabled On-Orbit Operations With Future Generation of Small Satellites," *Proceedings of the IEEE*, vol. 106, pp. 1-11, 02/19 2018, doi: 10.1109/JPROC.2018.2794829.
- [18] H. C. EDITORS, "Challenger Explosion," Online 15/02/ 2010. [Online]. Available: <https://www.history.com/topics/1980s/challenger-disaster>.

- [19] H. N. a. S. Laura, "Russia investigating failed Soyuz rocket launch," (in English), Online 2018. [Online]. Available: <https://edition.cnn.com/2018/10/11/europe/soyuz-rocket-russia-nasa-intl/index.html>.
- [20] A. Long, M. Richards, and D. Hastings, "On-Orbit Servicing: A New Value Proposition for Satellite Design and Operation," *Journal of Spacecraft and Rockets - J SPACECRAFT ROCKET*, vol. 44, pp. 964-976, 07/01 2007, doi: 10.2514/1.27117.
- [21] D. Akin and B. Sullivan, *A survey of serviceable spacecraft failures*. 2001.
- [22] A. K. Jonsson, R. A. Morris, and L. Pedersen, "Autonomy in Space Exploration: Current Capabilities and Future Challenges," in *2007 IEEE Aerospace Conference*, 3-10 March 2007 2007, pp. 1-12.
- [23] S. J. Russell and P. Norvig, "Artificial intelligence: a modern approach. Malaysia," ed: Pearson Education Limited, 2016.
- [24] M. Prosser and J. Rebolledo, "AI is kicking space exploration into hyper drive-here's how?," *Singularity hub*, 2018.
- [25] Y.-C. Liang, "Artificial Intelligence for Dynamic Spectrum Management," in *Dynamic Spectrum Management: From Cognitive Radio to Blockchain and Artificial Intelligence*, Y.-C. Liang Ed. Singapore: Springer Singapore, 2020, pp. 147-166.
- [26] A. L. Samuel, "Some Studies in Machine Learning Using the Game of Checkers," *IBM Journal of Research and Development*, vol. 3, no. 3, pp. 210-229, 1959, doi: 10.1147/rd.33.0210.
- [27] J. Alzubi, A. Nayyar, and A. Kumar, "Machine Learning from Theory to Algorithms: An Overview," *Journal of Physics: Conference Series*, vol. 1142, p. 012012, 11/01 2018, doi: 10.1088/1742-6596/1142/1/012012.
- [28] T. Mitchell, "Machine Learning, McGraw-Hill Higher Education," *New York*, 1997.
- [29] H. M. E. Misilmani and T. Naous, "Machine Learning in Antenna Design: An Overview on Machine Learning Concept and Algorithms," in *2019 International Conference on High Performance Computing & Simulation (HPCS)*, 15-19 July 2019 2019, pp. 600-607, doi: 10.1109/HPCS48598.2019.9188224.
- [30] P. C. Sen, M. Hajra, and M. Ghosh, "Supervised classification algorithms in machine learning: A survey and review," in *Emerging technology in modelling and graphics*: Springer, 2020, pp. 99-111.
- [31] I. H. Sarker, A. Kayes, S. Badsha, H. Alqahtani, P. Watters, and A. Ng, "Cybersecurity data science: an overview from machine learning perspective," *Journal of Big data*, vol. 7, no. 1, pp. 1-29, 2020.
- [32] H. U. Dike, Y. Zhou, K. K. Deverasetty, and Q. Wu, "Unsupervised Learning Based On Artificial Neural Network: A Review," in *2018 IEEE International Conference on Cyborg and Bionic Systems (CBS)*, 25-27 Oct. 2018 2018, pp. 322-327, doi: 10.1109/CBS.2018.8612259.
- [33] Z. Ghahramani, "Unsupervised learning," in *Summer School on Machine Learning*, 2003: Springer, pp. 72-112.
- [34] J. E. Van Engelen and H. H. Hoos, "A survey on semi-supervised learning," *Machine Learning*, vol. 109, no. 2, pp. 373-440, 2020.
- [35] R. Nian, J. Liu, and B. Huang, "A review on reinforcement learning: Introduction and applications in industrial process control," *Computers & Chemical Engineering*, vol. 139, p. 106886, 2020.
- [36] M. Mohammed, M. B. Khan, and E. B. M. Bashier, *Machine learning: algorithms and applications*. Crc Press, 2016.
- [37] S. Marsland, *Machine learning: an algorithmic perspective*. CRC press, 2015.
- [38] S. S. Haykin, "Neural networks and learning machines/Simon Haykin," ed: New York: Prentice Hall, 2009.
- [39] S. Shalev-Shwartz and S. Ben-David, *Understanding machine learning: From theory to algorithms*. Cambridge university press, 2014.
- [40] K. Crammer and Y. Singer, "On the algorithmic implementation of multiclass kernel-based vector machines," *Journal of machine learning research*, vol. 2, no. Dec, pp. 265-292, 2001.
- [41] B. Srebrov, O. Kounchev, and G. Simeonov, "Chapter 19 - Big Data for the Magnetic Field Variations in Solar-Terrestrial Physics and Their Wavelet Analysis," in *Knowledge Discovery in Big Data from Astronomy and Earth Observation*, P. Škoda and F. Adam Eds.: Elsevier, 2020, pp. 347-370.
- [42] P. Harrington, *Machine learning in action*. Manning Publications Co., 2012.
- [43] I. T. Jolliffe and J. Cadima, "Principal component analysis: a review and recent developments," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 374, no. 2065, p. 20150202, 2016.
- [44] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*. MIT press, 2018.
- [45] A. Burkov, *The hundred-page machine learning book*. Andriy Burkov Canada, 2019.
- [46] S. Cohen, "Chapter 2 - The basics of machine learning: strategies and techniques," in *Artificial Intelligence and Deep Learning in Pathology*, S. Cohen Ed.: Elsevier, 2021, pp. 13-40.
- [47] F. Burden and D. Winkler, "Bayesian Regularization of Neural Networks," in *Artificial Neural Networks: Methods and Applications*, D. J. Livingstone Ed. Totowa, NJ: Humana Press, 2009, pp. 23-42.
- [48] G. Shi, "Chapter 8 - Kriging," in *Data Mining and Knowledge Discovery for Geoscientists*, G. Shi Ed. Oxford: Elsevier, 2014, pp. 238-274.
- [49] A. Mayr, H. Binder, O. Gefeller, and M. Schmid, "The Evolution of Boosting Algorithms From Machine Learning to Statistical Modelling," *Methods of information in medicine*, vol. 53, 03/06 2014, doi: 10.3414/ME13-01-0122.
- [50] S. Mirjalili and J. S. Dong, *Multi-objective optimization using artificial intelligence techniques*. Springer, 2020.
- [51] K. Miettinen, "Introduction to multiobjective optimization: Noninteractive approaches," in *Multiobjective optimization*: Springer, 2008, pp. 1-26.
- [52] M. Laszczyk and P. B. Myszowski, "Survey of quality measures for multi-objective optimization: Construction of complementary set of multi-objective quality measures," *Swarm and Evolutionary Computation*, vol. 48, pp. 109-133, 2019.
- [53] P. Ngatchou, A. Zarei, and A. El-Sharkawi, "Pareto multi objective optimization," 2005: IEEE, pp. 84-91.
- [54] J. Ni, L. Wu, X. Fan, and S. X. Yang, "Bioinspired Intelligent Algorithm and Its Applications for Mobile Robot Control: A Survey," *Computational Intelligence and Neuroscience*, vol. 2016, p. 3810903, 2015/12/27 2016, doi: 10.1155/2016/3810903.
- [55] A. Darwish, "Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications," *Future Computing and Informatics Journal*, vol. 3, no. 2, pp. 231-246, 2018/12/01/ 2018, doi: <https://doi.org/10.1016/j.fcij.2018.06.001>.
- [56] X. Fan, L. Pang, P. Shi, G. Li, and X. Zhang, "Application of Bee Evolutionary Genetic Algorithm to Maximum Likelihood Direction-of-Arrival Estimation," *Mathematical Problems in Engineering*, vol. 2019, p. 6035870, 2019/02/25 2019, doi: 10.1155/2019/6035870.
- [57] S. Gao and Y. Wen, "An Improved Artificial Fish Swarm Algorithm and its Application," in *2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS)*, 6-8 June 2018 2018, pp. 649-652, doi: 10.1109/ICIS.2018.8466458.
- [58] Y. Wu, X.-Z. Gao, and K. Zenger, "Knowledge-based artificial fish-swarm algorithm," *IFAC proceedings volumes*, vol. 44, no. 1, pp. 14705-14710, 2011.
- [59] A. Babalik, A. Ozkis, S. A. Uymaz, and M. S. Kiran, "A multi-objective artificial algae algorithm," *Applied Soft Computing*, vol. 68, pp. 377-395, 2018/07/01/ 2018, doi: <https://doi.org/10.1016/j.asoc.2018.04.009>.
- [60] N. Rana, M. S. A. Latif, S. i. M. Abdulhamid, and H. Chiroma, "Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments," *Neural Computing and Applications*, vol. 32, no. 20, pp. 16245-16277, 2020/10/01 2020, doi: 10.1007/s00521-020-04849-z.
- [61] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, vol. 69, pp. 46-61, 2014/03/01/ 2014, doi: <https://doi.org/10.1016/j.advengsoft.2013.12.007>.



- [62] X. Meng, Y. Liu, X. Gao, and H. Zhang, "A New Bio-inspired Algorithm: Chicken Swarm Optimization," in *Advances in Swarm Intelligence*, Cham, Y. Tan, Y. Shi, and C. A. C. Coello, Eds., 2014// 2014: Springer International Publishing, pp. 86-94.
- [63] A. M. Ahmed, T. A. Rashid, and S. A. M. Saeed, "Cat Swarm Optimization Algorithm: A Survey and Performance Evaluation," *Computational Intelligence and Neuroscience*, vol. 2020, p. 4854895, 2020/01/22 2020, doi: 10.1155/2020/4854895.
- [64] S. Mirjalili, "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm," *Knowledge-Based Systems*, vol. 89, pp. 228-249, 2015/11/01/ 2015, doi: <https://doi.org/10.1016/j.knsys.2015.07.006>.
- [65] S. Deb, S. Fong, Z. Tian, R. K. Wong, S. Mohammed, and J. Fiaidhi, "Finding approximate solutions of NP-hard optimization and TSP problems using elephant search algorithm," *The Journal of Supercomputing*, vol. 72, no. 10, pp. 3960-3992, 2016/10/01 2016, doi: 10.1007/s11227-016-1739-2.
- [66] X. Feng, D. Wappling, H. Andersson, J. Ölvander, and M. Tarkian, *Multi-Objective Optimization in Industrial Robotic Cell Design*. 2010.
- [67] J. Handl, D. Kell, and J. Knowles, "Multiobjective optimization in bioinformatics and computational biology. IEEE/ACM Trans Comput Biol Bioinform (TCBB) 4:279-292," *IEEE/ACM transactions on computational biology and bioinformatics / IEEE, ACM*, vol. 4, pp. 279-92, 05/01 2007, doi: 10.1109/TCBB.2007.070203.
- [68] M. Gitizadeh, S. Farhadi, and S. Safarloo, "Multi-objective energy management of CHP-based microgrid considering demand response programs," in *2014 Smart Grid Conference (SGC)*, 9-10 Dec. 2014 2014, pp. 1-7, doi: 10.1109/SGC.2014.7090870.
- [69] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 67-82, 1997, doi: 10.1109/4235.585893.
- [70] A. Tharwat, E. H. Houssein, M. M. Ahmed, A. E. Hassanien, and T. Gabel, "MOGOA algorithm for constrained and unconstrained multi-objective optimization problems," *Applied Intelligence*, vol. 48, no. 8, pp. 2268-2283, 2018/08/01 2018, doi: 10.1007/s10489-017-1074-1.
- [71] A. Zhou, B.-Y. Qu, H. Li, S.-Z. Zhao, P. N. Suganthan, and Q. Zhang, "Multiobjective evolutionary algorithms: A survey of the state of the art," *Swarm and Evolutionary Computation*, vol. 1, no. 1, pp. 32-49, 2011.
- [72] W. Stadler, "A survey of multicriteria optimization or the vector maximum problem, part I: 1776-1960," *Journal of Optimization Theory and Applications*, vol. 29, no. 1, pp. 1-52, 1979.
- [73] N. Srinivas and K. Deb, "Multiobjective optimization using nondominated sorting in genetic algorithms," *Evol. Comput.*, vol. 2, no. 3, pp. 221-248, 1994, doi: 10.1162/evco.1994.2.3.221.
- [74] Q. Zhang and H. Li, "MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition," *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 6, pp. 712-731, 2007, doi: 10.1109/TEVC.2007.892759.
- [75] S. Z. Mirjalili, S. Mirjalili, S. Saremi, H. Faris, and I. Aljarah, "Grasshopper optimization algorithm for multi-objective optimization problems," *Applied Intelligence*, vol. 48, 04/01 2018, doi: 10.1007/s10489-017-1019-8.
- [76] A. R. Mehrabian and C. Lucas, "A novel numerical optimization algorithm inspired from weed colonization," *Ecological informatics*, vol. 1, no. 4, pp. 355-366, 2006.
- [77] Z. Yin, M. Wen, and C. Ye, "Improved invasive weed optimization based on hybrid genetic algorithm," *Journal of Computational Information Systems*, vol. 8, no. 8, pp. 3437-3444, 2012.
- [78] G. G. Roy, S. Das, P. Chakraborty, and P. N. Suganthan, "Design of Non-Uniform Circular Antenna Arrays Using a Modified Invasive Weed Optimization Algorithm," *IEEE Transactions on Antennas and Propagation*, vol. 59, no. 1, pp. 110-118, 2011, doi: 10.1109/TAP.2010.2090477.
- [79] X.-q. Zhao and J.-h. Zhou, "Improved kernel possibilistic fuzzy clustering algorithm based on invasive weed optimization," *Journal of Shanghai Jiaotong University (Science)*, vol. 20, no. 2, pp. 164-170, 2015/04/01 2015, doi: 10.1007/s12204-015-1605-z.
- [80] A. Ouyang, L.-B. Liu, Z. Sheng, and F. Wu, "A Class of Parameter Estimation Methods for Nonlinear Muskingum Model Using Hybrid Invasive Weed Optimization Algorithm," *Mathematical Problems in Engineering*, vol. 2015, 07/02 2015, doi: 10.1155/2015/573894.
- [81] K. M. Passino, "Biomimicry of bacterial foraging for distributed optimization and control," *IEEE Control Systems Magazine*, vol. 22, no. 3, pp. 52-67, 2002, doi: 10.1109/MCS.2002.1004010.
- [82] B. Bhushan and M. Singh, "Adaptive control of DC motor using bacterial foraging algorithm," *Applied Soft Computing*, vol. 11, no. 8, pp. 4913-4920, 2011/12/01/ 2011, doi: <https://doi.org/10.1016/j.asoc.2011.06.008>.
- [83] N. Rajasekar, N. Krishna Kumar, and R. Venugopalan, "Bacterial Foraging Algorithm based solar PV parameter estimation," *Solar Energy*, vol. 97, pp. 255-265, 2013/11/01/ 2013, doi: <https://doi.org/10.1016/j.solener.2013.08.019>.
- [84] N. Sanyal, A. Chatterjee, and S. Munshi, "An adaptive bacterial foraging algorithm for fuzzy entropy based image segmentation," *Expert Systems with Applications*, vol. 38, no. 12, pp. 15489-15498, 2011/11/01/ 2011, doi: <https://doi.org/10.1016/j.eswa.2011.06.011>.
- [85] W. Liu, B. Niu, H. Chen, and Y. Zhu, "Robot path planning using bacterial foraging algorithm," *Journal of Computational and Theoretical Nanoscience*, vol. 10, no. 12, pp. 2890-2896, 2013.
- [86] W. J. Tang, M. S. Li, Q. H. Wu, and J. R. Saunders, "Bacterial Foraging Algorithm for Optimal Power Flow in Dynamic Environments," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 55, no. 8, pp. 2433-2442, 2008, doi: 10.1109/TCSI.2008.918131.
- [87] A. K. Kar, "Bio inspired computing—a review of algorithms and scope of applications," *Expert Systems with Applications*, vol. 59, pp. 20-32, 2016.
- [88] H. Duan, X. Zhang, and C. Xu, "Bio-inspired computing," ed: Science Press, Beijing, China, 2011.
- [89] H. Bersini and F. J. Varela, "Hints for adaptive problem solving gleaned from immune networks," in *Parallel Problem Solving from Nature*, Berlin, Heidelberg, H.-P. Schwefel and R. Männer, Eds., 1991// 1991: Springer Berlin Heidelberg, pp. 343-354.
- [90] Z. Li, J. Li, and C. He, "Artificial immune network-based anti-collision algorithm for dense RFID readers," *Expert Systems with Applications*, vol. 41, pp. 4798-4810, 08/01 2014, doi: 10.1016/j.eswa.2014.01.033.
- [91] C. Guoqiang, W. Yuping, and Y. Yifang, "Community Detection in Complex Networks Using Immune Clone Selection Algorithm," *International Journal of Digital Content Technology and its Applications*, vol. 5, pp. 182-189, 06/30 2011, doi: 10.4156/jdcta.vol5.issue6.21.
- [92] S. Forrest, A. S. Perelson, L. Allen, and R. Cherukuri, "Self-nonsel self discrimination in a computer," in *Proceedings of 1994 IEEE Computer Society Symposium on Research in Security and Privacy*, 16-18 May 1994 1994, pp. 202-212, doi: 10.1109/RISP.1994.296580.
- [93] Z. Wang, J. Tan, D. Huang, Y. Ren, and Z. Ji, "A biological algorithm to solve the assignment problem based on DNA molecules computation," *Applied Mathematics and Computation*, vol. 244, pp. 183-190, 2014/10/01/ 2014, doi: <https://doi.org/10.1016/j.amc.2014.06.098>.
- [94] U. K. Yuso, M. N. A. Khalid, and A. T. Khader, "Artificial immune system for flexible manufacturing system machine loading problem," *ICIC Express Letters*, vol. 8, pp. 709-716, 01/01 2014.
- [95] M. Marinaki and Y. Marinakis, "A hybridization of clonal selection algorithm with iterated local search and variable neighborhood search for the feature selection problem," *Memetic Computing*, vol. 7, no. 3, pp. 181-201, 2015/09/01 2015, doi: 10.1007/s12293-015-0161-2.
- [96] D. Li, S. Liu, and H. Zhang, "Negative selection algorithm with constant detectors for anomaly detection," *Applied Soft Computing*, vol. 36, pp. 618-632, 2015/11/01/ 2015, doi: <https://doi.org/10.1016/j.asoc.2015.08.011>.

- [97] R. Reynolds, *An Introduction to Cultural Algorithms*. 1994.
- [98] M. Z. Ali and R. G. Reynolds, "Cultural algorithms: a Tabu search approach for the optimization of engineering design problems," *Soft Computing*, vol. 18, no. 8, pp. 1631-1644, 2014.
- [99] N. Guo, M. Yang, and J. Cheng, *Path planning method for robots in complex ground environment based on cultural algorithm*. 2009, pp. 185-192.
- [100] Q. Wu, J. Zhang, W. Huang, and Y. Sun, "An efficient image matching algorithm based on culture evolution," *Journal of Chemical and Pharmaceutical Research*, vol. 6, pp. 271-278, 01/01 2014.
- [101] P. Rakshit *et al.*, "Realization of an Adaptive Memetic Algorithm Using Differential Evolution and Q-Learning: A Case Study in Multirobot Path Planning," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 43, no. 4, pp. 814-831, 2013, doi: 10.1109/TSMCA.2012.2226024.
- [102] N. Pisanti, "DNA computing: a survey," *Bulletin of the EATCS*, vol. 64, pp. 188-216, 1998.
- [103] L. M. Adleman, "Molecular computation of solutions to combinatorial problems," *Science*, vol. 266, no. 11, pp. 1021-1024, 1994.
- [104] Z. Ezziane, "DNA computing: applications and challenges. Nanotechnology 17:R27-R39," *Nanotechnology*, vol. 17, p. R27, 12/21 2005, doi: 10.1088/0957-4484/17/2/R01.
- [105] H. Jiao, Y. Zhong, and L. Zhang, "An Unsupervised Spectral Matching Classifier Based on Artificial DNA Computing for Hyperspectral Remote Sensing Imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 8, pp. 4524-4538, 2014, doi: 10.1109/TGRS.2013.2282356.
- [106] B. S. E. Zoraida, M. Arock, B. S. M. Ronald, and R. Ponalagusamy, "DNA algorithm employing temperature gradient for Freeze-Tag Problem in swarm robotics," *Transactions of the Institute of Measurement and Control*, vol. 34, no. 2-3, pp. 278-290, 2012/04/01 2010, doi: 10.1177/0142331210366684.
- [107] A. Ebrahimnejad, M. Tavana, and H. Alrezaamiri, "A novel artificial bee colony algorithm for shortest path problems with fuzzy arc weights," *Measurement*, vol. 93, pp. 48-56, 2016.
- [108] M. Abbes and M. Allagui, "Centralized control strategy for energy maximization of large array wind turbines," *Sustainable Cities and Society*, vol. 25, pp. 82-89, 2016.
- [109] W. Liao, "Test data generation based on the automatic division of path," *Tien Tzu Hsueh Pao Acta Electronica Sinica*, vol. 44, p. 2254e61, 2016.
- [110] R. A. Chakravarthy and S. Palaniswami, "Effective Power Based Stable Path Routing for Energy Efficiency in Wireless Sensor Networks," *JCTN*, vol. 13, no. 7, pp. 4797-4806, 2016.
- [111] Y. Wu, B. Yan, and X. Qu, "Improved Chicken Swarm Optimization Method for Reentry Trajectory Optimization," *Mathematical Problems in Engineering*, vol. 2018, p. 8135274, 2018/01/31 2018, doi: 10.1155/2018/8135274.
- [112] D. Cui, "Projection pursuit model for evaluation of flood and drought disasters based on chicken swarm optimization algorithm," *Adv Sci Technol Water Resour*, vol. 36, no. 2, p. 5, 2016.
- [113] S. Banerjee and S. Chattopadhyay, "Improved Serially Concatenated Convolution Turbo Code (SCCTC) using chicken swarm optimization," in *2015 IEEE Power, Communication and Information Technology Conference (PCITC)*, 15-17 Oct. 2015 2015, pp. 268-273, doi: 10.1109/PCITC.2015.7438173.
- [114] Y. Gao, *Contemporary planetary robotics: An approach toward autonomous systems*. 2016, pp. 1-410.
- [115] P. Langley, J. E. Laird, and S. Rogers, "Cognitive architectures: Research issues and challenges," *Cognitive Systems Research*, vol. 10, no. 2, pp. 141-160, 2009.
- [116] D. Skelly, "Use Case: Autonomy for Space Systems." Noblis. [https://noblis.org/wp-content/uploads/2019/09/AutonomyAtScale\\_Book.pdf](https://noblis.org/wp-content/uploads/2019/09/AutonomyAtScale_Book.pdf) (accessed 14/02/2021, 2021).
- [117] A. McGovern and K. Wagstaff, "Machine learning in space: Extending our reach," *Machine Learning*, vol. 84, pp. 335-340, 09/01 2011, doi: 10.1007/s10994-011-5249-4.
- [118] G. Rabideau *et al.*, "Mission operations of Earth Observing-1 with onboard autonomy," in *2nd IEEE International Conference on Space Mission Challenges for Information Technology (SMC-IT'06)*, 17-20 July 2006 2006, pp. 7 pp.-373, doi: 10.1109/SMC-IT.2006.48.
- [119] C. Frost, "Challenges and opportunities for autonomous systems in space," in *Frontiers of Engineering: Reports on Leading-Edge Engineering from the 2010 Symposium*, 2010.
- [120] R. Alami, R. Chatila, S. Fleury, M. Ghallab, and F. Ingrand, "An Architecture for Autonomy," *The International Journal of Robotics Research*, vol. 17, 04/01 1998, doi: 10.1177/027836499801700402.
- [121] D. Atkinson, M. James, and R. Martin, "SHARP - Automated monitoring of spacecraft health and status," 02/01 1990, doi: 10.1117/12.21136.
- [122] L. Quan, Z. XingShe, L. Peng, and L. Shaomin, "Anomaly detection and fault Diagnosis technology of spacecraft based on telemetry-mining," in *2010 3rd International Symposium on Systems and Control in Aeronautics and Astronautics*, 8-10 June 2010 2010, pp. 233-236, doi: 10.1109/ISSCAA.2010.5633180.
- [123] S. K. Ibrahim, A. Ahmed, M. A. E. Zeidan, and I. E. Ziedan, "Machine Learning Techniques for Satellite Fault Diagnosis," *Ain Shams Engineering Journal*, vol. 11, no. 1, pp. 45-56, 2020/03/01/ 2020, doi: <https://doi.org/10.1016/j.asej.2019.08.006>.
- [124] M. Tipaldi and B. Bruenjes, "Survey on Fault Detection, Isolation, and Recovery Strategies in the Space Domain," *Journal of Aerospace Information Systems*, vol. 12, pp. 1-22, 02/05 2015, doi: 10.2514/1.1010307.
- [125] A. Guiotto, A. Martelli, and C. Paccagnini, "SMART-FDIR: Use of Artificial Intelligence in the implementation of a Satellite FDIR," *European Space Agency, (Special Publication) ESA SP*, vol. 532, p. 71, 01/01 2003.
- [126] A. Wander and R. Förstner, *Innovative fault detection, isolation and recovery on-board spacecraft: Study and implementation using cognitive automation*. 2013, pp. 336-341.
- [127] L. Lawal and C. Chatwin, *Optimization of Mass Volume Ratio of Spacecraft Structure for Advanced and High Powered Communication Satellites*. 2011.
- [128] G. Yu, Y. Tianshe, X. Nan, and X. Minqiang, "Fault detection and diagnosis for spacecraft using principal component analysis and support vector machines," in *2012 7th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, 18-20 July 2012 2012, pp. 1984-1988.
- [129] T. Yairi, N. Takeishi, T. Oda, Y. Nakajima, N. Nishimura, and N. Takata, "A Data-Driven Health Monitoring Method for Satellite Housekeeping Data Based on Probabilistic Clustering and Dimensionality Reduction," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 53, no. 3, pp. 1384-1401, 2017, doi: 10.1109/TAES.2017.2671247.
- [130] P. Robinson, M. Shirley, D. Fletcher, R. Alena, D. Duncavage, and C. Lee, "Applying Model-Based Reasoning to the FDIR of the Command and Data Handling Subsystem of the International Space Station," 02/01 2003.
- [131] M. Schwabacher, "Machine Learning for Rocket Propulsion Health Monitoring," 10/03 2005, doi: 10.4271/2005-01-3370.
- [132] A. Fijany, F. Vatan, A. Barrett, M. James, C. Williams, and R. Mackey, *A novel model-based diagnosis engine: Theory and applications*. 2005, pp. 2\_901-2\_910.
- [133] D. Iverson, "Data Mining Applications for Space Mission Operations System Health Monitoring," 05/12 2008, doi: 10.2514/6.2008-3212.
- [134] K. Hundman, V. Constantinou, C. Laporte, I. Colwell, and T. Soderstrom, "Detecting Spacecraft Anomalies Using LSTMs and Nonparametric Dynamic Thresholding," *arXiv preprint arXiv:1802.04431*, 2018.
- [135] J. Cervantes, F. Garcia-Lamont, L. Rodríguez-Mazahua, and A. Lopez, "A comprehensive survey on support vector machine classification: Applications, challenges and trends," *Neurocomputing*, vol. 408, pp. 189-215, 2020/09/30/ 2020, doi: <https://doi.org/10.1016/j.neucom.2019.10.118>.
- [136] S. Taburo lu, "A Survey on Anomaly Detection and Diagnosis Problem in the Space System Operation," 2019.

- [137] R. Navalgund, J. V. and P. Roy, "Remote sensing applications: An overview," *Current science*, vol. Vol. 93, 12/25 2007.
- [138] A. Asokan and J. Anitha, "Machine Learning based Image Processing Techniques for Satellite Image Analysis -A Survey," in *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, 14-16 Feb. 2019 2019, pp. 119-124.
- [139] J. H. Jeppesen, R. H. Jacobsen, F. Inceoglu, and T. S. Toftegaard, "A cloud detection algorithm for satellite imagery based on deep learning," *Remote Sensing of Environment*, vol. 229, pp. 247-259, 2019/08/01/2019, doi: <https://doi.org/10.1016/j.rse.2019.03.039>.
- [140] S. Suresh and S. Lal, "Modified differential evolution algorithm for contrast and brightness enhancement of satellite images," *Applied Soft Computing*, vol. 61, pp. 622-641, 2017/12/01/2017, doi: <https://doi.org/10.1016/j.asoc.2017.08.019>.
- [141] S. D R, P. Deepa, and V. K., "Remote Sensing Satellite Image Processing Techniques for Image Classification: A Comprehensive Survey," *International Journal of Computer Applications*, vol. 161, pp. 24-37, 03/15 2017, doi: 10.5120/ijca2017913306.
- [142] A. Schmidt, F. Lafarge, C. Brenner, F. Rottensteiner, and C. Heipke, "Forest point processes for the automatic extraction of networks in raster data," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 126, pp. 38-55, 2017, doi: 10.1016/j.isprsjprs.2017.01.012.
- [143] R. Jenice Aroma and K. Raimond, "A review on availability of remote sensing data," in *2015 IEEE Technological Innovation in ICT for Agriculture and Rural Development (TIAR)*, 10-12 July 2015 2015, pp. 150-155, doi: 10.1109/TIAR.2015.7358548.
- [144] V. Komissarov, "AI Applications for Satellite Imagery and Satellite Data." Emerj Artificial Intelligence Research. <https://emerj.com/ai-sector-overviews/ai-applications-for-satellite-imagery-and-data/> (accessed May 17, 2020, 2020).
- [145] C. P. Schwegmann, W. Kleynhans, and B. P. Salmon, "The development of deep learning in synthetic aperture radar imagery," in *2017 International Workshop on Remote Sensing with Intelligent Processing (RSIP)*, 18-21 May 2017 2017, pp. 1-2, doi: 10.1109/RSIP.2017.7958802.
- [146] C. P. Schwegmann, W. Kleynhans, and B. P. Salmon, "Manifold Adaptation for Constant False Alarm Rate Ship Detection in South African Oceans," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 8, no. 7, pp. 3329-3337, 2015, doi: 10.1109/JSTARS.2015.2417756.
- [147] D. Crisp, "The state-of-the-art in ship detection in Synthetic Aperture Radar imagery," 05/01 2004.
- [148] L. Haijiang, Z. Chenghu, W. Cheng, L. En, and L. Rui, "Monitoring sandy desertification of Otindag Sandy Land based on multi-date remote sensing images," *Acta Ecologica Sinica*, vol. 28, pp. 627-635, 02/01 2008, doi: 10.1016/S1872-2032(08)60029-3.
- [149] J. Tian and D. Chen, "Evaluating Satellite-Based Measurements for Mapping Air Quality in Ontario, Canada," *Journal of Environmental Informatics*, vol. 10, pp. 30-36, 09/01 2007, doi: 10.3808/jei.200700097.
- [150] F. Padula, J. MacDonough, D. Bondy, and M. Cook, "Automated supervised land use classification and change detection: An image fusion based approach," in *2010 IEEE International Geoscience and Remote Sensing Symposium*, 25-30 July 2010 2010, pp. 335-338, doi: 10.1109/IGARSS.2010.5651950.
- [151] B. P. Salmon, J. C. Olivier, K. J. Wessels, W. Kleynhans, F. v. d. Bergh, and K. C. Steenkamp, "Unsupervised Land Cover Change Detection: Meaningful Sequential Time Series Analysis," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 4, no. 2, pp. 327-335, 2011, doi: 10.1109/JSTARS.2010.2053918.
- [152] D. Sharma, D. Singh, and D. Kaskaoutis, "Impact of Two Intense Dust Storms on Aerosol Characteristics and Radiative Forcing over Patiala, Northwestern India," *Advances in Meteorology*, vol. 2012, 05/27 2012, doi: 10.1155/2012/956814.
- [153] B. Gharai, S. Jose, and M. Dv, "Monitoring intense dust storms over the Indian region using satellite data - a case study," *International Journal of Remote Sensing*, vol. 34, pp. 7038-7048, 10/01 2013, doi: 10.1080/01431161.2013.813655.
- [154] B. Yonel, E. Mason, and B. Yazıcı, "Deep Learning for Passive Synthetic Aperture Radar," *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 90-103, 2018, doi: 10.1109/JSTSP.2017.2784181.
- [155] S. Chen and H. Wang, "SAR target recognition based on deep learning," *DSAA 2014 - Proceedings of the 2014 IEEE International Conference on Data Science and Advanced Analytics*, pp. 541-547, 03/10 2015, doi: 10.1109/DSAA.2014.7058124.
- [156] S. Soenen, "Deep Learning and SAR Applications: A short overview of advancements and challenges in earth observation applications." Medium. <https://towardsdatascience.com/deep-learning-and-sar-applications-81ba1a319def> (accessed 2019).
- [157] J. Aroma and K. Raimond, "An Overview of Technological Revolution in Satellite Image Analysis," *Journal of Engineering Science and Technology Review*, vol. 9, pp. 1-5, 10/17 2016, doi: 10.25103/jestr.094.01.
- [158] L. M. P. Sathya "Classification and Segmentation in Satellite imagery using Back propagation Algorithm of ANN and K-Means Algorithm " *International Journal of Machine Learning and Computing*, pp. 422-426, 2011.
- [159] P. Sathya and M. Lakshmanan, "Classification and Segmentation in Satellite Imagery Using Back Propagation Algorithm of ANN and K-Means Algorithm," *International Journal of Machine Learning and Computing*, pp. 422-426, 01/01 2011, doi: 10.7763/IJMLC.2011.V1.63.
- [160] K. Ap, "Greedy Algorithm Based Deep Learning Strategy for User Behavior Prediction and Decision Making Support," *Journal of Computer and Communications*, vol. 06, pp. 45-53, 01/01 2018, doi: 10.4236/jcc.2018.66004.
- [161] K. Abhishek, A. Kumar, R. Ranjan, and S. Kumar, *A rainfall prediction model using artificial neural network*. 2012, pp. 82-87.
- [162] J. Weaver, B. Moore, A. Reith, J. McKee, and D. Lunga, "A Comparison of Machine Learning Techniques to Extract Human Settlements from High Resolution Imagery," in *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, 22-27 July 2018 2018, pp. 6412-6415.
- [163] M. Punia, P. K. Joshi, and M. C. Porwal, "Decision tree classification of land use land cover for Delhi, India using IRS-P6 AWiFS data," *Expert Syst. Appl.*, vol. 38, pp. 5577-5583, 05/01 2011, doi: 10.1016/j.eswa.2010.10.078.
- [164] Z. Yang, F.-L. Chung, and W. Shitong, "Robust fuzzy clustering-based image segmentation," *Applied Soft Computing*, vol. 9, pp. 80-84, 01/31 2009, doi: 10.1016/j.asoc.2008.03.009.
- [165] M. Awad, "An Unsupervised Artificial Neural Network Method for Satellite Image Segmentation," *International Arab Journal of Information Technology*, vol. 7, pp. 199-205, 04/01 2010.
- [166] A. Ghosh, N. Mishra, and S. Ghosh, "Fuzzy clustering algorithms for unsupervised change detection in remote sensing images," *Information Sciences*, vol. 181, pp. 699-715, 02/15 2011, doi: 10.1016/j.ins.2010.10.016.
- [167] x. y. Wang, X.-J. Zhang, H.-Y. Yang, and J. Bu, "A pixel-based color image segmentation using support vector machine and fuzzy C-means," *Neural networks : the official journal of the International Neural Network Society*, vol. 33, pp. 148-59, 05/11 2012, doi: 10.1016/j.neunet.2012.04.012.
- [168] L. Castellana, A. D'Addabbo, and G. Pasquariello, "A composed supervised/unsupervised approach to improve change detection from remote sensing," *Pattern Recognition Letters*, vol. 28, pp. 405-413, 03/01 2007, doi: 10.1016/j.patrec.2006.08.010.
- [169] P. Mitra, B. U. Shankar, and S. Pal, "Segmentation of multispectral remote sensing images using active support vector machines," *Pattern Recognition Letters*, vol. 25, pp. 1067-1074, 07/01 2004, doi: 10.1016/j.patrec.2004.03.004.
- [170] M. Wirth, M. Fraschini, M. Masek, and M. Bruynooghe, "Performance Evaluation in Image Processing," *EURASIP Journal on Advances in Signal Processing*, vol. 2006, 01/01 2006, doi: 10.1155/ASP/2006/45742.

- [171] Y. J. Zhang, "Evaluation and comparison of different segmentation algorithms," *Pattern recognition letters*, vol. 18, no. 10, pp. 963-974, 1997.
- [172] M. D. Heath, S. Sarkar, T. Sanocki, and K. W. Bowyer, "A robust visual method for assessing the relative performance of edge-detection algorithms," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 12, pp. 1338-1359, 1997, doi: 10.1109/34.643893.
- [173] M. A. Wirth, "Performance evaluation of image processing algorithms in CADe," *Technology in cancer research & treatment*, vol. 4, no. 2, pp. 159-172, 2005.
- [174] F. G. Ortíz-Gómez, R. M. Rodríguez-Osorio, M. Salas-Natera, and S. Landeros-Ayala, "Adaptive resources allocation for flexible payload enabling VHTS systems: Methodology and architecture," in *36th International Communications Satellite Systems Conference (ICSSC 2018)*, 15-18 Oct. 2018 2018, pp. 1-8, doi: 10.1049/cp.2018.1694.
- [175] G. Giambene, S. Kota, and P. Pillai, "Satellite-5G Integration: A Network Perspective," *IEEE Network*, vol. 32, no. 5, pp. 25-31, 2018, doi: 10.1109/MNET.2018.1800037.
- [176] N. Pachler, J. J. G. Luis, M. Guerster, E. Crawley, and B. Cameron, "Allocating Power and Bandwidth in Multibeam Satellite Systems using Particle Swarm Optimization," in *2020 IEEE Aerospace Conference*, 7-14 March 2020 2020, pp. 1-11, doi: 10.1109/AERO47225.2020.9172694.
- [177] F. Ortíz-Gómez, D. Tarchi, R. Martínez, A. Vanelli-Coralli, M. Salas Natera, and S. Landeros-Ayala, "Convolutional Neural Networks for Flexible Payload Management in VHTS Systems," *IEEE Systems Journal*, vol. PP, 10/01 2020, doi: 10.1109/JSYST.2020.3020038.
- [178] A. Kyrgiazos, "Irregular beam sizes and non-uniform bandwidth allocation in HTS," 2013.
- [179] F. Ortíz-Gómez, R. Martínez, and S. Landeros-Ayala, *Method of Optimizing the Costs of a Satellite Network in Ka and Q/V Bands in the Feeder Link*. 2017.
- [180] P. V. R. Ferreira *et al.*, "Reinforcement Learning for Satellite Communications: From LEO to Deep Space Operations," *IEEE Communications Magazine*, vol. 57, no. 5, pp. 70-75, 2019, doi: 10.1109/MCOM.2019.1800796.
- [181] Z. Na, Z. Pan, X. Liu, Z. Deng, Z. Gao, and Q. Guo, "Distributed Routing Strategy Based on Machine Learning for LEO Satellite Network," *Wireless Communications and Mobile Computing*, vol. 2018, p. 3026405, 2018/06/14 2018, doi: 10.1155/2018/3026405.
- [182] S. Jaekel and B. Scholz, "Utilizing Artificial Intelligence to achieve a robust architecture for future robotic spacecraft," in *2015 IEEE Aerospace Conference*, 7-14 March 2015 2015, pp. 1-14, doi: 10.1109/AERO.2015.7119180.
- [183] Y. Gao and S. Chien, "Review on space robotics: Toward top-level science through space exploration," *Science Robotics*, vol. 2, no. 7, 2017.
- [184] F. Ingrand and M. Ghallab, "Deliberation for autonomous robots: A survey," *Artificial Intelligence*, vol. 247, 11/28 2014, doi: 10.1016/j.artint.2014.11.003.
- [185] C. Premebida, R. Ambrus, and Z. Marton, "Intelligent Robotic Perception Systems," 2018.
- [186] K. Yoshida, "Achievements in space robotics," *IEEE Robotics & Automation Magazine*, vol. 16, no. 4, pp. 20-28, 2009.
- [187] C. Cadena *et al.*, "Past, Present, and Future of Simultaneous Localization and Mapping: Toward the Robust-Perception Age," *IEEE Transactions on Robotics*, vol. 32, no. 6, pp. 1309-1332, 2016.
- [188] J. Fuentes-Pacheco, J. Ascencio, and J. Rendon-Mancha, "Visual Simultaneous Localization and Mapping: A Survey," *Artificial Intelligence Review*, vol. 43, 11/13 2015, doi: 10.1007/s10462-012-9365-8.
- [189] C. Stachniss, *Robotic Mapping and Exploration*. 2009.
- [190] C. Zhou, B. Huang, and P. Fránti, "A review of motion planning algorithms for intelligent robotics," *arXiv preprint arXiv:2102.02376*, 2021.
- [191] R. Smith and P. Cheeseman, "On the Representation and Estimation of Spatial Uncertainty," *The International Journal of Robotics Research*, vol. 5, 02/01 1987, doi: 10.1177/027836498600500404.
- [192] J. J. Leonard and H. F. Durrant-Whyte, "Mobile robot localization by tracking geometric beacons," *IEEE Transactions on Robotics and Automation*, vol. 7, no. 3, pp. 376-382, 1991.
- [193] A. R. Khairuddin, M. S. Talib, and H. Haron, "Review on simultaneous localization and mapping (SLAM)," in *2015 IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, 27-29 Nov. 2015 2015, pp. 85-90.
- [194] M. W. M. G. Dissanayake, P. Newman, S. Clark, H. F. Durrant-Whyte, and M. Csorba, "A solution to the simultaneous localization and map building (SLAM) problem," *IEEE Transactions on Robotics and Automation*, vol. 17, no. 3, pp. 229-241, 2001.
- [195] M. Montemerlo, S. Thrun, D. Koller, and B. Wegbreit, *FastSLAM: A Factored Solution to the Simultaneous Localization and Mapping Problem*. 2002.
- [196] M. Montemerlo, S. Thrun, D. Koller, and B. Wegbreit, "FastSLAM 2.0: An Improved Particle Filtering Algorithm for Simultaneous Localization and Mapping that Provably Converges," *Proc. IJCAI Int. Joint Conf. Artif. Intell.*, 06/25 2003.
- [197] F. Dellaert and M. Kaess, "Square Root SAM: Simultaneous Localization and Mapping via Square Root Information Smoothing," *I. J. Robotic Res.*, vol. 25, pp. 1181-1203, 12/01 2006, doi: 10.1177/0278364906072768.
- [198] C. Kim, R. Sakhivel, and W. K. Chung, "Unscented FastSLAM: A Robust Algorithm for the Simultaneous Localization and Mapping Problem," in *Proceedings 2007 IEEE International Conference on Robotics and Automation*, 10-14 April 2007 2007, pp. 2439-2445.
- [199] L. Moreno, S. Garrido, D. Blanco, and M. Muñoz, "Differential evolution solution to the SLAM problem," *Robotics and Autonomous Systems*, vol. 57, pp. 441-450, 04/01 2009, doi: 10.1016/j.robot.2008.05.005.
- [200] G. Mannarini, D. N. Subramani, P. F. J. Lermusiaux, and N. Pinaridi, "Graph-Search and Differential Equations for Time-Optimal Vessel Route Planning in Dynamic Ocean Waves," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 8, pp. 3581-3593, 2020, doi: 10.1109/TITS.2019.2935614.
- [201] P. C. Chen and Y. K. Hwang, "SANDROS: a dynamic graph search algorithm for motion planning," *IEEE Transactions on Robotics and Automation*, vol. 14, no. 3, pp. 390-403, 1998, doi: 10.1109/70.678449.
- [202] S. M. LaValle and J. J. Kuffner Jr, "Randomized kinodynamic planning," *The international journal of robotics research*, vol. 20, no. 5, pp. 378-400, 2001.
- [203] O. Brook, T. Hasegawa, S. Lavalley, and T. Simeon, "Algorithms for planning and control of robot motions [TC Spotlight]," *IEEE Robotics & Automation Magazine*, vol. 16, no. 1, pp. 14-15, 2009, doi: 10.1109/MRA.2009.932129.
- [204] Z. Yi, N. Liu, and C. Jun, "Stacking robot interpolation algorithm research and application for irregular cigarette packs," in *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 25-26 March 2017 2017, pp. 1134-1138, doi: 10.1109/IAEAC.2017.8054190.
- [205] D. González, J. Pérez, R. Lattarulo, V. Milanés, and F. Nashashibi, "Continuous curvature planning with obstacle avoidance capabilities in urban scenarios," in *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 8-11 Oct. 2014 2014, pp. 1430-1435, doi: 10.1109/ITSC.2014.6957887.
- [206] N. Morales, J. Toledo, and L. Acosta, "Path planning using a multiclass support vector machine," *Applied Soft Computing*, vol. 43, pp. 498-509, 2016.
- [207] M. Everett, Y. F. Chen, and J. P. How, "Motion Planning Among Dynamic, Decision-Making Agents with Deep Reinforcement Learning," *arXiv e-prints*, p. arXiv: 1805.01956, 2018.
- [208] S. Song, X. Hu, J. Yu, L. Bai, and L. Chen, "Learning a deep motion planning model for autonomous driving," in *2018 IEEE Intelligent Vehicles Symposium (IV)*, 2018: IEEE, pp. 1137-1142.

- [209] M. Gómez, R. V. González, T. Martínez-Marín, D. Meziat, and S. Sánchez, "Optimal motion planning by reinforcement learning in autonomous mobile vehicles," *Robotica*, vol. 30, pp. 159 - 170, 2011.
- [210] E. S. Low, P. Ong, and K. C. Cheah, "Solving the optimal path planning of a mobile robot using improved Q-learning," *Robotics and Autonomous Systems*, vol. 115, pp. 143-161, 2019.
- [211] A. Khan, V. Kumar, and A. Ribeiro, "Graph policy gradients for large scale unlabeled motion planning with constraints," *arXiv preprint arXiv:1909.10704*, 2019.
- [212] S. You, M. Diao, L. Gao, F. Zhang, and H. Wang, "Target tracking strategy using deep deterministic policy gradient," *Applied Soft Computing*, vol. 95, p. 106490, 2020.
- [213] M. Maimone, Y. Cheng, and L. Matthies, "Two Years of Visual Odometry on the Mars Exploration Rovers," *J. Field Robotics*, vol. 24, pp. 169-186, 03/01 2007, doi: 10.1002/rob.20184.
- [214] D. Wolf and G. Sukhatme, "Mobile Robot Simultaneous Localization and Mapping in Dynamic Environments," *Auton. Robots*, vol. 19, pp. 53-65, 07/01 2005, doi: 10.1007/s10514-005-0606-4.
- [215] C.-C. Wang, C. Thorpe, M. Hebert, S. Thrun, and H. Durrant-Whyte, "Simultaneous Localization, Mapping and Moving Object Tracking," *I. J. Robotic Res.*, vol. 26, 09/01 2007, doi: 10.1177/0278364907081229.
- [216] R. Ambruş, N. Bore, J. Folkesson, and P. Jensfelt, "Meta-rooms: Building and maintaining long term spatial models in a dynamic world," in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 14-18 Sept. 2014 2014, pp. 1854-1861.
- [217] V. Krüger, D. Kragic, A. Ude, and C. Geib, "The meaning of action: A review on action recognition and mapping," *Advanced Robotics*, vol. 21, pp. 1473-1501, 09/01 2007, doi: 10.1163/156855307782148578.
- [218] S. Clark. "Space Station's Dextre Robot Passes Crucial Test." Space.com. <https://www.space.com/10554-space-station-dextre-robot-passes-crucial-test.html> (accessed 3/21/2021, 2021).
- [219] N. Sünderhauf *et al.*, "The Limits and Potentials of Deep Learning for Robotics," *The International Journal of Robotics Research*, vol. 37, 04/18 2018, doi: 10.1177/0278364918770733.
- [220] L. Pedersen, D. Kortenkamp, D. Wettergreen, and I. Nourbakhsh, "A Survey of Space Robotics," 11/06 2003.
- [221] Coleshill, L. Oshinowo, R. Rembala, B. Bina, D. Rey, and S. Sindelar, "Dextre: Improving maintenance operations on the International Space Station," *Acta Astronautica*, vol. 64, pp. 869-874, 05/01 2009, doi: 10.1016/j.actaastro.2008.11.011.
- [222] "2017 Space Launch Statistics." Spaceflight101. <https://spaceflight101.com/2017-space-launch-statistics/> (accessed).
- [223] S. Chien and R. Morris, "Space Applications of Artificial Intelligence," *Ai Magazine*, vol. 35, pp. 3-6, 12/01 2014, doi: 10.1609/aimag.v35i4.2551.
- [224] J. Bresina, A. Jonsson, P. Morris, and K. Rajan, *Activity Planning for the Mars Exploration Rovers*. 2005, pp. 40-49.
- [225] W. Xu, B. Liang, D. Gao, and Y. Xu, "A space robotic system used for on-orbit servicing in the Geostationary Orbit," in *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 18-22 Oct. 2010 2010, pp. 4089-4094.
- [226] J. H. Saleh, E. Lamassoure, and D. E. Hastings, "Space Systems Flexibility Provided by On-Orbit Servicing: Part 1," *Journal of Spacecraft and Rockets*, vol. 39, no. 4, pp. 551-560, 2002/07/01 2002, doi: 10.2514/2.3844.
- [227] D. Brugali and E. Prassler, "Software engineering for robotics [From the Guest Editors]," *Robotics & Automation Magazine, IEEE*, vol. 16, pp. 9-15, 04/01 2009, doi: 10.1109/MRA.2009.932127.
- [228] M. Quigley *et al.*, *ROS: an open-source Robot Operating System*. 2009.
- [229] N. Hawes *et al.*, "The STRANDS Project: Long-Term Autonomy in Everyday Environments," *IEEE Robotics & Automation Magazine*, vol. 24, no. 3, pp. 146-156, 2017.
- [230] M. Cashmore *et al.*, "Rosplan: Planning in the robot operating system," *Proceedings International Conference on Automated Planning and Scheduling, ICAPS*, vol. 2015, pp. 333-341, 01/01 2015.
- [231] M. Beetz, F. Bálint-Benczédi, N. Blodow, D. Nyga, T. Wiedemeyer, and Z. Márton, "RoboSherlock: Unstructured information processing for robot perception," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, 26-30 May 2015 2015, pp. 1549-1556.
- [232] P. Wadhvani and P. Saha. "Space Robotics Market Size By Solution (Product [Rovers/Landers, Probes, Arms/Manipulator Systems], Software, Services), By Application (Deep Space [Space Exploration, Space Transportation], Near Space [Space Exploration, Space Transportation]), By End-Use (Commercial, Government), Industry Analysis Report, Regional Outlook, Application Potential, Price Trend, Competitive Market Share & Forecast, 2019 - 2025." Global Market Insights. <https://www.gminsights.com/industry-analysis/space-robotics-market> (accessed March 22, 2021, 2021).
- [233] K. Wagstaff and B. Bornstein, "HOW MUCH MEMORY RADIATION PROTECTION DO ONBOARD MACHINE LEARNING ALGORITHMS REQUIRE?," 01/01 2009.
- [234] F. Gieseke, G. Moruz, and J. Vahrenhold, "Resilient K-d Trees: K-Means in Space Revisited," in *2010 IEEE International Conference on Data Mining*, 13-17 Dec. 2010 2010, pp. 815-820, doi: 10.1109/ICDM.2010.94.
- [235] D. Cassel. "The Hardware and Software Used in Space." The New Stack. <https://thenewstack.io/the-hardware-and-software-used-in-space/> (accessed 19th April, 2021, 2021).
- [236] Military & Aerospace Electronics. "Radiation-Hardened Space Electronics Enter the Multi-Core Era." Endeavor Business Media LLC. <https://www.militaryaerospace.com/computers/article/16709760/radiationhardened-space-electronics-enter-the-multicore-era> (accessed March 22, 2021, 2021).
- [237] S. Abdelghafar, A. Darwish, and A. E. Hassanien, "Intelligent Health Monitoring Systems for Space Missions Based on Data Mining Techniques," *Machine Learning and Data Mining in Aerospace Technology*, p. 65.
- [238] G. I. Sayed, A. Darwish, and A. E. Hassanien, "A new chaotic whale optimization algorithm for features selection," *Journal of classification*, vol. 35, no. 2, pp. 300-344, 2018.
- [239] A. Darwish, A. E. Hassanien, and S. Das, "A survey of swarm and evolutionary computing approaches for deep learning," *Artificial Intelligence Review*, vol. 53, no. 3, pp. 1767-1812, 2020.
- [240] G. I. Sayed, A. Darwish, and A. E. Hassanien, "Quantum multiverse optimization algorithm for optimization problems," *Neural Computing and Applications*, pp. 1-18, 2019.
- [241] A. Bendale and T. E. Boulton, "Towards Open Set Deep Networks," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 27-30 June 2016 2016, pp. 1563-1572, doi: 10.1109/CVPR.2016.173.
- [242] P. Battaglia, J. Hamrick, and J. Tenenbaum, "Simulation as an engine of physical scene understanding," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 110, 10/21 2013, doi: 10.1073/pnas.1306572110.
- [243] W. J. Scheirer, A. d. R. Rocha, A. Sapkota, and T. E. Boulton, "Toward Open Set Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 7, pp. 1757-1772, 2013, doi: 10.1109/TPAMI.2012.256.
- [244] A. Nguyen, J. Yosinski, and J. Clune, "Deep neural networks are easily fooled: High confidence predictions for unrecognizable images," in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 7-12 June 2015 2015, pp. 427-436, doi: 10.1109/CVPR.2015.7298640.
- [245] G. Gal, C. Santos, L. Rapp, R. e. Markovich, and L. v. d. Torre, "Artificial intelligence in space," *ArXiv*, vol. abs/2006.12362, 2020.
- [246] E. Bird, J. Fox-Skelly, N. Jenner, R. Larbey, E. Weitkamp, and A. Winfield, "The ethics of artificial intelligence: Issues and initiatives," *European Parliamentary Research Service*, 2020.
- [247] L. B. Solum, "Legal personhood for artificial intelligences," *NCL Rev.*, vol. 70, p. 1231, 1991.

- [248] G. A. Gal, C. Santos, L. Rapp, R. Markovich, and L. van der Torre, "Artificial intelligence in space," *arXiv preprint arXiv:2006.12362*, 2020.
- [249] T. C. King, N. Aggarwal, M. Taddeo, and L. Floridi, "Artificial intelligence crime: An interdisciplinary analysis of foreseeable threats and solutions," *Science and engineering ethics*, vol. 26, no. 1, pp. 89-120, 2020.
- [250] R. Williams, "Lords select committee, artificial intelligence committee, written evidence (AIC0206)," ed, 2018.
- [251] M. Stankovic, R. Gupta, B. Rossert, G. Myers, and M. Nicoli, "Exploring Legal, Ethical and Policy Implications of Artificial Intelligence," 09/01 2017.
- [252] N. J. S. John P. Carlin, Charles L. Capito, Joseph A. Benkert, Panagiotis C. Bayz, Amy S. Josselyn and Jonathan M. Babcock, "U.S. Department of Commerce Imposes Immediate Export Controls on Artificial Intelligence Software Used to Automatically Detect and Identify Objects Remotely," *The Journal of Robotics, Artificial Intelligence & Law*, vol. 3, no. 4, 2020. [Online]. Available: <https://media2.mofo.com/documents/2007-carlin-journal-robotics-ai-law.pdf>.
- [253] R. L. Finn, D. Wright, and M. Friedewald, "Seven types of privacy," in *European data protection: coming of age*: Springer, 2013, pp. 3-32.
- [254] G. Popkin, "Technology and satellite companies open up a world of data," *Nature*, vol. 557, no. 7706, pp. 745-748, 2018.
- [255] Y. Duan, J. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of Big Data - evolution, challenges and research agenda," *Int. J. Inf. Manag.*, vol. 48, pp. 63-71, 2019.
- [256] Y. K. Dwivedi *et al.*, "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," *International Journal of Information Management*, vol. 57, p. 101994, 2021/04/01/ 2021, doi: <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>.
- [257] T. N. Dinh and M. T. Thai, "Ai and blockchain: A disruptive integration," *Computer*, vol. 51, no. 9, pp. 48-53, 2018.
- [258] J. D. Harris and B. Waggoner, "Decentralized and Collaborative AI on Blockchain," in *2019 IEEE International Conference on Blockchain (Blockchain)*, 14-17 July 2019 2019, pp. 368-375, doi: 10.1109/Blockchain.2019.00057.
- [259] A. Kak and I. F. Akyildiz, "Large-Scale Constellation Design for the Internet of Space Things/CubeSats," in *2019 IEEE Globecom Workshops (GC Wkshps)*, 9-13 Dec. 2019 2019, pp. 1-6, doi: 10.1109/GCWkshps45667.2019.9024594.
- [260] I. F. Akyildiz and A. Kak, "The Internet of Space Things/CubeSats," *IEEE Network*, vol. 33, no. 5, pp. 212-218, 2019, doi: 10.1109/MNET.2019.1800445.
- [261] K. Woellert, P. Ehrenfreund, A. J. Ricco, and H. Hertzfeld, "Cubesats: Cost-effective science and technology platforms for emerging and developing nations," *Advances in Space Research*, vol. 47, no. 4, pp. 663-684, 2011.
- [262] D. Zeebaree, "Management of Wireless Communication Systems Using Artificial Intelligence-Based Software Defined Radio," 08/16 2020.
- [263] N. Saeed, M.-S. Alouini, and T. Y. Al-Naffouri, "Towards the Internet of X-things: New Possibilities for Underwater, Underground, and Outer Space Exploration," *arXiv*, p. arXiv:1903.11996, 2019.
- [264] N. Saeed, A. Elzanaty, H. Almorad, H. Dahrouj, T. Al-Naffouri, and M.-S. Alouini, "CubeSat Communications: Recent Advances and Future Challenges," *ArXiv*, vol. abs/1908.09501, 2019.
- [265] S. O'NEAL, "Houston, We Have a Solution: Blockchain in the Space Industry," August, 06, 2018. [Online]. Available: <https://cointelegraph.com/news/here-is-how-blockchain-will-help-to-explore-space>
- [266] M. Torky, T. Gaber, and A. E. Hassanien, *Blockchain in Space Industry: Challenges and Solutions*. 2020.
- [267] I. Kassabalidis, M. A. El-Sharkawi, R. J. Marks, P. Arabshahi, and A. A. Gray, "Swarm intelligence for routing in communication networks," in *GLOBECOM'01. IEEE Global Telecommunications Conference (Cat. No.01CH37270)*, 25-29 Nov. 2001 2001, vol. 6, pp. 3613-3617 vol.6, doi: 10.1109/GLOCOM.2001.966355.
- [268] S. Sowmya and P. D. S. K. Malarchelvi, "A survey of jamming attack prevention techniques in wireless networks," ed.
- [269] X. Ronghua, C. Yu, B. Erik, and C. Genshe, "Exploration of blockchain-enabled decentralized capability-based access control strategy for space situation awareness," *Optical Engineering*, vol. 58, no. 4, pp. 1-16, 2/1 2019, doi: 10.1117/1.OE.58.4.041609.
- [270] D. Hyland-Wood, P. Robinson, R. Saltini, S. Johnson, and C. Hare, *Methods for Securing Spacecraft Tasking and Control via an Enterprise Ethereum Blockchain*. 2019.