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Artificial intelligence-powered space systems including launch, space, ground and user segments: Current status and future challenges

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A R T I C L E   I N F O

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A B S T R A C T

The integration of artificial intelligence (AI) technologies across all segments of space systems, including the launch, space, ground, and user segments, holds immense potential to revolutionize space exploration, satellite operations, and communication networks. This paper presents a comprehensive overview of AI-powered systems in each segment, highlighting their key functionalities, benefits, and challenges. In the launch segment, AI algorithms can optimize launch vehicle trajectories, predict launch conditions, and facilitate the safety of space missions. Machine learning techniques can enable real-time decision-making and autonomous control during launch operations, improving launch success rates and reducing costs. Within space segment, AI-powered satellites can have enhanced capabilities in autonomous navigation, attitude control, and mission planning. These systems leverage AI algorithms to analyze sensor data, detect anomalies, and autonomously adapt to dynamic space environments, increasing mission resilience and flexibility. In the ground segment, AI-powered systems can facilitate satellite operations, data processing, and communication management. Intelligent ground stations utilize machine learning algorithms to optimize antenna pointing, schedule satellite contacts, and process large volumes of satellite data efficiently, enabling faster and more reliable communication services. Finally, in the user segment, AI technologies can enhance the user experience and enable innovative applications in space science, earth observation, and satellite-based services. AI-powered data analytics platforms can provide users with actionable insights from satellite imagery, sensor data, and telemetry, enabling informed decision-making and driving advancements in various domains. Despite the significant benefits offered by AI-powered systems across all segments, challenges such as data quality, algorithm robustness, and ethical considerations remain critical areas for further research and development. Addressing these challenges will be essential to fully harnessing the potential of AI in advancing space exploration, satellite operations, and space-based applications. Through research findings, and technological advancements, this paper aims to provide insights into the current state-of-the-art and future prospects of AI-powered systems in space, paving the way for continued innovation in space exploration.

1. Introduction

The integration of artificial intelligence (AI) technologies [1–5] across all segments of space systems, including the launch, space, ground, and user segments, holds immense potential to revolutionize space exploration, satellite operations, and communication networks [6–17]. Recently, this research area has been one of the most active research areas worldwide. Several survey papers have been published on this subject [6–17]. In all this research, AI models include artificial neural networks (ANNs), recurrent neural networks (RNNs), long short-term memory (LSTM), and convolution neural networks (CNNs), as well as their combinations, known as hybrid models (Fig. 1). A variety of AI/machine learning (ML) methods, as listed in Fig. 2, have been applied. In this paper, a comprehensive review is carried out with a focus on the AI applications to all the segments of space systems.

The paper is organized as follows: Section 2 presents the applications

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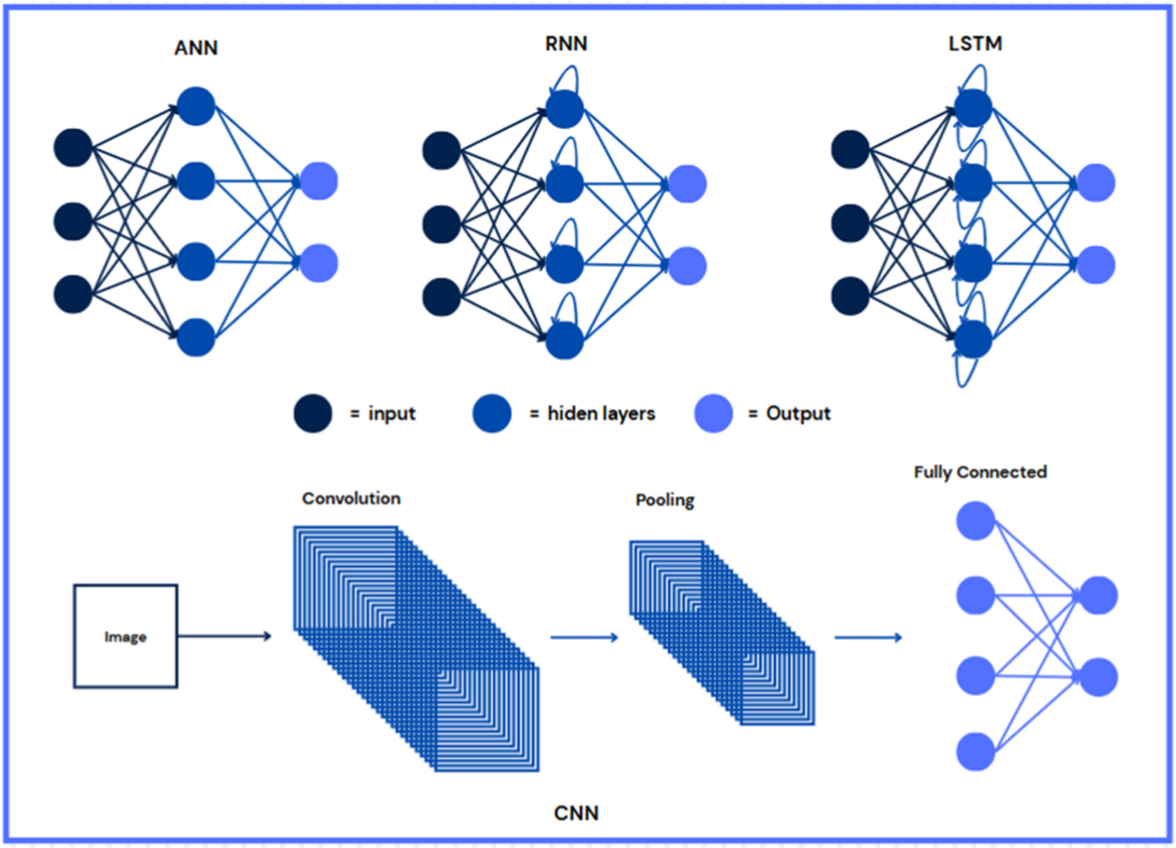

Fig. 1. Architecture of artificial intelligence models: Artificial neural network (ANN), recurrent neural network (RNN), long short-term memory (LSTM), and convolutional neural network (CNN).

of AI in the launch segment, followed by a discussion of AI applications in the space segment in Section 3. Sections 4 and 5 cover the applications of AI in the ground and user segments, respectively. The challenges associated with AI applications are discussed in Section 6, followed by concluding remarks in Section 7.

2. Launch segment

In this segment, AI algorithms play an integral role in optimizing launch vehicle trajectories, predicting launch conditions, and ensuring the safety and efficiency of space missions [18–28]. Machine learning (ML) techniques facilitate real-time decision-making and autonomous control during launch operations, thereby improving success rates and reducing costs, as summarized in Table 1. The details of AI applications (listed in Fig. 3) are as follows.

2.1. Launch vehicle design & manufacturing

Goyal et al. [18] highlighted that AI can be applied to optimize launch vehicle design, focusing on structures, mechanisms, materials, avionics, batteries, engines, thermal, and mass properties. Three case studies: Anomaly Detection in Propulsion Systems, Damage Detection in Large-Scale Structures, and Data Analytics Suite for Launch Telemetry Assessment, were presented to demonstrate the efficacy of AI-enabled launch vehicle design. Artificial intelligent rockets, such as the Epsilon launcher, can also reduce launch costs [19,20]. Additive manufacturing (3D printing) is being proposed for integration with AI-based design tools to enable rapid adjustments for optimized performance, thereby transforming the production of complex rocket components such as rocket engines [21]. These advancements demonstrate how AI-based solutions not only streamline design iterations but also enable real-time adaptability during the manufacturing process, resulting in increased efficiency and reduced costs. AI-driven simulations further predict stress points and potential design flaws, allowing for better material selection and improving launch vehicle durability.

2.2. Optimization of launch vehicle trajectories

AI algorithms can optimize launch vehicle trajectories by analyzing vast amounts of data to find the most efficient paths while considering factors such as weather conditions, payload characteristics, and orbital mechanics. This optimization process reduces fuel consumption, minimizes risks, and increases overall mission success rates. Sánchez-Sánchez and Izzo [22] proposed a deep learning-based approach where deep neural networks approximate the solution of optimal control problems. Their method, trained offline using data from pseudospectral optimization, is capable of real-time evaluation onboard for landing trajectory optimization, showing significant reduction in inference time compared to traditional solvers. Bataleblu and Roshanian [23] addressed the robust optimization of ascent trajectories under uncertainties using computational intelligence methods, particularly evolutionary algorithms. Their results demonstrated improved robustness in the presence of modeling errors and environmental disturbances compared to conventional techniques. The reinforcement learning-based orbital flight phase optimization was proposed by Tian et al. [24]. The suggested approach resulted in increased efficiency in multistage launch operations. Zhou et al. [25] introduced a fast trajectory optimization framework for reusable launch vehicles using a combination of analytical guidance and an adaptive-noise maximum entropy reinforcement learning algorithm. Their hybrid approach effectively balances solution optimality and convergence speed, particularly in high-dimensional launch vehicle dynamics. Malyuta et al. [26] provided

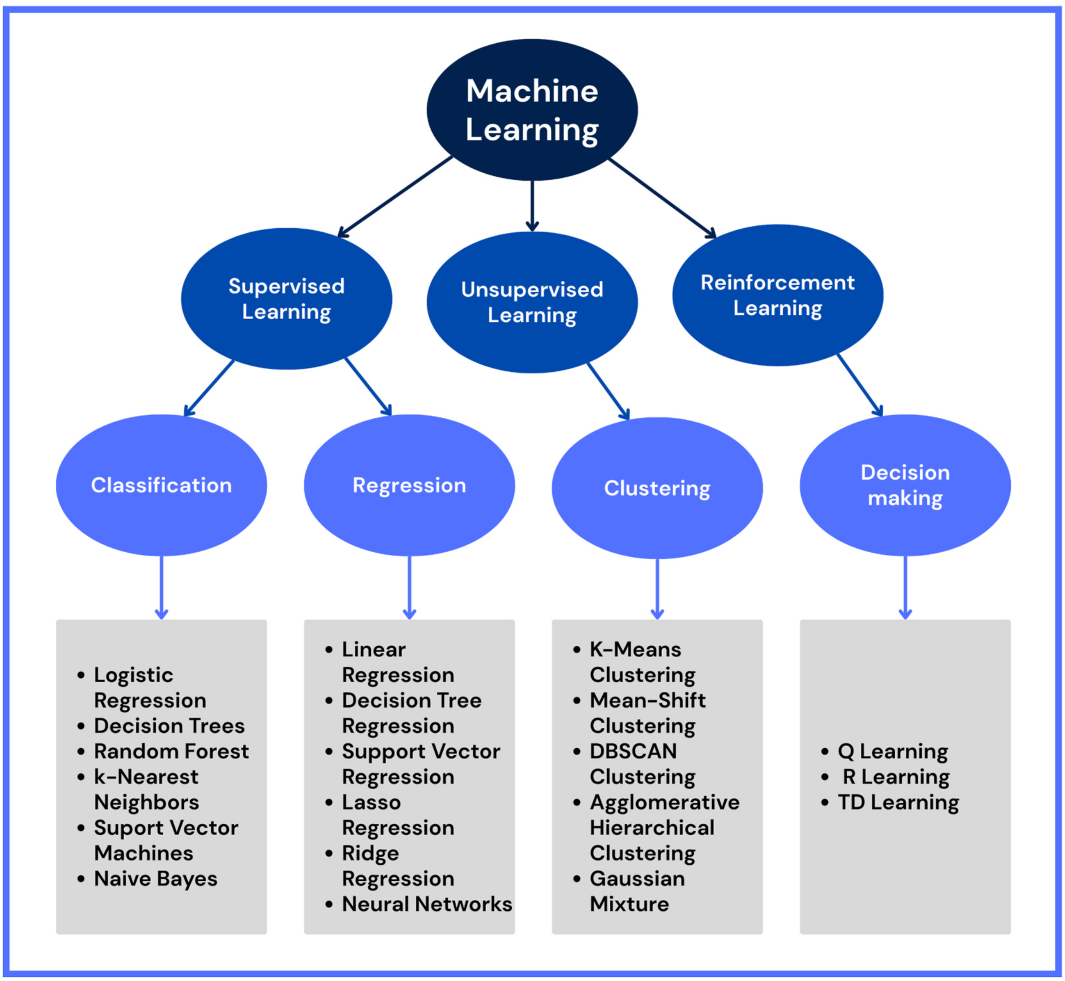

Fig. 2. Machine learning methods.

Table 1
Applications of artificial intelligence in the launch segment.

Application	AI Method	Results
Launch Vehicle Design & Manufacturing	Goyal et al. [18]: Neural networks for launch vehicle design. AI-driven additive manufacturing [19–21]	Optimized design, reduced costs, and real-time adaptability [19–21]: I mproved material selection and launch vehicle durability.
Optimization of Launch Vehicle Trajectories	Deep learning (DNNs), RL, evolutionary algorithms, hybrid methods [22–26]	Real-time trajectory optimization, increased fuel efficiency, and improved robustness.
Real-Time Decision-Making and Autonomous Control	ML-based monitoring, anomaly detection, autonomous sequencing, DNN guidance [27–30]	Enhanced launch precision, autonomous valve control, anomaly detection, and reduced human intervention.
Predictive Maintenance	Alvord et al. [31]: Physics-based and data-driven predictive maintenance models.	Scheduled maintenance, reduced cost, and enhanced vehicle reliability.
Re-entry and Recovery	Xue et al. [32]: Self-learning control with NAS and reinforcement learning (RL). Xu et al. [33]: Neural network predictor-corrector guidance for re-entry. Shen et al. [34]: Neural network integrated with convex optimization. Xue et al. [35]: Deep RL-based intelligent flight control for landings.	Successful handling of wind field interference and model deviations, and improved recovery adaptability. Reduced computational time, enhanced aerodynamic parameter identification, and precise control. Met computational efficiency and solution accuracy for real-time implementation. Met accuracy requirements for safe and precise landings.
Engine Control	Waxenegger-Wilfing et al. [36]: RL for transient control of liquid rocket engines. Dresia et al. [37]: Neural network-based nonlinear control of expander-bleed engines.	Real-time closed-loop control with high interaction frequency, and optimized engine start-up phase. Improved tracking response, minimized overshoots, and enhanced operational performance.

a comprehensive survey of recent advancements in trajectory optimization techniques, including direct methods, sampling-based methods, and learning-augmented optimization. Their work highlights the growing trend toward combining traditional optimal control with learning-based techniques for real-time, onboard guidance and control of launch vehicles.

2.3. Real-time decision-making and autonomous control

During launch operations, machine learning (ML) techniques enable real-time decision-making and autonomous control, where AI systems monitor critical parameters such as altitude, velocity, and fuel efficiency [27]. These systems detect anomalies and make instant adjustments, enhancing launch precision and reducing the need for human intervention. Toro Medina and Kim [28] described the Autonomous Operations System (AOS) for cryogenic propellant loading, where real-time decision-making uses the Redline Monitoring and NASA Library modules to analyze telemetry from tank levels and valve states, detecting anomalies like valve failures, while the Automated Control Sequencer autonomously adjusts valves during chilldown or loading to ensure precise fuel management. Powell [29] proposed an automation architecture for ground and ascent phases, with real-time decision-making processing telemetry for velocity, altitude, and fuel efficiency to identify anomalies like engine issues, and autonomous control adjusting propellant flow or thrust for optimal performance. Federici et al. [30] applied a deep neural network for autonomous spacecraft guidance during proximity operations, such as orbital rendezvous, using real-time decision-making to monitor relative position, velocity, and fuel consumption, detect trajectory errors, and autonomously adjust thrusters for precise orbits. Together, these studies show how real-time decision-making drives autonomous control across launch phases, enhancing mission reliability.

2.4. Predictive maintenance

AI-powered systems are revolutionizing predictive maintenance for reusable launch vehicles (RLVs) by monitoring vehicle health in real time and predicting potential failures before they occur [18]. This proactive maintenance approach minimizes the risk of launch delays or failures, ensuring efficient and reliable operations. Alvord et al. [31] demonstrated how the application of predictive maintenance capabilities to RLVs transforms unscheduled maintenance into scheduled maintenance, helping to reduce both cost and manpower requirements. By correlating physics-based models with data-driven models, the system captures new information from operational data and provides insights into risk reduction, improving overall vehicle reliability. Finally, the AI-powered predictive maintenance improves overall system reliability.

2.5. Re-entry and recovery

AI can play an important role in enabling reusable launch vehicle (RLV) re-entry and recovery using advanced algorithms such as neural networks and reinforcement learning (RL) (as illustrated in Table 1), for optimizing the re-entry trajectory and ensuring that launch vehicles land safely and efficiently after completing their missions [32–34]. Recent developments in re-entry guidance have demonstrated the effectiveness of hybrid control strategies that combine machine learning with traditional optimization methods [35]. The details are as follows.

2.5.1. Self-learning control method for launch vehicle recovery

Xue et al. [32] proposed a self-learning control method for the vertical recovery of RLVs using neural network architecture search (NAS) and Bayesian hyperparameter optimization. This approach decouples deep network structure search and reinforcement learning hyperparameter optimization, enabling the system to adapt dynamically during the vehicle's re-entry phase. The control network demonstrated high adaptability in the simulation environment, successfully handling wind field interference and model parameter deviations. The trained network improved the generalization ability and met real-time deployment capabilities for launch vehicle recovery.

2.5.2. Neural network-based Reentry guidance for reusable launch vehicles

Xu et al. [33] introduced a neural network predictor-corrector guidance method for RLV re-entry, which uses a combination of sample dimensionality reduction, Newton-Raphson iterative correctors, and Extended Kalman Filters (EKF) to enhance aerodynamic parameter identification in real-time. The proposed method reduced computational time and improved the real-time performance of the guidance system, allowing for precise re-entry control. Shen [34] introduced a real-time powered descent guidance approach that integrates neural networks with convex optimization. In this method, the neural network is trained offline to approximate the control policy, while convex optimization is employed online to ensure constraint satisfaction and robustness. This hybrid framework achieves a balance between computational efficiency and solution accuracy, making it highly suitable for real-time re-entry and landing scenarios involving reusable launch vehicles.

Fig. 3. Artificial intelligence applications in launch segment.

2.5.3. *Intelligent control for launch vehicle landing*

In a related study, Xue et al. [35] developed a new intelligent flight control method for rocket landings based on deep reinforcement learning (RL), which integrates knowledge-based models and data-driven learning. The approach incorporates Markov decision processes, LSTM networks, and imitation learning to improve landing precision and control robustness. The proposed method has successfully met the accuracy requirements for rocket landing, generating real-time control instructions that ensure safe and precise landings.

While several AI-based re-entry guidance and landing algorithms have shown encouraging results in simulation environments, few have reached real-world operational deployment. Future studies should bridge this gap by focusing on testing, certification, and integration with mission-grade avionics. In addition, thermal protection remains a critical component of re-entry systems. The integration of both robust AI systems and effective thermal protection strategies is essential for the

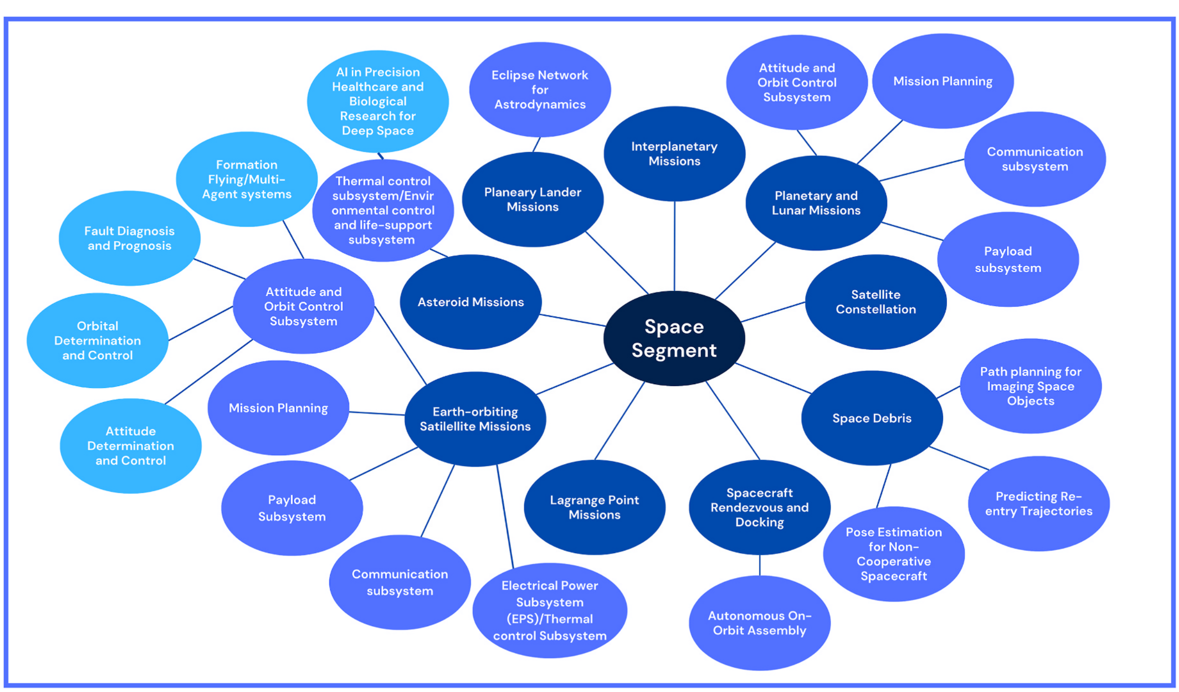

Fig. 4. Artificial intelligence applications in space segment.

safe and efficient operation of RLVs.

2.6. Engine control

In the realm of liquid rocket engine control, reinforcement learning (RL) offers promising advancements in optimizing engine performance during critical phases such as start-up and shutdown.

2.6.1. Transient control of liquid rocket engines

Waxenegger-Wilfing et al. [36] studied a deep reinforcement learning approach to optimize the transient start-up phase of a gas-generator liquid rocket engine. While RL offers real-time control advantages, the method faces challenges regarding stability guarantees. The system achieved high interaction frequency, with control actions predicted in 0.7 ms, allowing for real-time closed-loop control. Compared to Model Predictive Control (MPC), the RL-based system has demonstrated superior real-time performance [33,36].

2.6.2. Nonlinear control of expander-bleed engines

Dresia et al. [37] investigated closed-loop control of the LUMEN expander-bleed engine using reinforcement learning and neural networks. This method is integrated into a transient simulation environment to improve engine performance during operation. The proposed neural network controller provided faster tracking responses compared to open-loop sequences, avoiding overshoots that could potentially damage the engine.

2.7. Summary and emerging trends

AI is significantly improving the launch segment by enabling efficient launcher design and manufacturing, trajectory optimization, and autonomous launch operations. AI-driven launch vehicle design and manufacturing integrate machine learning with additive manufacturing to optimize structures, propulsion, and materials. Deep neural networks, evolutionary algorithms, and reinforcement learning are increasingly used for trajectory optimization, providing fuel-efficient, trajectories even under uncertain conditions. During launch, real-time decision-making and predictive maintenance systems monitor telemetry, detect anomalies, and anticipate component failures—enhancing the reliability of launch vehicles and reusable launch vehicles (RLVs). Advanced re-entry and recovery algorithms, including self-learning controllers and hybrid AI-models, enable precision landings. Furthermore, reinforcement learning–based engine control ensures efficient engine operations during critical phases such as start-up and shutdown. Emerging trends highlight the growing use of hybrid AI frameworks, digital twins, and reinforcement learning–based optimization for adaptive trajectory planning, autonomous fault recovery, and intelligent launch operations. Overall, these developments are driving advancements toward autonomous launch systems, where AI enhances every phase—from design, manufacturing, and trajectory planning to in-flight control and post-launch recovery.

3. Space segment

In this segment, AI applications are grouped into nine categories (Fig. 4), with a summary presented in Table 2, as follows.

3.1. Earth-orbiting (EO) satellite missions

AI enhances the EO satellite missions by optimizing satellite operations, such as autonomous station-keeping and fault management [38]. The details are as follows.

3.1.1. Mission planning

Sherwood et al. [39] discussed the use of machine learning and pattern recognition to enhance mission capabilities. The goal is to increase scientific returns by enabling intelligent downlink selection and autonomous retargeting of satellite sensors. This approach allows for more efficient decision-making during space missions, enhancing the overall performance of the system. Mark et al. [40] examined the next generation of space processors for onboard processing of advanced AI/ML algorithms, especially deep learning algorithms; these include various combinations of CPUs, GPUs, FPGAs, and purpose-built ASICs. A reference architecture is defined, and the services required for the development and deployment, and hardware evaluation of AI/ML applications are presented.

3.1.2. Payload subsystem

In 2020, the European Space Agency (ESA) launched a mission that used ϕ-sat-1, which employs a convolutional neural network to determine cloud coverage [41–43]. This system (refer to Fig. 5) would discard any cloudy images to avoid downlinking unusable images. The ESA is currently working on the ϕ-sat-2 mission, which will explore the capabilities of onboard processing with artificial intelligence [44]. This mission has six applications that use AI. As illustrated in Table 2, the satellite can turn images into maps, identify clouds, classify the clouds, detect and classify vessels, compress the images, and find anomalies in wildfires and marine ecosystems. One significant advancement is that new AI applications can be developed, installed, and operated on the

Table 2
Applications of artificial intelligence in the space segment.

Application	AI Method	Results
Earth-Orbiting (EO) Satellite Missions	Sherwood et al. [39]: Machine learning and pattern recognition for mission planning. ESA [41–44]: Convolutional neural networks (CNNs) for onboard processing and cloud classification.	Sherwood et al. [39]: Increased scientific returns, enabled intelligent downlink selection and autonomous sensor retargeting, and improved decision-making during missions.ESA [41–44]: Automated filtering of cloud-obscured images, and improved efficiency in downlinking useable satellite data.
Attitude and Orbit Control Subsystem (AOCS)	Lim et al. [46]: Markov neural network and temporal neural network for guidance and navigation. Zheng et al. [47]: Feedforward neural networks with state transition matrices. Zou et al. [51–54]: Chebyshev neural networks for attitude control. Muthusamy and Kumar [67, 68]: Chebyshev neural networks and genetic algorithms for failure prognosis.	Lim et al. [46]: Improved accuracy in system identification and efficiency in orbital control, especially for parabolic and hyperbolic orbits.Zheng et al. [47]: High accuracy and computational efficiency in orbit determination and control.Zou et al. [51–54]: Improved precision and robustness in satellite control under unknown mass moments and disturbances. Muthusamy and Kumar [67, 68]: Achieved 93.5 % success in fault isolation, with predictions for remaining useful life (RUL) accuracy of 96.25 %.
Propulsion Subsystem	Zheng et al. [47]: Neural networks for optimizing propulsion systems.	Improved fuel efficiency, thrust balance, and mission duration.
Payload Subsystem	ESA [41–44]: ϕ-Sat-1 and ϕ-Sat-2 missions using CNNs for onboard AI processing.	Cloud classification, anomaly detection, and onboard wildfire monitoring with real-time adaptability in AI applications.
Thermal Control Subsystem	Petković et al. [74]: Machine learning for thermal power consumption prediction in spacecraft.	Enhanced durability and reliability in environmental control and life-support systems.

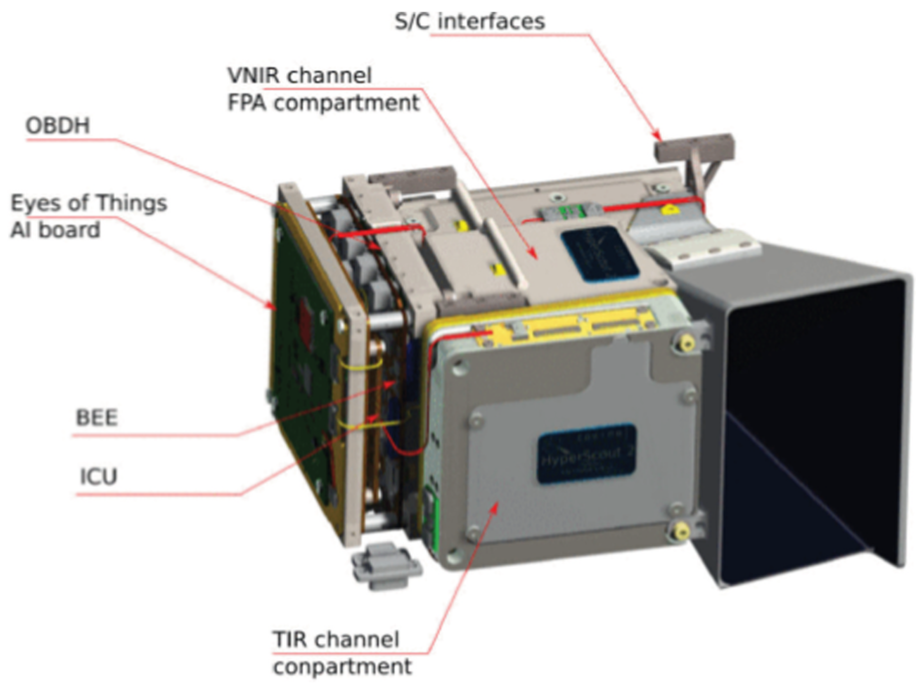

Fig. 5. HyperScout 2 and EoT (Eyes of Things) assembled [42].

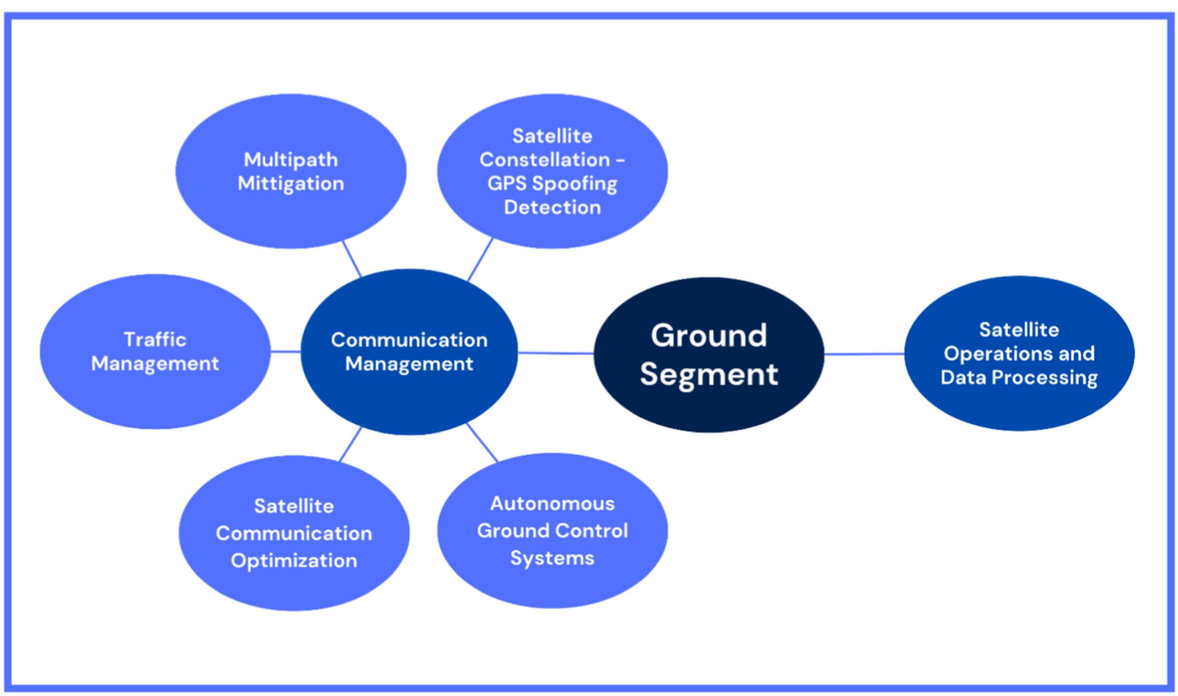

Fig. 6. Artificial intelligence applications in ground segment.

ϕ-sat-2 satellite while it is in orbit. Similarly, Mouerer et al.'s work [45] on the SONATE2 satellite focuses on autonomous decision-making and self-reconfiguration, further highlighting the importance of onboard AI for efficient data processing in space missions. The SONATE2 satellite exemplifies how satellites equipped with AI can handle complex tasks such as anomaly detection and resource optimization without requiring constant ground control.

3.1.3. Attitude and orbit control subsystem (AOCS)

3.1.3.1. Orbit determination & control. Lim et al. [46] proposed a Markov neural network and a temporal neural network for guidance, navigation and control design. Their network showed results that were more accurate in system identification than conventional approaches. Zheng et al. [47] describes a way of deriving an analytic solution for true anomaly using a feedforward neural network with a state transition matrix. The results demonstrate that the developed state transition matrix achieves high accuracy while maintaining computational efficiency. Furthermore, the proposed method can also be adapted for use with parabolic and hyperbolic orbits. Although AI-based methods for orbit determination have shown improved accuracy in simulations, they have not consistently outperformed classical algorithms in operational missions. Nevertheless, there is considerable potential for AI applications in autonomous orbit control for distributed satellite systems.

3.1.3.2. Attitude determination & control. In satellite attitude control, artificial intelligence techniques have been shown to improve control accuracy, robustness, and adaptability under uncertain conditions, mostly in computer simulations and some proof-of-concept demonstrations in space missions. MacKunis et al. [48] introduced an adaptive neural network (NN)-based satellite attitude control method to mitigate uncertainties caused by Control Moment Gyroscopes (CMG) failures. This adaptive approach improves performance by adjusting in real time to unexpected variations in satellite dynamics, thus enhancing satellite stability during critical operations. Yao [49] proposed a neural adaptive attitude tracking controller for spacecraft with prescribed performance guarantees. His method focuses on handling spacecraft inertia uncertainty using NN models, with validation through simulations that highlight superior performance in attitude tracking control under complex scenarios. Lungu et al. [50] utilized dynamic inversion and feed-forward neural networks for double-gimbal magnetically suspended control moment gyroscope (DGMSCMG) control, a system designed for precise satellite maneuvering. Their method ensures robust control and high angular rate precision, even in the presence of external disturbances, by combining traditional control methods with AI techniques.

Zou and Kumar's work [51–54] has significantly advanced nonlinear and adaptive control of satellites. They developed a finite-time (FT) tracking controller that integrates Terminal Sliding Mode Control (SMC) with Chebyshev Neural Networks (NNs) to handle unmodeled dynamics and external disturbances. The Chebyshev NN approximates nonlinear functions online while a robust term mitigates NN approximation errors. The results demonstrate high precision in attitude control, even under unknown mass moments of inertia and bounded disturbances.

3.1.3.3. Formation flying/multi-agent systems (MAS). AI-driven control has also made substantial strides in the realm of spacecraft formation flying. Zou and Kumar [55] applied Chebyshev Neural Networks in controlling multi-agent spacecraft systems for formation flying. Their adaptive output feedback control ensures that spacecraft maintain precise relative positions without the need for velocity measurements.

Further work by Zou and Kumar [56] introduced a Neural Network-Based Adaptive Output Feedback Formation Control strategy for multi-agent systems, ensuring robust attitude coordination under input saturation. Their research in multi-agent consensus control has demonstrated that Terminal Sliding Mode Control (TSMC) combined with Chebyshev NNs significantly improves formation control under uncertain dynamic conditions [57].

Borah and Kumar [58–60] expanded on this by introducing a Reinforced Unscented Kalman Filter (RUKF) based on Q-learning, which provides state estimation for multi-agent systems (MAS) in the presence of sensor faults. The RUKF enables spacecraft to achieve consensus and precise fault detection, ensuring reliable communication and performance across multi-agent formations.

3.1.3.4. Fault diagnosis and prognosis. Fault diagnosis and prognosis play a critical role in ensuring the long-term operability and reliability of satellites. Kumar and his team [61–63] have examined fault tolerant control (FTC), AI and predictive analytics for aerospace systems. Their research into satellite fault diagnosis and prognosis, particularly in attitude and orbit control subsystems (AOCS) integrates AI algorithms, enabling real-time monitoring and prediction of system failures, thereby ensuring timely interventions [64–66]. Furthermore, Kumar and his team [67,68] have proposed data-driven methods for fault detection and isolation (FDI) and failure prognosis in Reaction Wheels (RWs) and Control Moment Gyroscopes (CMGs). These innovative methods employ Chebyshev Neural Networks (NNs) and genetic algorithms, achieving a 93.5 % success rate in isolating faults across 8 motors (4 gimbal and 4 spin) [67]. Additionally, a Bayesian updating model has been employed for Remaining Useful Life (RUL) prediction of CMGs, achieving 96.25 % accuracy when only 30 % of the data is available [68].

Furthermore, Kumar and his team [69–71] have examined RW failures in the Kepler spacecraft. Their methods included advanced AI techniques, including Growing Neural Networks (GNNs), Long Short-Term Memory (LSTM) models, Variable Sequence LSTM (VarLSTM), Weibull analysis, friction models, and genetic algorithms, to predict RW failures. The proposed methodology successfully detected RW faults more than 3 months ahead of actual failure, with RUL predictions closely matching the actual failure dates.

3.1.4. Communication subsystem

Hacket et al. [72] proposes a multi-objective reinforcement-learning algorithm that acts as a radio-resource-allocation controller. The results indicate that reinforcement learning-based multi-objective optimization is not only feasible but also beneficial for satellite communications. Future work will focus on implementing a hybrid RLNN2-lookup table approach. Furthermore, incorporating other techniques related to deep Q learning, such as experience replay, advanced stochastic gradient descent algorithms, and regularization techniques, could greatly enhance the performance of the cognitive engine.

3.1.5. Electrical power subsystem (EPS)/thermal control subsystem (TCS)/Environmental control and life-support subsystem (ECLSS)

Cena et al. [73] considered a physics-informed (PI) real-valued non-volume preserving (Real NVP) model for fault detection in the electrical power subsystem (EPS) of satellites. Their results show that the proposed approach outperforms existing fault detection methods and offers a competitive advantage in meeting robustness, reliability, and power constraint requirements.

In the area of thermal control subsystems, Petković et al. [74] compiled six datasets from the telemetry data of the Mars Express Spacecraft. Each data consists of context data and thermal power consumption measurements spanning three Martian years, sampled at six different time resolutions ranging from 1 min to 60 min. These datasets, characterized by their heterogeneity, complexity, and scale, are used as benchmarks for evaluating the performance of artificial intelligence and machine learning methods.

3.1.5.1. AI in precision healthcare and biological research for deep space. Scott et al. [75] proposed precision healthcare systems supported by AI, which are designed to ensure astronaut health in long-duration space missions by enabling biomonitoring and predictive health interventions. Sanders et al. [76] further expanded on this by proposing AI-assisted biology experiments, which utilize self-driving laboratories to autonomously perform biological research in deep space, contributing to the maintenance of human health in extraterrestrial environments.

3.2. Planetary and lunar missions

AI plays a vital role in planetary missions by enabling autonomous navigation, hazard detection, and efficient data processing [77–85]. Rovers like Perseverance use AI to navigate challenging terrains and perform scientific analysis without real-time input from Earth. AI-driven systems optimize mission planning and trajectory adjustments, while onboard AI helps spacecraft process data and make decisions autonomously. Furthermore, AI enhances robotic systems in sample collection, onboard data analysis, and fault detection. These advancements ensure missions operate efficiently, even in distant and unpredictable environments.

3.2.1. Mission planning

AI is increasingly being used in mission planning to automate scheduling and optimize resource allocation during planetary missions. Autonomous planning systems are making these missions more efficient and adaptable to the changing conditions of space environments [77]. NASA's Artemis mission considers the applications of AI to achieve its mission objectives [78–80].

3.2.2. Payload subsystem

Cúñez and Franklin [81] developed a neural network capable of detecting and tracking barchan dunes in various environments, including Earth and Mars. Their model achieved an accuracy score above 70 %, demonstrating the potential for AI in monitoring planetary surface dynamics.

The Jet Propulsion Laboratory [82] highlighted the role of AI in assisting scientists in discovering fresh craters on Mars. Their AI system, built using convolutional neural networks (CNNs), enables the automated classification of impact craters from images sent by the Mars Reconnaissance Orbiter (Table 2). This automated system significantly accelerates the process of identifying craters, which would otherwise require extensive manual effort. Similarly, Dunkel et al. [83] showed how AI-powered systems onboard the International Space Station use deep learning to analyze remote sensing imagery in real-time, providing immediate insights into planetary observations.

3.2.3. Attitude and orbit control subsystem

Kumar [84] examined artificial intelligence (AI) and digital twin-powered smart Lunar Gateway and planetary exploration missions. His research focused on the integration of AI techniques with digital twin technologies to enhance mission planning and autonomous spacecraft operations. This approach enables real-time monitoring and control of spacecraft attitude and orbit, improving mission efficiency and system reliability during planetary exploration.

3.2.4. Communication subsystem

Ferreira et al. [85] proposed a neural-network-based reinforcement learning (RL) algorithm designed to return data from satellites back to Earth, specifically for deep space exploration missions. The key advantage highlighted in the study is the algorithm's ability to autonomously learn and adapt in real time to its environment, which is critical in deep space operations where communication delays make real-time decision-making difficult. The RL approach optimizes the use of satellite communication resources and minimizes latency, ultimately improving the overall efficiency of data transmission from low-Earth orbit (LEO) to deep space environments.

3.3. Lagrange point missions

Miller and Linares [86] explored the use of reinforcement learning (RL) in low-thrust optimal control for spacecraft operating at Lagrange points. They highlighted that RL could be leveraged to generate optimal thrust profiles for spacecraft in these dynamically complex environments. Similarly, LaFarge et al. [87] presented autonomous closed-loop guidance for low-thrust, multi-body dynamical systems using reinforcement learning, showing that the method was effective in generating low-energy transfers between Lagrange points.

Das-Stuart et al. [88] provided an additional study in this domain, introducing reinforcement learning and supervised learning strategies for rapid trajectory design in multi-body systems. Their work focused on handling complex dynamical environments using machine learning (ML) algorithms to autonomously generate trajectories that optimize fuel efficiency and time constraints.

Further reinforcement learning (RL) applications include those by Yanagida et al. [89], who examined long time-of-flight, three-body transfers using deep RL, while Zaidi et al. [90] developed a cascaded deep RL technique for multi-revolution low-thrust spacecraft transfers. Both studies demonstrated the growing importance of AI-driven methods in computing transfer maneuvers in low-thrust trajectories, particularly between geostationary transfer orbits (GTO) and geosynchronous equatorial orbits (GEO).

The combined research of Sullivan and Bosanac [91] and Bonasera et al. [92] explored using RL for designing low-thrust transfer strategies between Libration point orbits in the Earth-Moon system. Both works emphasized RL's potential for minimizing control effort while optimizing trajectory precision, showing the effectiveness of multi-objective RL approaches for low-thrust spacecraft trajectory designs.

Reinforcement learning has been employed successfully in various orbit transfer designs for multi-body systems, as demonstrated by the collective work of Miller and Linares [86], LaFarge et al. [87], and Das-Stuart et al. [88]. These studies showcase the expanding role of AI in autonomous trajectory planning and spacecraft control in complex multi-body environments such as those at Lagrange points.

Reinforcement learning (RL) has been effectively employed in low-thrust, multi-body dynamical environments for spacecraft trajectory design and control. Specifically, Miller and Linares [86] explored RL for low-thrust optimal control, presenting results that highlight RL's potential for developing autonomous spacecraft guidance systems. Their work emphasizes RL's ability to autonomously generate transfer trajectories in multi-body systems, optimizing both trajectory design and fuel usage. Sullivan et al. [93] extended this work, focusing on multi-objective RL to design low-thrust transfer trajectories between libration point orbits. This method, trained using Proximal Policy Optimization (PPO) [94], showcases RL's ability to optimize multiple objectives, such as minimizing fuel consumption while achieving precise positioning in complex, multi-body gravitational environments.

Bosanac et al. [95] applied RL to design reconfiguration maneuvers for a starshade in a Sun-Earth L2 southern halo orbit, demonstrating RL's utility in multi-body systems and the benefits of using PPO for optimizing maneuvers with minimal control effort. Sullivan and Bosanac [96] developed the Multi-Reward Proximal Policy Optimization (MRPPO) framework to train multiple policies simultaneously, each addressing unique objectives. This approach accelerates convergence and reduces computational time in chaotic environments, while preserving PPO's stability and robustness. Sullivan et al. [97] extended this study and incorporated a "moving reference" concept into MRPPO, which autonomously generates reference trajectories during training, eliminating the need for initial guesses. This allows policies to adapt dynamically during training, ensuring that the best trajectories serve as updated reference points. They applied this method to guide a low-thrust-enabled SmallSat from an L1 northern halo orbit to an L2 southern halo orbit in the Earth-Moon circular restricted three-body problem (CR3BP). The results showed locally optimal solutions, with a focus on trade-offs between flight time and propellant mass usage.

Holt et al. [98,99] explored reinforced Lyapunov control in the context of low-thrust transfers, advancing the understanding of control stability and optimization in space environments. They demonstrated how reinforcement learning (RL) can be used to achieve optimal control with guaranteed stability in complex multi-body gravitational systems. Zavoli and Federici [100] applied RL for robust trajectory design in interplanetary missions, showing how these methods can adapt to complex gravitational environments.

Sreesawet and Dutta [101] introduced a sequential algorithm for low-thrust orbit-raising trajectories, breaking the global optimization problem into simpler sub-problems. This method was further enhanced by Arora and Dutta [102], who incorporated artificial neural networks (ANN) to adapt the weight of sub-optimal control problems. Furthermore, Dutta et al. [103] presented a comparative assessment of a sequential algorithm with a deep RL. Additionally, Zaidi et al. [90] used a cascaded deep RL for a cislunar mission, particularly for transfer from super-GTO to near-rectilinear halo orbit (NRHO).

Federici et al. [104] proposed a new RL-based guidance law for cislunar orbit transfers using Proximal Policy Optimization (PPO). This method identified optimal control solutions for low-thrust transfers between Lyapunov orbits around L1 and L2 in the Earth-Moon system, demonstrating the viability of RL for future autonomous space missions.

3.4. Asteroid missions

Izzo and Gómez [105] proposed a machine learning approach, based on *geodesyNets*, which learns density models of irregular bodies such as the asteroids Bennu, Eros, and Itokawa, as well as the comet Churyumov-Gerasimenko. GeodesyNets are three-dimensional, differentiable functions that represent the density of a target asteroid or comet.

Gaudet and Furfaro [106] applied artificial intelligence (AI)-based controllers to enable spacecraft to hover and orbit irregularly shaped asteroids. Using RL techniques, their simulation results demonstrated that RL successfully learns the non-uniform gravitational and rotational fields of simulated asteroids, generating a thrust profile for robust hovering. Willis, Izzo, and Hennes [107] improved this work by enhancing the accuracy of the approach by an order of magnitude and applying it to a generalized gravitational model of asteroids. Their network weights were trained using neuroevolution.

In addition to learning-based methods for hovering and orbiting irregular bodies, recent research has extended deep learning applications to real-time optimal control and trajectory planning for asteroid landing missions. Cheng et al. [108] proposed a deep neural network-based real-time optimal control scheme that effectively addresses the challenges of highly irregular gravitational fields. Similarly, Ma [109] introduced a neural convex optimization approach tailored for real-time trajectory generation during asteroid landings, combining the interpretability of convex optimization with the flexibility of neural networks. Ni [110] further accelerated the training process of deep learning-based guidance systems by introducing a homotopy method, improving convergence speed and deployment readiness for autonomous landing missions. These contributions underscore the growing relevance of deep learning for fast and reliable decision-making in asteroid proximity operations.

Parmar and Guzzetti [111] developed a convolutional neural network (CNN) coupled with a long short-term memory (LSTM) network for spacecraft path-planning in binary asteroid systems. Their system was able to learn impulsive maneuvers, although more training time was needed to achieve performance results comparable to a human pilot. Gaudet, Linares, and Furfaro [112] proposed terminal adaptive guidance using reinforcement meta-learning for asteroid close-proximity operations. They showed that RL techniques could be effective in autonomous spacecraft guidance under highly dynamic conditions.

3.5. Interplanetary missions

Izzo et al. [113] proposed deep artificial neural networks for optimizing guidance profiles in interplanetary missions. Their neural network was able to generate optimal guidance solutions for Earth-to-Mars transfers, offering enhanced computational efficiency and accuracy for space trajectory design. Witsberger and Longuski [114] developed an interplanetary trajectory design model combining a recurrent neural network (RNN) and a genetic algorithm. Their method addressed the challenges of multi-body orbital dynamics. Similarly, Smet, Scheeres, and Parker [115] systematically explored orbital transfers within the Martian system, leveraging artificial neural networks (ANNs) to identify efficient solar gravity-driven orbital transfers.

3.6. Spacecraft rendezvous and docking

Kumar [116] proposed a smart on-orbit servicing mission to extend the operational life of defunct satellites in graveyard orbits. This mission involves servicing satellites with minimal human intervention. Fereoli, Schaub, and Lizia [117] explored meta-reinforcement learning techniques for spacecraft proximity operations, with a focus on cislunar space environments. Their research advances autonomous decision-making for spacecraft during critical maneuvers.

3.6.1. Autonomous on-orbit assembly

Tavana, Faghihi, de Ruiter, and Kumar [118] developed a reinforcement learning-based strategy for autonomous on-orbit assembly. This research examined the application of RL to ensure autonomous systems could handle complex assembly tasks in space. They also proposed a machine learning-based model predictive control (MPC) strategy [119] for improving motion planning in autonomous on-orbit assembly missions, further contributing to the development of highly intelligent spacecraft systems.

3.7. Planetary lander missions

Furfaro et al. [120] utilized Deep Neural Networks (DNNs) for autonomous lunar landing tasks. Their architecture included a Convolutional Neural Network (CNN) for processing simulated lunar imagery, and a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) units to estimate landing controls in a 2D environment. The DNN successfully managed the classification of thrust vector magnitudes and regression of thrust vector angles, making it suitable for autonomous lunar landing missions. Gaudet et al. [121] applied deep RL for six-degree-of-freedom planetary powered descent and landing. This model utilized Policy Gradient Optimization as the learning algorithm, allowing the system to achieve nearly fuel-optimal trajectories despite challenges in fuel efficiency. Additionally, Gaudet and Furfaro's earlier work [106] focused on adaptive pinpoint landing using reinforcement learning, achieving improvements in fuel-efficient Mars landing.

Sánchez-Sánchez and Izzo [122] proposed Guidance and Control Networks (G&CNets), leveraging deep neural networks to manage real-time optimal control for planetary landing problems. Their work demonstrated the effectiveness of DNNs in real-time control for complex landing scenarios.

3.7.1. Eclipse Networks for astrodynamics

Biscani and Izzo [123] developed Eclipse Networks (EclipseNets) to tackle the orbital dynamics of small objects, such as debris or pebbles, when they enter shadow cones of other celestial bodies. EclipseNets are a differential model combined with a feedforward neural architecture to predict the impact of these shadow zones on the dynamics of objects, especially in the context of lander mission planning. Kumar [124] examined the use of artificial intelligence for autonomous guidance, navigation, and fault-tolerant control of a lunar lander. The research explored the integration of AI techniques for improving the accuracy and reliability of lunar landing missions. Elemasetty and Kumar [125] proposed exploiting cosmic resources in the space industry using penalized linear regression models. This research addresses the efficient utilization of extraterrestrial resources, which could support planetary lander missions by providing access to essential materials for sustained operations.

3.8. Satellite constellation

Tohidi and Mosavi [126] introduced an artificial neural network technique aimed at identifying global positioning system (GPS) spoofing attacks. Specifically, they proposed a multi-layer perceptron NN trained using Particle Swarm Optimization (PSO), demonstrating improved detection performance. The results showed that their system outperforms traditional Bayes-optimal and Bayesian classifiers by 4 % and 2 %, respectively.

3.9. Space debris

3.9.1. Path-planning for imaging space objects

Brandonisio et al. [127] applied reinforcement learning for smart path-planning in imaging uncooperative space objects. Their work focuses on improving spacecraft's ability to capture high-quality images of debris or malfunctioning satellites, which is important for maintaining the health of the space environment and mitigating debris risks.

3.9.2. Predicting Re-entry trajectories

Jung et al. [128] developed a recurrent neural network model to predict the re-entry trajectories of uncontrolled space objects using limited datasets. Their model demonstrated superior performance over classical dynamics-based methods in predicting uncontrolled re-entry paths, emphasizing the potential for future improvements with larger datasets.

3.9.3. Pose estimation for non-cooperative spacecraft

Gao et al. [129] proposed a novel neural network architecture called SU-Net for pose estimation of non-cooperative spacecraft using inverse synthetic aperture radar (SAR) images. Their results demonstrated highly accurate pose estimation, crucial for enabling successful on-orbit servicing and docking of malfunctioning or drifting spacecraft. Renaut et al. [130] explored CNN-based pose estimation of a non-cooperative spacecraft with symmetries from LiDAR point clouds, achieving significant advancements in addressing the challenges posed by non-cooperative spacecraft.

3.10. Summary and emerging trends

AI is rapidly transforming the space segment by embedding autonomy and intelligence across satellite subsystems and mission operations. It enables onboard decision-making through autonomous mission planning, fault management, and adaptive control with minimal ground intervention. ML-based guidance, navigation, and control (GN&C) systems using neural network and reinforcement learning models enhance precision in attitude, orbit, and formation control, even under uncertain conditions. AI-enhanced payloads, such as ESA's Φ-sat and SONATE2, employ CNNs for onboard image classification, cloud detection, and anomaly filtering, thereby significantly enhancing science mission performance. Fault diagnosis and health management systems utilize neural networks, genetic algorithms, and predictive analytics to identify and mitigate anomalies in critical subsystems like reaction wheels and control moment gyroscopes, enhancing mission reliability. Furthermore, deep neural networks and reinforcement learning support planetary, Lagrange point, and asteroid missions by enabling autonomous navigation and real-time trajectory control in complex multi-body systems. Emerging trends highlight the increasing use of hybrid physics-informed neural networks, onboard edge AI, and reinforcement learning frameworks for adaptive decision-making, cooperative satellite operations, and enhanced autonomy in deep-space missions. Overall, these approaches—spanning deep neural networks, reinforcement learning, and hybrid physics-informed neural networks—are driving the transition from human-supervised to autonomous space operations with intelligent, interconnected, and adaptive spacecraft capable of performing reliably from Earth orbit to deep space.

4. Ground segment

In this segment, there are two categories of AI applications (Fig. 6), with a summary presented in Table 3, as follows.

4.1. Satellite operations and data processing

AI-powered systems have significantly transformed satellite operations and data processing within the ground segment. AI/ML algorithms deployed at ground stations or mission control centers can enable autonomous health monitoring, anomaly detection, predictive maintenance, and task scheduling [17]. Several research studies highlight the effectiveness of AI in these functions. Hermann et al. [131] evaluated various methods including AI algorithms for anomaly detection in spacecraft telemetry on benchmark and real-world data. Among them, LSTM networks show promising results in identifying anomalies, with limitations in complex systems without clear failure signals. Abdelghafar et al. [132] proposed an optimized predictive model for anomaly detection using the Grey Wolf Optimization (GWO) algorithm combined with an Extreme Learning Machine (ELM), referred to as GWO-ELM. The performance of GWO-ELM on the NASA shuttle valve benchmark dataset demonstrated high prediction efficiency and stability in detecting anomalies with low computational time. The model also showed superior performance compared to the basic ELM algorithm with randomized parameter selection and a support vector machine (SVM) algorithm. Huang [133] has examined an AI-based autonomous ground station for anomaly detection of satellite attitude control systems, especially reaction wheels.

Table 3
Applications of artificial intelligence in the ground segment.

Application	AI Method	Results
Satellite Operations and Data Processing	Hermann et al. [131]: LSTM networks Abdelghafar et al. [132]: GWO-ELM predictive model Li and Wang [134]: Convolutional neural networks	Hermann et al. [131]: Promising results for anomaly detection in spacecraft telemetry. Abdelghafar et al. [132]: S uperior performance compared to the basic ELM algorithm for anomaly detection. Li and Wang [134]: I mprovement in processing high-volume image data and analytical capabilities
Autonomous Ground Control Systems	Xiao et al. [136]: Fast-Iterative-GRU (FI-GRU) algorithm and II-DRL algorithm	Improved antenna positioning and tracking
Satellite Communication Optimization	Hackett et al. [72]: Cognitive engines using multi-objective reinforcement learning	Useful for satellite communications
Traffic Management	Jiang et al. [137]: deep reinforcement learning framework Heo et al. [138]: machine learning models Kalmykov et al. [139]: a federated learning approach	Jiang et al. [137]: Dynamically manage bandwidth allocation, and optimizing data transmission.Heo et al. [138]: Predicting traffic loads and enhancing scheduling capabilities.Kalmykov et al. [139]: M anaging dynamic data traffic and improving resource utilization.
Satellite Constellation – GPS/GNSS Spoofing Detection	Tohidi & Mosavi [126]: Multi-layer perceptron neural networks with Particle Swarm Optimization (PSO) Zhang et al. [140]: Fully Connected Neural Networks (FCNNs) and Long Short-Term Memory (LSTM) networks	Tohidi & Mosavi [126]: 4 % improved detection rate of spoofing attacks, enhancing the security of GNSS satellite systems. Zhang et al. [140]: Satellite visibility prediction: 80.1 % accuracy; pseudorange error prediction: 4.9 m to the labeled errors.
Multipath Mitigation	Abdallah & Kassas [141]: CNNs for detecting and mitigating multipath interference.	Reduced positioning errors in urban environments, and improved accuracy of satellite signals in complex reflections.

In addition to satellite operations, AI can significantly enhance data processing in the ground segment. For example, AI can enable automated and efficient handling of complex satellite imagery from Earth observation satellites to support critical applications like environmental monitoring and disaster response. Lu et al. [134] propose a ground-station server-assisted framework for deploying high-performance CNN models on LEO satellites to enable efficient remote sensing image processing. Each CNN layer uses a single "seed feature map" to generate additional feature maps based on specific rules with randomly generated hyperparameters, effectively reducing floating-point operations (FLOPs) and overall model size. This design allows the ground station to facilitate on-orbit model updates, and experiments on multiple datasets show that the framework outperforms existing state-of-the-art approaches.

4.2. Communication management

AI can enhance communication management between ground stations and satellites by dynamically allocating bandwidth and optimizing data transmission processes [135]. This enhanced communication can reduce latency and transmission errors, thereby improving the overall reliability, efficiency, and quality of satellite communication services. Fontanesi et al. [135] presented a comprehensive survey on the application of artificial intelligence in satellite communications, covering both onboard and ground segment implementations, as well as associated hardware and software developments.

4.2.1. Autonomous ground control systems

Xiao et al. [136] proposed an AI-based multi-layered satellite ground communication network framework to optimize ground station antenna angles and response time. A fast prediction-based algorithm, called Fast-Iterative-GRU (FI-GRU), was designed for antenna positioning in static environments, while the fourth improved Q-learning search algorithm, called Intelligent-Improved Deep RL algorithm (II-DRL algorithm) was applied to enhance the efficiency of the antenna tracking controller.

4.2.2. Satellite communication optimization

Hackett et al. [72] proposed the implementation of a multi-objective reinforcement-learning algorithm using deep artificial neural networks acting as a radio-resource-allocation controller. The developed Cognitive Engine (CE) was integrated into a fielded space-flight system and tested in both ground-based and space-based systems. The ground segment consisted of engineering-model software-defined radios, commercial modems, and radio frequency (RF) equipment that emulated the target space-to-ground communication channel. The space-based system included a remotely controlled transmitter onboard the International Space Station, which operated in conjunction with a ground-based receiver located at NASA Glenn Research Center. The flight tests demonstrated the potential for reinforcement learning–based systems for satellite communications.

4.2.3. Traffic management

AI can enable efficient and autonomous handling of data traffic, resource allocation, and ground station operations critical for seamless satellite communications. Jiang et al. [137] developed a deep reinforcement learning framework to dynamically manage bandwidth allocation in low Earth orbit (LEO) satellite ground segments, optimizing data transmission efficiency across distributed ground stations. Heo et al. [138] proposed a machine learning model for predicting traffic loads in satellite-terrestrial integrated networks, enhancing the scheduling capabilities of ground stations to support reliable communication links. Kalmykov et al. [139] introduced a federated learning approach to manage dynamic data traffic in LEO satellite ground stations, improving resource utilization by adapting to fluctuating network demands. These AI-driven solutions leverage advanced learning algorithms to enable scalable and autonomous traffic management, reducing latency and ensuring robust satellite network performance. Future research should focus on integrating these approaches across multi-constellation systems and addressing challenges in real-world deployment, such as interoperability and computational constraints, to further enhance ground segment operations.

4.2.4. Satellite constellation – GPS/Global Navigation Satellite System (GNSS) spoofing detection

Tohidi and Mosavi [126] introduce a multi-layer perceptron neural network (NN) classifier trained with Particle Swarm Optimization (PSO) to detect GNSS spoofing attacks. Their approach demonstrated a 4 % improvement in detection rates compared to traditional classifiers. Zhang et al. [140] develop a deep learning network architecture combining Fully Connected Neural Networks (FCNNs) and Long Short-Term Memory (LSTM) networks to predict GNSS satellite visibility and pseudorange errors. Their approach achieved an 80.1 % accuracy rate in satellite visibility predictions and can predict pseudorange errors with an average difference of 4.9 m to the labeled errors.

4.2.5. Multipath mitigation

Abdallah and Kassas [141] applied deep learning models, particularly Convolutional Neural Networks (CNNs), to differentiate between line-of-sight (LOS) and non-line-of-sight (NLOS) signals. Their model, trained on synthetic data simulating GNSS environments, extracted spatial features from GNSS signals and used them to classify signals as either multipath or LOS. When applied to LTE signals in varied multipath-rich environments, this model achieved position RMS errors of 1.67 m, 3.38 m, 1.73 m, and 2.16 m across four experiments, significantly lower than those obtained using conventional techniques. Furthermore, the deep learning approach improved the accuracy of classifying NLOS signals, enhancing the reliability of positioning estimates in complex environments where multipath interference is prevalent.

Savas and Dovis [142] used K-means clustering to detect and mitigate multipath interference in GNSS signals. Their algorithm clustered incoming GNSS signals based on features like signal strength and angle of arrival, successfully separating multipath from direct LOS signals. This method substantially improved positioning accuracy in urban canyons and indoor environments compared to traditional methods. Further improvements may involve using advanced clustering algorithms like DBSCAN and integrating machine learning models to dynamically adjust cluster parameters based on environmental changes [141,142].

Suzuki et al. [143] implemented a CNN-based method to classify GNSS signals into LOS and NLOS categories, using features such as signal-to-noise ratio (SNR) and time delay as input. The convolutional layers of the CNN automatically learned spatial patterns to differentiate NLOS multipath signals. The CNN significantly outperformed traditional multipath detection techniques, particularly in urban environments with complex reflections.

Munin et al. [144] utilized CNNs to detect multipath interference in GNSS receivers. Trained on synthetic GNSS signals, the CNN learned to distinguish between direct LOS and multipath-affected signals, integrating real-time multipath detection into GNSS receivers. The CNN method provided superior performance in detecting multipath interference, leading to improved positioning accuracy in challenging environments. Future development should involve larger, more diverse datasets, including real-world GNSS signals, and combining CNNs with other neural networks such as Recurrent Neural Networks (RNNs) to address the temporal dynamics of GNSS signals more effectively.

4.3. Summary and emerging trends

AI applications in the ground segment have evolved from basic anomaly detection systems to fully integrated, autonomous systems that support satellite operations, data processing, and communication management. AI-driven solutions can enable autonomous operation through real-time monitoring, predictive maintenance, and automated command of satellite subsystems, thereby reducing operator workload and enhancing mission reliability. CNNs and other deep neural network architectures provide data-driven intelligence by efficiently processing large volumes of satellite imagery and telemetry data, enabling quick fault prediction and anomaly detection. Reinforcement learning and deep neural network architectures enhance communication efficiency by optimizing bandwidth allocation, antenna tracking, and interference mitigation, allowing dynamic adaptation across distributed ground-station networks. Emerging trends highlight that hybrid and distributed neural network learning, including federated and edge learning, are increasingly bridging satellites and ground systems to enable continuous model updates without full data transfer. Overall, these AI-enabled systems enhance decision-making, reliability, and responsiveness, marking a shift toward intelligent, self-learning ground segments that operate collaboratively with satellites to achieve efficient, resilient, and autonomous mission operations.

5. User segment

Artificial Intelligence has helped improve the efficiency of analysing remote sensing data (see Fig. 7). The volume of remote sensing data continues to grow and AI-driven techniques are proving to be useful [145]. This section discusses how artificial intelligence is being used for the large amount of remote sensing data produced each day. The examples presented below represent only a subset of the extensive research being conducted in this area. In recent years, the application of AI in analyzing satellite data, particularly for challenging tasks such as volcanic eruption detection, flood mapping, land classification, precision agriculture, and space situational awareness, has shown highly promising results (summarized in Table 4).

5.1. Volcanic eruption detection

Rosso et al. [146] developed a method using convolutional neural networks (CNNs) and satellite multispectral imagery to detect volcanic eruptions directly from satellites. Their method showed promising results in accurately identifying eruptions, enhancing the monitoring capabilities for such natural disasters.

5.2. Precision agriculture

Firdaus et al. [147] applied CNNs and genetic algorithms to optimize agricultural practices by analyzing satellite imagery. Their approach helps reduce CO2 emissions, minimizes land degradation, and maximizes economic factors, showing great promise for precision agriculture.

5.3. Classifying hyperspectral images

Hu et al. [148] utilized deep convolutional neural networks (CNNs) for classifying hyperspectral images, showing superior performance compared to traditional methods like support vector machines. However, overfitting remains a challenge in their approach.

5.4. Flood maps

Schumann et al. [149] advocated for developing AI-based algorithms to generate real-time flood maps onboard satellites, particularly SAR satellites. Their work emphasizes the importance of combining AI with satellite technology for efficient flood monitoring.

5.5. Land classification

Sharma et al. [150] used a U-Net model for automatic land

Table 4
Applications of artificial intelligence in the user segment.

Application	AI Method	Results
Volcanic Eruption Detection	Rosso et al. [145]: Convolutional Neural Networks (CNNs)	Rosso et al. [145]: Promising detection capabilities using multispectral imagery.
Precision Agriculture	Firdaus et al. [146]: Convolutional Neural Networks, Genetic Algorithms	Firdaus et al. [146]: CNNs can effectively solve satellite imagery for precision agriculture
Land Classification and deforestation Identification	Chitra et al. [150]: ResNet architecture model Sharma et al. [149]: U-Net (CNN) Ortega et al. [152]: FCN Silva et al. [152]: Neural network Wang et al. [153]: Maximum likelihood classification model Arekhi and Jafarzadeh [154]: Maskov chain model-based, a multilayer and a perceptron neural network Bavaghar [155]: Logistic regression Singh et al. [156]: Multi-layer perceptron	Chitra et al. [150]: Reached accuracies above 90 % (40,000 images) Sharma et al. [149]: High performance in identifying land features Ortega et al. [153]: mean average precision scores greater than 80 % Silva et al. [152]: F1 score of 99 % Wang et al. [153]: R squared results bigger than 0.85 Arekhi and Jafarzadeh [154]: accuracy of 83 %–87 % Bavaghar [155]: classification percentage of 72.5 % Singh et al. [156]: accuracy of 93 %
Kelp Forest Canopy Cover Identification	Marquez et al. [167]: Mask region-based convolutional neural networks	Marquez et al. [167]: accuracy between 0.87 and 0.93–2368 "kelp" polygons
Flood Mapping	Schumann et al. [148]: Convolution neural network	Schumann et al. [148]: Proposed flood maps in real time
Crop Type Mapping	Nowakowski et al. [158]: Tree-based machine learning algorithms Nowakowski et al. [159]: Transfer learning Spiller et al. [160]: One-dimensional convolutional neural network	Nowakowski et al. [158]: overall accuracy of 85 % Nowakowski et al. [159]: accuracy rates of up to 90 % Spiller et al. [160]: achieving prediction accuracy of 100 %
Storm Detection	Shi et al. [166]: Support vector machine	Shi et al. [166]: F values above 77 %
Hurricane monitoring	Alshaye et al. [171]: CNN	Alshaye et al. [171]: accuracy 96.6 % (60,500 images)
Ship Localization	Bhattacharjee et al. [162]: Deep neural network	Bhattacharjee et al. [162]: 94.88 % precision and 79.68 % recall (39,716 ship chips)
Ocean	Guirado et al. [168]: CNN for whale detection Yan and Huang [169]: CNN for sea ice detection	Guirado et al. [168]: F1 score of 81 % Yan and Huang [169]: accuracies above 90 %
Earthquake warning system	Brum et al. [170]: ANN	Brum et al. [170]: accuracies 85–94 %
Image Classification	Hu et al. [147]: Deep Convolutional Neural Networks (DCNNs) for Hyperspectral Images Zaidenberg et al. [157]: Quantum neural networks Sebastianelli et al. [161]: Circuit-based hybrid quantum convolutional neural network	Hu et al. [147]: accuracy can reach over 90 % (8,000 to 50,000 labeled pixels) Zaidenberg et al. [157]: achieving 94.73 % accuracy (27,000 labeled and georeferenced images) Sebastianelli et al. [161]: overall accuracy of 98 % (27000 labeled and georeferenced images)

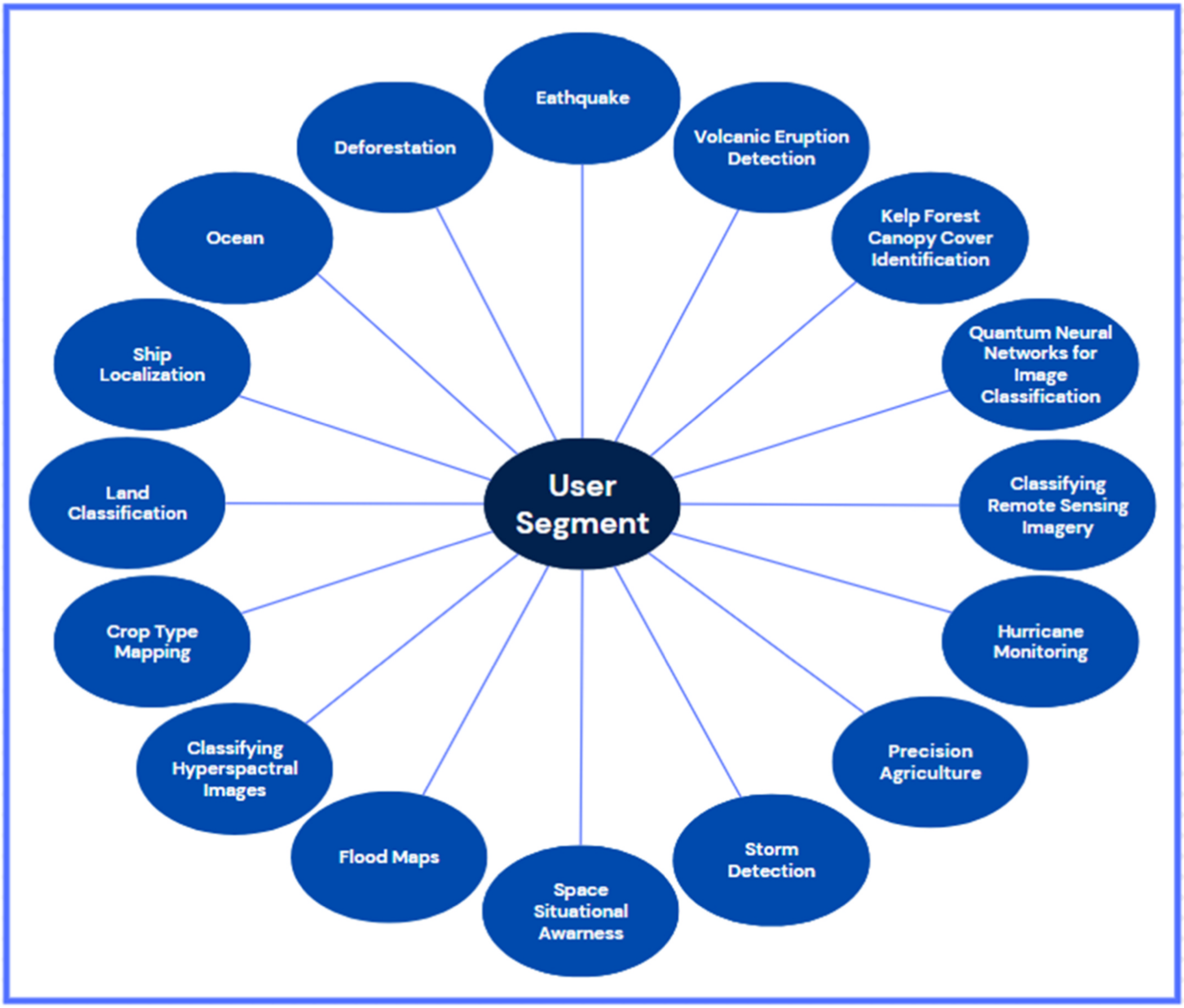

Fig. 7. Artificial intelligence applications in user segment.

classification based on National Agriculture Imagery Program (NAIP) data, demonstrating strong performance in identifying land features. While extensive research exists, particularly from the International Society for Photogrammetry and Remote Sensing (ISPRS) community, a comprehensive review is beyond the scope of this survey. Instead, this paper focuses on key methodologies and representative studies to highlight significant advancements in land classification using machine learning.

5.6. Deforestation

Several authors have contributed to deforestation monitoring and prediction. Chitra et al. [151] proposed a ResNet-based model for detecting and classifying deforestation using satellite images with over 90 % accuracy. Ortega et al. [152] applied U-Net and Res-Unet to detect deforestation in the Amazon rainforest, achieving mean average precision scores above 80 %.

Silva et al. [153] achieved an F1 score of 99 % using neural networks on Sentinel-1 images. Wang et al. [154] used a maximum likelihood classification model, achieving R-squared values above 0.85 in deforestation area estimation.

Arekhi and Jafarzadeh [155] used a Maskov chain model-based neural network, a multilayer neural network and a perceptron neural network to predict the distribution of deforestation in western Iran's Zagros forest and achieved accuracies of 83 %–87 %. Bavaghar [156] used logistic regression to predict the distribution of deforestation in Iran's western Gilan Hyreanian forest and obtained a classification accuracy of 72.5 %.

Singh et al. [157] applied a Multi-layer perceptron neural network to predict the distribution of deforestation in Assam forest ecosystems and achieved an accuracy of 93 %.

5.7. Quantum neural networks for image classification

Zaidenberg et al. [158] explored the application of quantum neural networks (QNNs) for remote sensing imagery classification. Their quantum convolutional neural networks (QCNNs) achieved impressive accuracies of 94.73 %, highlighting the potential of quantum machine learning in this domain, though challenges like data processing limitations persist.

5.8. Crop type mapping

Nowakowski et al. [159] applied tree-based machine learning algorithms for mapping crop types with an overall accuracy of 85 %. They further explored transfer learning methods to improve crop type classification, achieving accuracy rates of up to 90 % [160]. Spiller et al. [161] presented an approach for crop-type mapping utilizing hyperspectral imagery and a one-dimensional convolutional neural network (CNN), achieving prediction accuracy of 100 %. However, this high accuracy may suggest the task is too straightforward for the CNN model.

5.9. Classifying remote sensing imagery

Sebastianelli et al. [162] introduced a circuit-based hybrid quantum convolutional neural network (QCNN) for classifying remote sensing imagery, achieving an impressive overall accuracy of 98 % (Fig. 8). The QCNN outperforms classical methods, with the best results coming from models utilizing quantum entanglement.

5.10. Ship localization

Bhattacharjee et al. [163] proposed a deep neural network for ship localization using SAR images. Their model achieved 94.88 % precision and 79.68 % recall, outperforming traditional methods by a significant margin.

5.11. Space Situational Awareness

AIDahoul et al. [164] presented a decision fusion method aimed at Space Situational Awareness, utilizing an EfficientDet model with an EfficientNet-v2 backbone for detecting space objects. The results indicate that this combination surpasses state-of-the-art techniques, achieving an accuracy of 94 % and a performance metric of 1.9223 % for object classification, along with mean precision of 78.45 % and mean recall of 92.00 % for object detection. Furthermore, AlDahoul et al. [165] developed a multi-modal learning solution using deep learning models to recognize spacecraft and debris, achieving accuracy rates of up to 85 %. Their work enhances the capabilities of space situational awareness systems.

Recently, Vasile et al. [166] presented a data processing pipeline for the identification and classification of unknown space objects based on their hyperspectral images. The pipeline employs Artificial Neural Network (ANN) and a least squares match with a library of known spectra for material identification, followed by a supervised machine learning algorithm, k-nearest neighbours (KNN) model, to classify the object into one of several categories.

5.12. Storm detection

Shi et al. [167] developed an automatic storm detection system using remote sensing data and support vector machines (SVM). Their method demonstrated promising results, especially with feature vector combinations.

5.13. Kelp forest canopy cover identification

Marquez et al. [168] proposed a mask region-based convolutional neural networks to automatically process data from open-source satellite imagery to identify kelp forest canopy cover. The findings yield accuracy results between 0.87 and 0.93, depending on the index used and show that the Mask R-CNN is a cost-effective tool for long-term marine ecological monitoring.

5.14. Ocean

Guirado et al. [169] proposed a CNN to detect and count whales in aerial and satellite images. The results showed an F1 score of 81 % (Table 4). Yan and Huang [170] presented a CNN for sea ice detection from GNSS-R data. They achieved accuracies above 90 %.

5.15. Earthquake

Brum et al. [171] used an artificial neural network for an earthquake warning system. The results show that the ANN method achieved an accuracy of 85.71 % for predicting the Tres Picos Mw = 8.2 earthquake between 1:30 UTC and 4:00 UTC, approximately 3 hours prior to the seismic event and achieved a 94.60 % accuracy in terms of earthquake magnitude classification.

5.16. Hurricane monitoring

Alshaye et al. [172] proposed a CNN model for hurricane monitoring and achieved an accuracy of 96.6 %. Kucuka et al. [173] examined severe weather prediction using the transformer-based nowcasting of radar composites from satellite images.

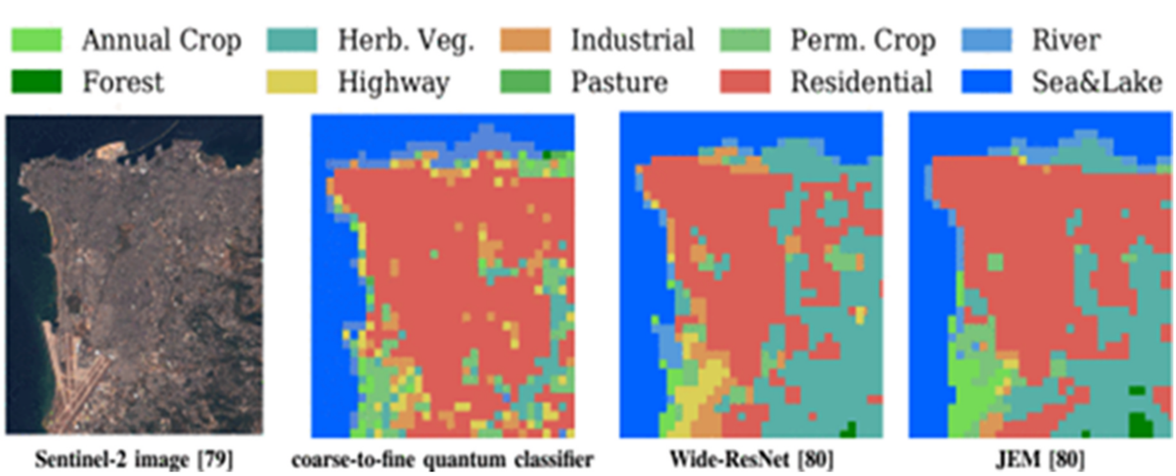

Fig. 8. Land-use and land-cover (LULC) semantic maps on never-seen Onera Satellite Change Detection Dataset (OSCD) city Beirut. (a) Input Image. (b) Coarse-to-fine quantum classifier. (c) Wide-ResNet. (d) JEM [162].

5.17. Summary and emerging trends

AI is transforming the user segment by enhancing the speed, accuracy, and scalability of remote sensing data analysis. With the exponential growth of satellite imagery and geospatial data, AI-driven models—particularly CNNs, DNNs, and RL frameworks— can enable automated analysis across applications such as environmental monitoring, agriculture, disaster management, and space situational awareness. CNN-based systems have achieved remarkable success in volcanic eruption detection, flood mapping, deforestation tracking, land-use classification, and precision agriculture, often surpassing traditional algorithms in both accuracy and processing efficiency. AI models such as U-Net, ResNet, and Mask R-CNN have also proven effective for environmental monitoring, including detecting deforestation, identifying kelp forests, and mapping oceanic life and storm systems. In addition, AI-powered systems for space situational awareness employ DNNs to detect and classify spacecraft and debris with unprecedented precision. These examples demonstrate that AI-methods can significantly improve satellite data analysis by leveraging both spatial and spectral data, making them superior to traditional methods [174]. Emerging trends highlight the integration of hybrid deep learning and quantum machine learning models for enhanced accuracy in remote sensing analysis. Overall, these advancements are driving more efficient and cost-effective use of satellite data, expanding satellite applications, and enabling new scientific discoveries.

6. Challenges

Despite the significant benefits offered by AI-powered systems across all segments, challenges such as data quality and availability, algorithm robustness and reliability, and ethical and regulatory considerations remain critical areas for further research and development [175,176]. Addressing these challenges will be essential to fully harnessing the potential of AI in advancing space exploration, satellite operations, and space-based applications.

6.1. Data quality and availability

One of the primary challenges in implementing AI-powered space systems is ensuring data quality and availability [175]. AI algorithms require large volumes of high-quality data for training and validation. However, acquiring and curating such data can be challenging, especially in space environments where data transmission is limited and costly, and high-quality data is scarce [176,177]. Future efforts should focus on developing techniques for efficient data acquisition, preprocessing, and augmentation to enhance the quality and availability of training data [178].

6.2. Algorithm robustness and reliability

AI algorithms must be robust and reliable to perform effectively in space applications [179,180]. The harsh and unpredictable conditions of space, including radiation exposure and extreme temperatures, can affect the performance of AI systems. Ensuring the robustness of algorithms through rigorous testing, validation, and redundancy measures is crucial to maintaining the reliability of AI-powered space systems [181,182].

6.3. Ethical and regulatory considerations

The integration of AI in space systems raises important ethical and regulatory considerations. Issues such as data privacy, algorithmic bias, and accountability need to be addressed to ensure the responsible and transparent use of AI technologies [182,183]. Establishing ethical guidelines and regulatory frameworks will be essential to fostering trust and acceptance of AI-powered space systems among stakeholders and the general public [184].

7. Concluding remarks

The paper presents a detailed review of the AI applications in space systems, focusing on the launch segment, space segment, ground segment, and user segment. It is noted that numerous papers have been published across all these segments; however, a large number of papers are concentrated in the user segment, followed by the space segment, with a focus on attitude and orbit control systems. The most significant impact of AI has been observed in the user segment, followed by the space segment, launch segment, and ground segment.

While AI demonstrates great potential, particularly in anomaly detection, autonomous navigation, mission planning, and onboard processing, many of the reported advances are still at the proof-of-concept or simulation stage. Some applications, such as ESA's Φ-Sat-1 onboard cloud filtering [41–43], and Kepler's post-facto fault diagnosis [69–71], have reached higher Technology Readiness Levels (TRL 7). However, areas like AI-driven trajectory guidance, turbopump control, and real-time satellite autonomy are still in early TRL stages (3–5). Going forward, the research on AI for space systems must prioritize system-level integration, robustness certification, and AI-specific TRL tracking to support actual mission deployment. This will be crucial for safe and scalable adoption of AI in space system. We hope that the applications of AI will soon revolutionize space research, making the dream of "low-cost access to space" a reality.

CRediT authorship contribution statement

Krishna Dev Kumar: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Uday Kiran Elemasetty:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Aleya Morin:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Andreas Nüchter:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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