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SURVEY PAPER

On the Role of Artificial Intelligence in Aerospace Engineering: Current State of the Art and Future Trajectories

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Abstract
The rapid development of AI has resulted in an unprecedented paradigm shift across various industries, with aerospace among the laureates of this transformation. This review paper attempts to explore and provide comprehensive overview of the aerospace research imperatives from the AI perspective, detailing the technical sides of the full lifecycle from vehicle design and operational optimisation to advanced air traffic management systems. By examining real-world engineering implementations, the review demonstrates how AI-driven solutions are directly addressing longstanding challenges in aerospace, such as optimising flight performance, reducing operational costs and improving system reliability. A significant emphasis is placed on the crucial roles of AI in health monitoring and predictive maintenance, areas that are pivotal for ensuring the safety and longevity of aerospace endeavors, and which are now increasingly adopted in industry for remaining useful life (RUL) forecasting and condition-based maintenance strategies. The paper also discusses AI embedded in quality control and inspection processes, where it boosts accuracy, efficiency and fault detection capability. The review provides insight into the state-of-the-art applications of AI in planetary exploration, particularly within the realms of autonomous scientific instrumentation and robotic prospecting, as well as surface operations on extraterrestrial bodies. An important case study is India's Chandrayaan-3 mission, demonstrating the application of AI in both autonomous navigation and scientific exploration within the challenging environments of space. By furnishing an overview of the field, the paper frames the ever-important, increasing domains of AI as the forefront in the advancement of aerospace engineering and opens avenues for further discussion regarding the limitless possibilities at the juncture of intelligent systems and aerospace innovation.

Abbreviation

ADS-B	automatic dependent surveillance broadcast
AI	artificial intelligence
ANN	artificial neural networks
ATFM	air traffic flow management
ATM	air traffic management
ATS	air traffic service
BiLSTM	bidirectional long short-term memory

CCD	charged coupled device
ConvLSTM	convolutional long short-term memory
COS	continued operational safety
CRNN	convolutional recurrent neural network
CV	computer vision
DAE	deep autoencoders
DCB	direct capacity balancing
DBN	deep belief network
DPP	descriptive predictive prescriptive
EA	evolutionary algorithm
FO	flight operations
GA	genetic algorithm
GAN	generative adversarial network
GDP	ground delay programs
GEO	geostationary earth orbit
GRU	gated recurrent unit
HS	health state
IBC	individual blade control
LAD	logical analysis of data
LEO	low earth orbit
LR	logistic regression
LSTM	long short-term memory
MDP	Markov decision process
ML	machine learning
MLM	multi-level models
RNN	recurrent neural network
ROCD	rate of climb or descend
RF	random forest
RL	reinforcement learning
RUL	remaining useful life
SDR	service difficulty reports
SVM	support vector machines
SVR	support vector regression
TCAS	traffic collision avoidance system
TCN	temporal convolutional neural network
TFMI	traffic flow management initiatives
t-SNE	t-distributed stochastic neighbour embedding
UAS	unmanned aircraft systems
UAV	unmanned aerial vehicles
VAE	variational autoencoder
VSLAM	visual simultaneous localisation and mapping
VO	visual odometry
XAI	explainable artificial intelligence

1.0 Introduction and background

Aerospace engineering, always at the centre of innovation and creativity, has made a tremendous impact in the modern world. The stories of the first flight by the Wright brothers and the historic moon landing are introduced to children at a very young age. Although the field of aerospace engineering traditionally relied heavily on calculations, extensive physical testing and trial-and-error methods, it was not without setbacks and occasionally catastrophic incidents that required enormous time and resources. Today, advancements in modern technologies such as artificial intelligence (AI) and machine learning (ML) have transformed the field, as shown in Fig. 1, leveraging data-driven approaches to save time and effort [1, 2].

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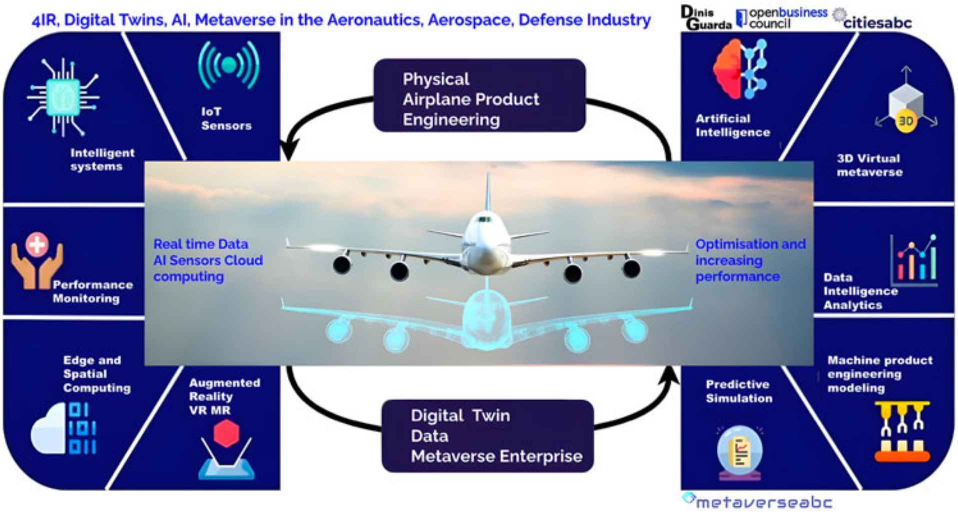

Figure 1. Application of AI in aerospace engineering [3].

AI has become a crucial tool in aerospace engineering [4, 5], a field historically grounded in the standards of mechanical, electrical and materials engineering [6, 7]. The integration of AI into aerospace is not merely a trend but a significant advancement essential to addressing the growing complexity and demands of aviation ventures [8]. AI's ability to enhance decision-making, streamline design procedures and manage vast datasets positions it as a valuable asset, extending the possibilities of space exploration and aviation [9]. For example, AI systems can review past data and simulations to pinpoint opportunities for enhancing designs, forecast system responses in various situations and suggest optimisations that may not be obvious to human engineers [10].

In addition to technical applications, AI addresses broader operational and strategic challenges in aerospace. In space missions, where situations are unpredictable and beyond human influence, AI's quick processing and response to new data are highly valuable [11]. AI systems can independently adapt satellite and spacecraft operations based on changing circumstances, like flares or orbital debris [12]. This functionality guarantees the longevity and triumph of missions by facilitating real-time decision-making without monitoring. AI also makes a difference in improving the adaptability of aerospace endeavours. With the rise in frequency and complexity of space missions, effectively managing them poses a growing challenge [13]. AI exceeds expectations in taking care of the magnitude and complexity of directing aerospace projects through optimising asset distribution, observing mission advancement and guaranteeing that all frameworks work ideally. Also, the intriguing viewpoint of AI cultivates collaboration over areas inside aerospace engineering. For example, AI can blend information from aerodynamics, propulsion systems and materials science to offer a viewpoint on a project's practicality and potential performance. This integration plays a part in fostering designs and progressive innovations by empowering a unified problem approach that draws upon the qualities of each specialised area.

AI has become an element in the aerospace industry, driving innovations that push the boundaries of practices in design, manufacturing, operations and maintenance [14]. The introduction of AI into aerospace dates back to the 20th century when technological advancements and data analytics capabilities experienced significant growth. Initially, AI applications in aerospace focused on enhancing flight operations efficiency. Algorithms were created to optimise flight routes by considering factors such as weather conditions, aircraft weight, and air traffic to determine fuel-efficient trajectories [15, 16]. This phase also marked the use of AI for maintenance, where ML models were trained to detect system failures based on historical data patterns thus preventing costly downtimes and improving safety measures [17, 18].

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AI in aerospace moved beyond simple improvements to become essential in automating important flight systems. Advanced algorithms were integrated into autopilot systems to reduce pilot workload during flight phases and enhance safety by minimising errors [19]. Concurrently, AI applications expanded to include automating air traffic control processes using ML algorithms to manage scenarios while optimising routing and scheduling, for increased airspace capacity and reduced delays [20, 21]. AI developments in aerospace and unmanned aerial vehicles (UAVs) peaked in the mid-2000s. Drones equipped with AI have been used by both the military and the general public to perform autonomous activities like surveillance, reconnaissance and targeted operations [22]. This technological progress led to the creation of AI systems for analysing time and environmental data to make independent navigational decisions, which is crucial for operating in various and unpredictable conditions [23, 24].

Furthermore, AI has transformed the way aerospace design and manufacturing are done. Engineers now use digital twins and augmented reality to model and test aircraft components [25–27]. These AI-enhanced simulations can predict how designs will perform under stress conditions and operational settings, reducing the need for physical prototyping. In recent times, the integration of AI into aerospace has reached a stage with projects like autonomous passenger aircraft and interplanetary exploration vehicles such as Mars rovers moving ahead. AI technologies enable these vehicles to carry out tasks on distant planets like navigating terrain, conducting scientific experiments, and collecting data independently and effectively [28]. Incorporating AI into aerospace not only streamlines processes but also paves the way for innovative technologies and applications that were once thought unattainable. With advancements in AI technology, its utilisation in the aerospace sector is projected to grow, potentially reshaping the industry's future course.

2.0 AI in aircraft and spacecraft systems

The aerospace industry, renowned for its unrelenting pursuit of precision and safety, has undergone a paradigm shift with the incorporation of AI into maintenance processes. Traditional methods, while useful, often fail to address nascent issues before they escalate. In contrast, AI employs advanced sensing, ML and deep-learning techniques to anticipate and mitigate maintenance issues in aircraft and spacecraft systems. This integration represents a significant move from reactive to proactive approaches, providing aerospace engineers and technicians with predictive capabilities to resolve potential issues before they occur. This section investigates the revolutionary influence of AI in Aircraft Health Monitoring and predictive paintenance, focusing on its role in improving operating efficiency, assuring safety and optimising resource utilisation in the aerospace industry.

2.1 Aircraft Health Monitoring and predictive maintenance

In today's competitive airline industry, cost-consciousness and operational efficiency are paramount, driving the need for innovative approaches to cost reduction, particularly in maintenance. Despite recent improvements, unplanned maintenance still accounts for over 25% of maintenance spending and contributes to 5% of wasted fuel consumption. Predictive maintenance, coupled with data analytics, presents a promising solution to address these challenges, although implementation hurdles still exist.

Predictive maintenance utilises aircraft-generated and operational data to assess onboard systems' health, monitored by sensors tracking key parameters. This data enables proactive maintenance scheduling, potentially preventing significant performance declines or system failures. Flight Data Acquisition Units (FDAUs) collect and analyse this data, with some information transmitted from avionics systems via data buses like ARINC-429. Various methods exist for accessing and transmitting predictive maintenance data, including real-time transmission via ACARS or WiFi, or storage on removable media like compact flash drives. However, challenges such as cost and data volume must be considered. Data cleaning is essential before analysis, involving the consolidation and error correction of diverse data formats and sources, including paper documents.

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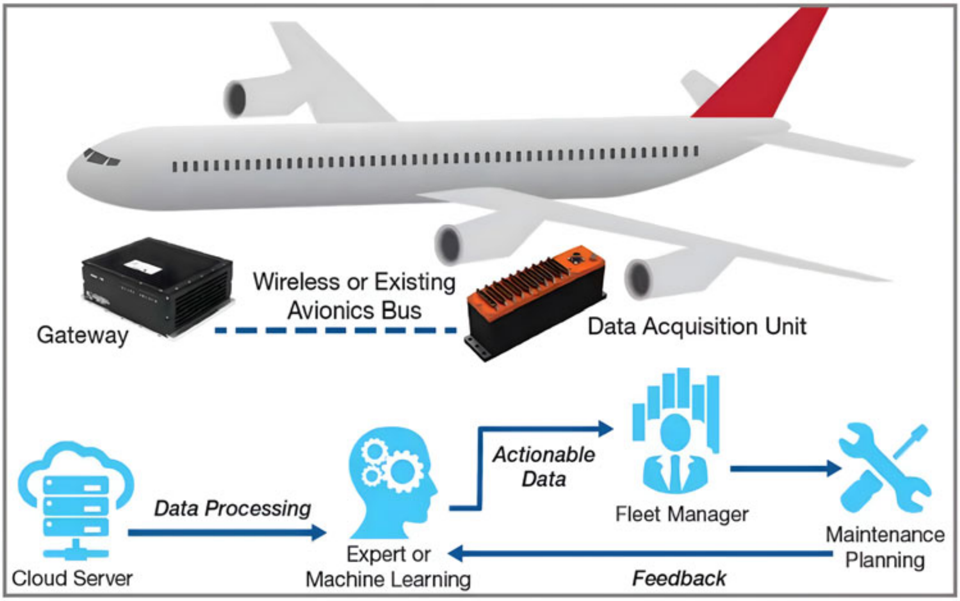

Figure 2. *Application of AI in predictive maintenance [29].*

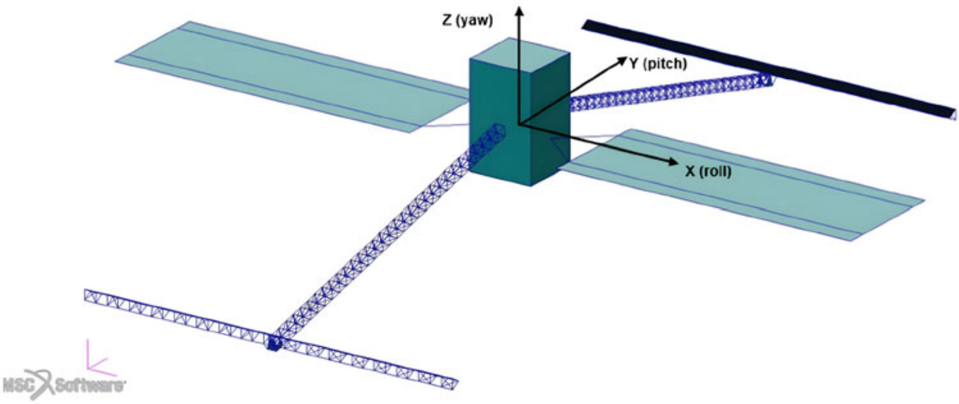

Figure 3. *Spacecraft with large and foldable structures [30].*

Recent years have witnessed the integration of AI and ML in aircraft maintenance, enabling anomaly detection and proactive component maintenance planning. However, challenges persist, such as the ‘no fault found’ (NFF) dilemma, where components exhibiting anomalous behaviour may pass testing, complicating maintenance optimisation. Modern aircraft generate vast amounts of data, posing challenges in data utilisation. While data collection is straightforward, establishing baseline conditions for anomaly detection is crucial. AI and ML algorithms play a pivotal role in identifying trends and exceedances, enabling proactive maintenance and operational practices as shown in Fig. 2.

In the aerospace domain, both aircraft and spacecraft require high levels of precision and safety. The adoption of AI represents a transformative strategy for addressing maintenance challenges. Moving away from traditional methods, AI utilises advanced sensing technologies, combined with ML and DL algorithms, to predict and mitigate issues before they become critical problems. Spacecraft, often equipped with extensive systems such as antennas, booms and solar arrays as shown in Fig. 3, are susceptible to the effects of transient thermal states and material fatigue, impacting their overall integrity and functionality.

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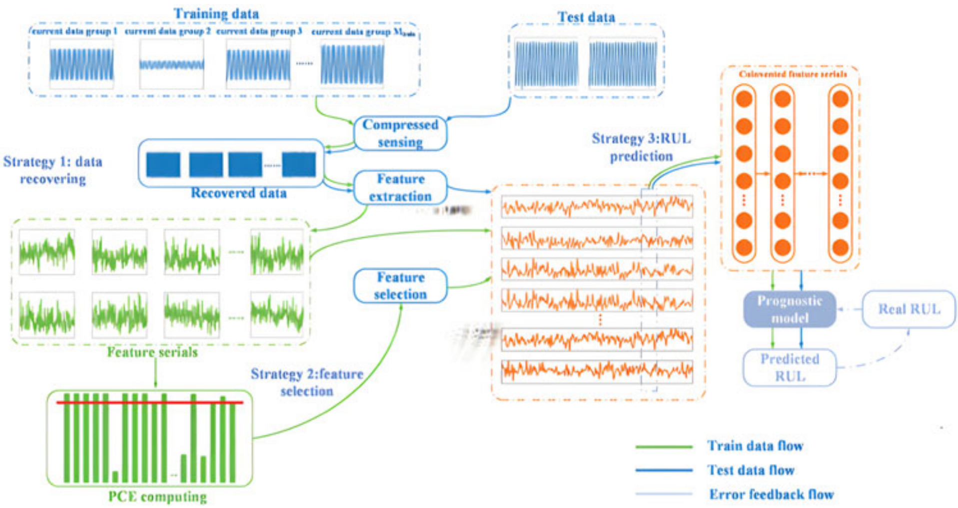

Figure 4. *Block diagram of CRNN for RUL [31].*

Traditional damage identification methods typically involve comparisons with undamaged counterparts, focusing on properties such as stiffness and mass. However, these methods struggle to detect minor damage. Addressing this limitation, Paolo et al. [30] introduced a Bi-LSTM network to classify structural damages based on the number of beam elements that have failed within a truss system.

Forecasting the RUL of spacecraft components is critical to minimising unnecessary maintenance and preventing unforeseen equipment failures. Danyang et al. [31] have advanced this domain by devising a convolutional recurrent neural network (CRNN) shown in Fig. 4 that uses stator current data to predict the RUL of spacecraft bearings. Additionally, Gang et al. [32] introduced a fault detection framework using spacecraft sensor data. Their model integrates a variational autoencoder (VAE) and a gated recurrent unit (GRU) network to effectively extract features from the data, facilitating real-time fault detection in spacecraft.

Sara et al. [33] employed telemetry parameters to assess performance using a support vector machine for regression (SVR). Subsequent analyses, including k-means clustering, t-distributed stochastic neighbour embedding (t-SNE) and logical analysis of data (LAD), were utilised to construct the dataset. Following dataset creation, fault tree analysis was applied for fault detection in data derived from Egyptsat-1 shown in Fig. 5.

Moving on to aircraft systems, engines represent a critical component where predictive maintenance and fault detection methodologies play a pivotal role in enhancing fuel efficiency, optimising maintenance schedules and improving decision-making processes. Changchang et al. [34] employed deep belief networks (DBN) for condition assessment and fault detection, followed by long short-term memory (LSTM) networks for RUL prediction. Their methodology, applied to the NASA C-MAPSS dataset, demonstrated lower error rates compared to traditional methods. Maria et al. [35] developed a numerical tool that leverages artificial neural networks (ANN) and support vector machines (SVM) to simulate and predict engine performance under both healthy and degraded conditions. Their approach focuses on identifying faulty components by analysing engine data, which includes parameters such as altitude, Mach number and rotation speed, alongside measurable variables like exhaust gas temperature and fuel mass flow rate. This method facilitates a detailed assessment of engine health and performance anomalies. Like in spacecraft to predict RUL, Ade et al. [36] implemented a convolutional long short-term memory (ConvLSTM) network. This network was tailored to analyse data from 21 sensors within an engine shown in Fig. 6, utilising the NASA C-MAPSS dataset. Further, the authors extended their research by applying advanced deep learning techniques, specifically, temporal convolutional neural

Figure 5. Egyptsat-1 [Credit: Egypt's NARSS].

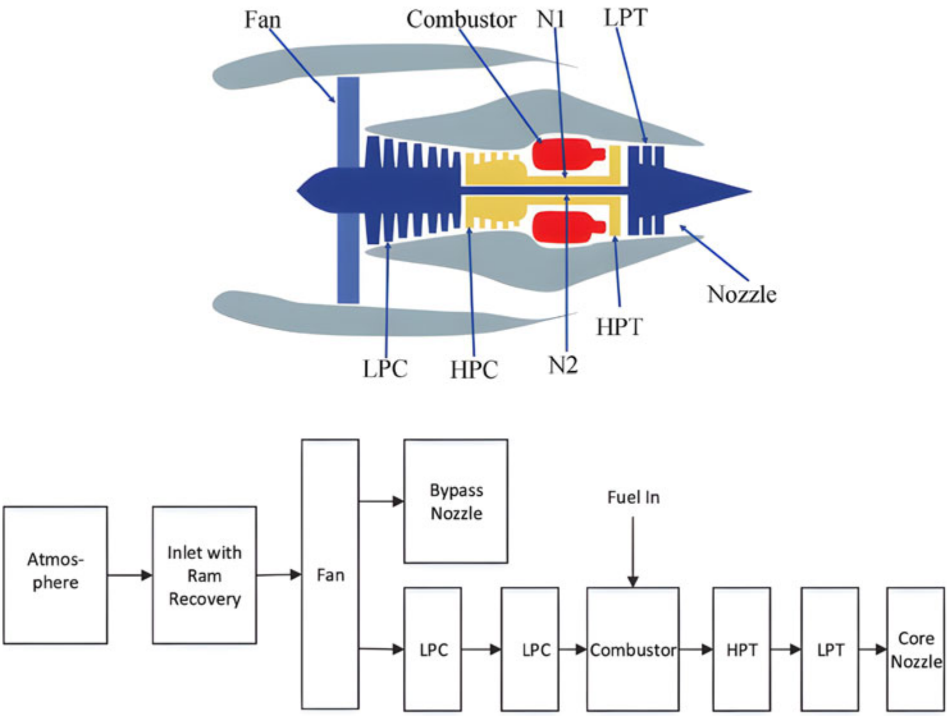

Figure 6. *Engine structure used for NASA C-MAPSS dataset [37].*

networks (TCNN) and transformers to the same NASA dataset, which encompasses readings from 26 sensors alongside three operational settings.

The majority of the methodologies reviewed herein primarily focus on static analysis. However, Chuang et al. [38] introduced a dynamic predictive model shown in Fig. 7, distinct in its approach to forecasting health state (HS) and RUL. This model leverages an ensemble of deep autoencoders (DAE)

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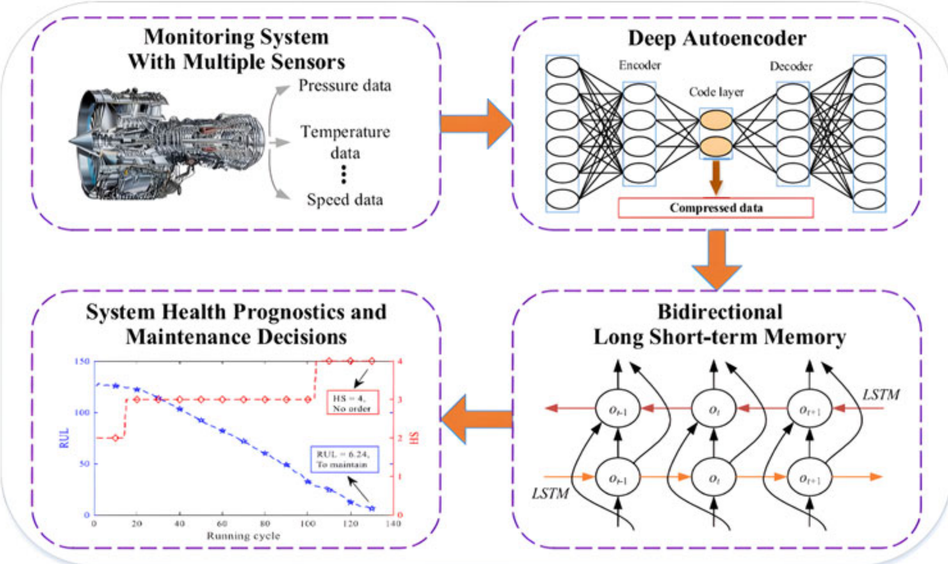

Figure 7. Block flow diagram of using DL to predict RLU [38].

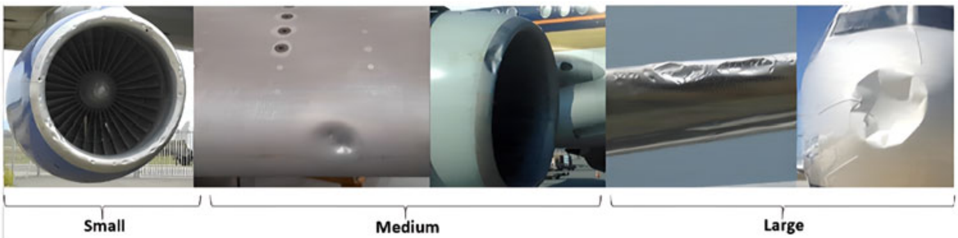

Figure 8. Dents of various size on aircraft structures [39].

paired with bidirectional long short-term memory networks (Bi-LSTM), and it has been trained utilising the NASA C-MAPSS dataset.

In another application, AI is being utilised for automated aircraft maintenance inspection to detect structural dents shown in Fig. 8 on various aircraft components. While numerous defects are visually detectable, smaller defects might elude unaided human observation. Dogru et al. [39] addressed this issue by proposing a masked R-CNN framework that incorporates transfer learning. Their dataset was specifically designed to include a variety of dent sizes.

2.2 Air traffic management

AI is revolutionising air traffic management (ATM) through diverse applications: ATM is the complex choreography that maintains safe and efficient air travel. As airspace becomes increasingly congested, researchers are employing AI to revolutionise ATM, envisioning a future where human expertise and machine intelligence work collaboratively. Brittain and Wei [40] proposed a framework using deep multi-agent reinforcement learning for autonomous air traffic control systems. Trained in the BlueSky simulation environment, AI agents prioritise safety and efficiency, resolving conflicts in high-density traffic scenarios. In safety-critical domains like ATM, transparency is paramount, driving the adoption of explainable AI (XAI) frameworks. Xie et al. [20] emphasise interpretable AI models within ATM

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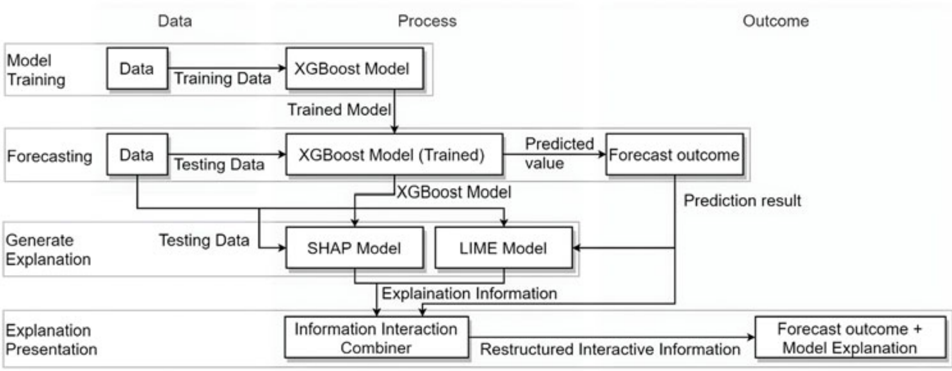

Figure 9. *Framework of prediction model [20].*

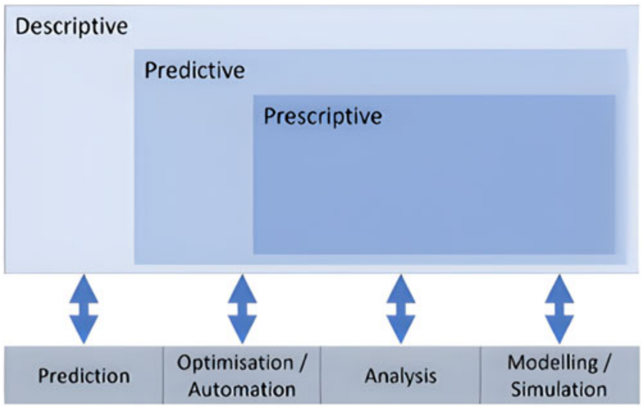

Figure 10. *Synthesis of explainable AI (XAI) conceptual framework [41].*

(Fig. 9), investigating post-hoc explanations to elucidate decision processes. Augustin et al. [41] extend this work with the DPP (descriptive, predictive, prescriptive) model (Fig. 10), enhancing human-centred AI systems in ATM.

Building on predictive applications, ML techniques are transforming ATM operations: the applications of AI in ATM extend beyond conventional air traffic control, notably exploring ML techniques in predicting ground delay programmes (GDPs) [42]. These programmes, activated due to disruptions like adverse weather, leverage ML algorithms (SVMs, LR, RF) to process historical data, deriving a 'regional convective weather variable' that enhances GDP forecasting accuracy. Tang et al. [43] systematise these advances, highlighting AI's role in automating tasks across ATM sectors (ATS, AM, ATFM, FO) while identifying data quality and user expertise as persistent challenges.

In operational contexts, AI addresses both air and space traffic challenges: in space traffic management, Vasile et al. [44] integrate machine learning with orbital mechanics for collision risk mitigation. For air traffic, Kistan et al. [45] demonstrate deep neural networks (DNNs) in Airborne Collision Avoidance System (ACAS) Xa, achieving 40% performance gains over Traffic Collision Avoidance System (TCAS), while Gallego et al. [46] combine DBSCAN, multi-level models (MLM) and ANNs to analyse aircraft vertical trajectories and predict altitude levels. Evolutionary algorithms also show promise – Lertworawanich et al. [47] apply genetic algorithms (GA) with K-means clustering to optimise direct capacity balancing (DCB) overload management.

ML-driven traffic flow analysis exemplifies AI's spatial-temporal capabilities: Gui et al. [48] analyse air traffic flow using automatic dependent surveillance broadcast (ADS-B) data, with LSTM networks

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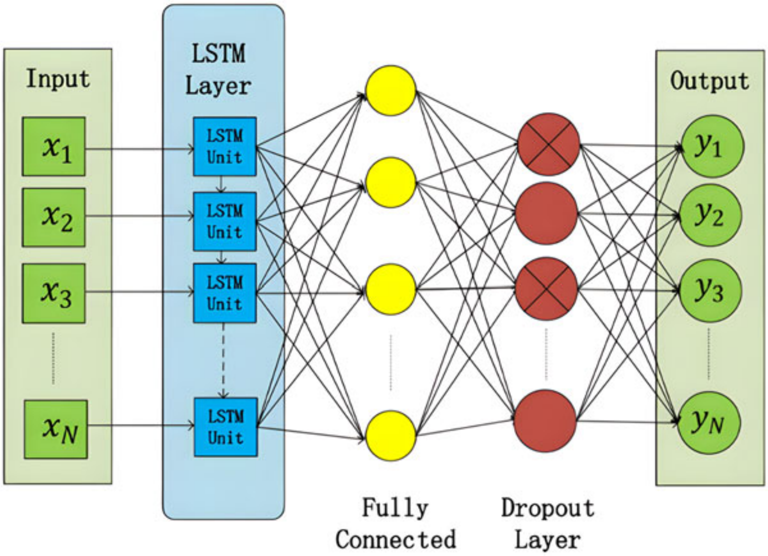

Figure 11. *Architecture of the LSTM-based air traffic model [48].*

outperforming SVR in managing flow variations (Fig. 11). This aligns with broader trends where temporal modeling excels in dynamic ATM environments.

2.3 Quality control in aerospace manufacturing

In the rapidly evolving domain of aerospace, significant strides in ML, deep learning (DL) and computer vision (CV) are transforming aircraft inspection methodologies. This section explores the technical intricacies of algorithms deployed in quality control and visual inspection processes. High-resolution and sensitive charge-coupled device (CCD) cameras, combined with sophisticated imaging systems, serve as the foundational technology for this application [49]. A notable research initiative has developed an integrated system for automated aircraft surface inspection, utilising CCD cameras and CV algorithms. This system incorporates drones, tablets, and pan-tilt-zoom (PTZ) cameras to methodically survey surfaces, emphasising detailed defect identification – from hairline fractures to fluid leaks – rather than mere image acquisition [50].

Expanding beyond 2D imaging, envision a robotic inspector equipped with dual 2D cameras and a 3D scanner, designed to confirm assemblies match their 3D computer-adided design (CAD) models [51]. While routine inspections verify component presence and alignment, complexities like flexible part spacing or interference detection require 3D datasets. The employed CV algorithm involves three steps: handling parasitic edges, weighting edges and determining gradient orientations.

Further exploration reveals the use of ANNs to enhance continued operational safety (COS) for aircraft, spacecraft, and unmanned aircraft systems (UAS) [7]. Leveraging databases like service difficulty reports (SDR) and NASA, these ANNs predict certification-critical parameters via supervised learning, improving aerospace component reliability.

Beyond component inspection, spatial awareness systems rely on visual simultaneous localisation and mapping (VSLAM) and visual odometry (VO) to ascertain vehicle orientation and position [52]. Concurrently, CV-driven defect categorisation – such as corrosion, cracks and punctures – streamlines maintenance workflows [53].

At the forefront of CV advancements, convolutional neural networks (CNNs) like U-Net excel in defect detection. U-Net's architecture combines contracting paths (context capture) with expanding paths (precise localisation), integrating convolutional and pooling layers for feature extraction and upscaling. This preserves spatial information, enabling effective segmentation in biomedical and aerospace visual analysis.

2.4 Autonomous navigation and control

Many DL frameworks designed for visual scene interpretation, navigation, guidance and control in UAS primarily utilise CNNs. Traditional AI problem-solving algorithms, often optimisation-based, are rooted in mathematical methodologies and can find near-optimal solutions for nondeterministic polynomial-time (NP)-hard problems.

Learning-based methods encompass both model-based AI algorithms and modern techniques, including reinforcement learning (RL) and deep reinforcement learning (DRL), which use Markov decision processes (MDP) or partially observable MDP (POMDP), as well as asynchronous advantage actor-critic (A3C) architectures for decentralised training.

While the AI sector expands rapidly, many effective methods for autonomous UAV navigation remain underexplored. Autonomous UAV navigation enhances flexibility in dynamic environments, relying on optimisation-based approaches such as particle swarm optimisation (PSO), ant colony optimisation (ACO), genetic algorithm (GA), simulated annealing (SA), pigeon-inspired optimisation (PIO), cuckoo search (CS), A^* algorithm, differential evolution (DE) and grey wolf optimiser (GWO). Researchers have adapted these algorithms for mission-specific constraints to achieve optimal results [54].

This survey bridges technical foundations with practical applications by outlining UAV characteristics and types to familiarise readers with architectures, summarising navigation systems and real-world implementations, and detailing the principles of AI algorithms used for autonomous navigation.

2.5 Image recognition and computer vision

Recent advancements in image recognition and CV have significantly impacted numerous industries, including aerospace. Leveraging sophisticated algorithms and ML techniques, these technologies analyse visual data to extract meaningful information from images and videos. In aerospace, CV is crucial for two primary applications: AI-driven remote sensing and quality inspection of components.

In remote sensing, AI enhances data processing efficiency and accuracy, automating object recognition/classification and detecting environmental changes for improved decision-making. As noted by Lary [55], AI's ability to process geospatial data is instrumental here. Among AI's six primary directions identified by Wu [56] – CV, natural language processing, robotics, cognitive computing, game theory/ethics and ML – the latter is particularly vital. Wang et al. [57] emphasise ML's necessity in advancing remote sensing capabilities.

For quality inspection, CV systems use cameras and algorithms to perform tasks traditionally reliant on human vision. The aerospace industry increasingly adopts intelligent visual inspection systems to ensure component quality. Advances in ML, especially DL, have enabled automatic solutions for inspecting internal/external components, from surface defects to structural integrity.

2.6 Maintenance and documentation

AI has become a pivotal force in aviation maintenance, offering innovative solutions across diverse applications. Inspection technologies leverage CNNs with autonomous drones to automate visual inspections, enhancing defect detection accuracy for issues like dents through image augmentations and pre-classification techniques [58]. Complementing this, ML and Internet of Things (IoT)-based methods predict thermal performance in aircraft wing anti-icing systems, outperforming traditional computational fluid dynamics with ANNs [59].

Beyond component-specific applications, AI drives sustainability efforts: environmental impact analysis integrates statistical and ML methods to assess fuel burn, emissions and noise, supporting

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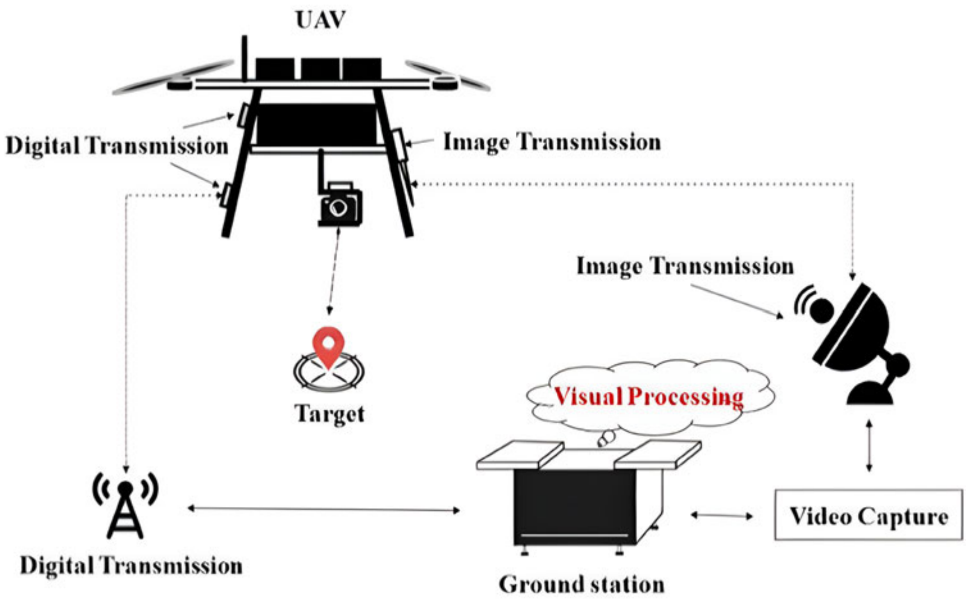

Figure 12. *UAV dynamic tracking system [70].*

data-driven sustainable aviation [60]. For maintenance optimisation, DNNs detect corrosion in aircraft lap joints with human-level precision, enabling condition-based maintenance [39]. In rotorcraft, fuzzy neural networks and individual blade control (IBC) reduce hub vibrations, informing better control laws [61].

Predictive capabilities extend to core systems: generalised regression neural networks (GRNN) accurately forecast exhaust gas temperature baselines for engine health [62]. ML models also advance lithium-ion battery research for aviation, focusing on health estimation and fault diagnosis [63].

Global aviation authorities recognise AI's transformative potential. International bodies such as the International Civil Aviation Organisation (ICAO) emphasise AI training for professionals, while the European Union Aviation Safety Agency (EASA) proposes AI oversight frameworks and EUROCONTROL's FLY AI report prioritises air traffic management adoption [64–66]. Regional initiatives, including the European Commission's AI strategy, promote human-centric AI in transportation, while the Federal Aviation Administration (FAA) and International Air Transport Association (IATA) drive research and development and workforce readiness [67–69].

3.0 AI in unmanned systems

UAVs are being used in a variety of technical disciplines, ushering in a new era of possibilities. They possess unique capabilities in various industries, from object monitoring to wireless communication networks, addressing challenges and increasing efficiency. UAVs are employed in dynamic object tracking as shown in Fig. 12.

For the described study, PTZ cameras are employed to ensure the UAV maintains the target object within its visual field while minimising the distance to the object. Target identification is performed using the YOLOv3 (You Only Look Once) algorithm at the ground station. All experimental procedures are carried out utilising the AirSim simulation environment [70]. This integration of advanced computer vision techniques enables real-time, accurate object tracking and monitoring, supporting various aerospace and industrial applications. In the study presented by Kalinov et al. [71], the authors introduce a novel integration of unmanned ground robots (UGRs) for global localisation and UAV systems for barcode scanning applications shown in Fig. 13. The UGR system utilises infrared (IR) sensors to

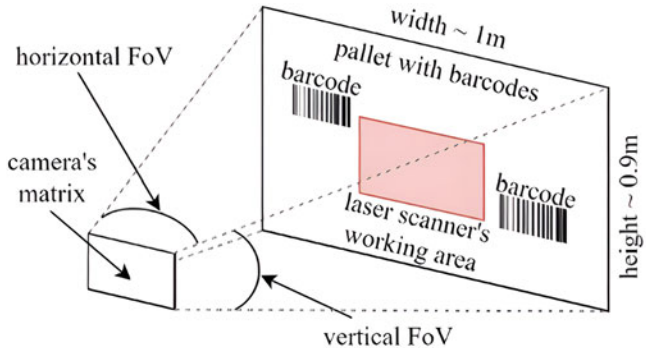

Figure 13. *Barcode view from UAV [71].*

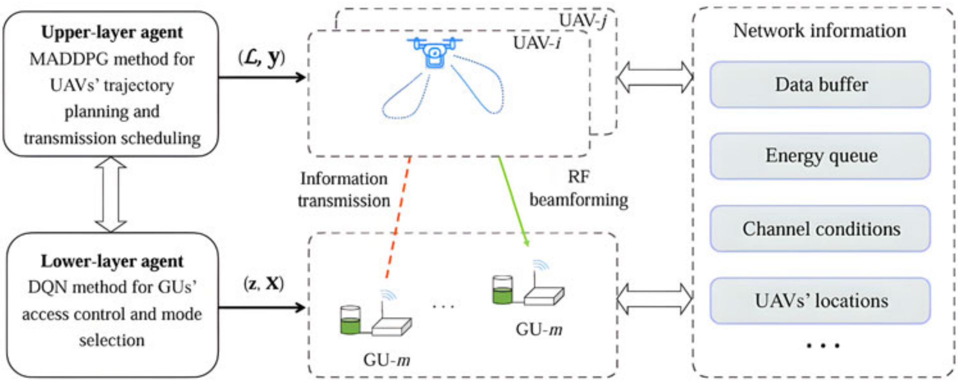

Figure 14. *Framework of RL in UAV application [73].*

determine the precise location of the UAV, which is equipped with a CNN-based U-Net architecture designed to enhance the accuracy of barcode detection. An innovative active prediction mechanism is implemented to augment efficiency. This mechanism directs the scanning efforts towards areas identified through learned patterns, thus minimising redundant scans and enhancing operational efficiency. Such a technology holds significant potential for adoption in the aerospace sector, promising substantial improvements in inventory management and cost reductions.

Considering the global dependence on communication and the issue of spectrum scarcity, Wang and Peng [72] describe the creation of a cognitive drone network (CDN) that applies CNN to extract energy matrix information for cooperative spectrum sensing. This approach utilises CNN to learn deep features from energy matrix data, eliminating the need to determine a detection threshold and enhancing adaptability to diverse noise environments.

RL models shown in Fig. 14 are widely used in diverse UAV scenarios as reported by Luo et al. [73]. A DRL architecture tailored for optimising trajectory planning, transmission scheduling and access control within UAV-assisted wireless sensor networks. The framework integrates DNNs utilising CNNs to process spatial information and recurrent neural networks (RNNs) to handle temporal dependencies. Additionally, Yanan et al. [74] addresses the application of conventional reinforcement learning techniques, specifically deep Q-networks (DQNs) and deep deterministic policy gradient (DDPG) to UAV communication challenges modelled as MDPs. It provides an analysis of using DQNs for effective power management and transmission target determination, along with the application of DDPG in devising joint optimisation strategies. These RL-based approaches collectively advance UAV autonomy and efficiency across communication, navigation and resource management tasks.

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4.0 AI in space exploration

The space industry, categorised into upstream and downstream sectors, has seen limited integration of AI compared to other sectors. AI's evolution, from statistical methods to sophisticated models like very large transformers, has predominantly utilised general-purpose data. Satellite data, however, has been less explored, with current AI applications in space focusing on specific tasks like detecting buildings and ships from satellite imagery using finely tuned models. The potential for AI in space exploration is significant, especially in roles like detecting planetary craters and supporting autonomous robots in future missions. Significant investments from organisations like the National Geospatial-Intelligence Agency and ESA Space Solutions are fostering the growth of AI applications in space. Initiatives by companies such as SkyServe, which aims to deploy AI models directly on satellites, and Satellogic, which releases labeled data openly, indicate a promising direction toward developing foundational AI models that could revolutionise the space industry [75, 76]. Although the full potential of AI in space has not yet been realised, the ongoing investments and innovations suggest a pivotal role for AI in future space technologies and exploration.

4.1 Space rovers

ML can be effectively utilised in the aerospace sectors to enhance mathematical computations. Rovers shown in Fig. 15, which are devices engineered for exploring the surfaces of planets and other celestial bodies, stand to benefit significantly from ML applications. In the context of rovers, ML algorithms facilitate a range of tasks including autonomous navigation, path planning and anomaly detection. Additionally, these algorithms are instrumental in mechanical applications such as structural analysis, materials selection, design optimisation, fault detection and diagnostics, among others. A notable study explored the implementation of a ML technique known as Q-Learning, detailed in Ref. (77). Q-Learning is a model-free reinforcement learning algorithm where an agent learns optimal policies by iteratively updating a Q-table that maps state-action pairs to expected cumulative rewards. The rover interacts with its environment, receiving rewards for desirable behaviours (e.g., avoiding obstacles, conserving energy) and penalties for undesirable ones. Through trial-and-error interactions, it maximises the long-term reward signal defined by Equation (1), as illustrated for the rover in Fig. 15:

$$Q\left(s_t, a_t\right) \leftarrow Q\left(s_t, a_t\right) + \alpha \left[r_{t+1} + \gamma \max_a Q\left(s_{t+1}, a\right) - Q\left(s_t, a_t\right)\right] \tag{1}$$

where α is the learning rate, γ the discount factor, and s_t, a_t, r_{t+1} represent the state, action and reward at time t. This approach is particularly suited for rover navigation in unpredictable extraterrestrial environments, where predefined rules may fail. The field-programmable gate array (FPGA) implementation enables hardware acceleration of these computations, critical for real-time decision-making under resource constraints. Specifically, Q-learning has been applied in rovers to improve decision-making and navigation strategies. The research also demonstrated the deployment of Q-learning in both single neuron and multilayer perceptron architectures on a Xilinx Virtex 7 FPGA.

Concurrently, another study focused on the locomotion challenges of tensegrity robots, which are utilised for planetary exploration, as described in Ref. (79). This research proposed an advanced version of the mirror descent guided policy search (MDGPS) algorithm to autonomously learn effective locomotion gaits, addressing the intricate dynamics of these robots. Furthermore, an innovative approach to identifying rare geological phases on Mars was investigated, employing a Bayesian classifier trained with spectral data from the Compact Reconnaissance Imaging Spectrometer for Mars (CRISM), as outlined in Ref. (80). This classifier aids in the detection of unique geological features, showcasing the broad applicability of ML in space exploration contexts. Building on this, further explorations into the Jezero crater have revealed jarosite and silica on its floor, while chlorite-smectite and Al-rich phyllosilicates have been detected along the crater walls. These mineralogical findings suggest a complex history of water activity within the Jezero region. Moreover, the application of ML techniques has proven to be significantly more effective than traditional methods for such reconnaissance, underscoring the potential of ML to enhance geological analysis in planetary exploration.

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Figure 15. *Mars rover's robotic arm drove a drill bit into flat patch of the rock [78].*

In a study conducted by Neil et al. [81], a novel pathfinding algorithm for navigation across uneven terrains was developed. The algorithm employs a heuristic known as the gradient convolution, which integrates a metric called the angular cost estimate (ACE). ACE quantifies the irregularity of the terrain beneath the rover's wheels. The approach utilises a deep convolutional neural network (DCNN) architecture akin to the UNet model. This architecture processes height maps to produce ACE cost maps, thereby optimising computational efficiency. The implementation achieved an overall accuracy of 95.3%. This example illustrates the application of ML techniques to enhance performance and reduce computational demands in scenarios where traditional models are inadequate.

4.2 Satellites and earth observation

In the expansive realm of outer space, satellites are integral to global connectivity. The incorporation of AI and ML technologies is revolutionising the utilisation of satellite systems as shown in Fig. 16. This section explores the application of ML and DL across various satellite operations. Geostationary Earth Orbit (GEO) satellites, predominantly utilised for communication services such as broadcasting, broadband Internet access and telecommunications, benefit significantly from these advancements. Research in this domain has employed models including SVMs, DNNs and DQNs to optimise resource allocation. Such innovations not only foster more efficient system designs but also contribute to substantial cost reductions [82].

In low Earth orbit (LEO) constellations, which are utilised for communication and Earth observation with hundreds to thousands of satellites, monitoring each satellite's state poses challenges. Autoencoders extract features from parameters like position, velocity and mission type, while ML classifiers (random forest (RF), SVM, neural networks) identify orbit states for debris mitigation and spectrum allocation [83]. Remote sensing applications further demonstrate ML's versatility: MIDAPS-AI combines decision trees, neural networks and SVM on LEO/GEO satellites for disaster management and debris detection [84], while nanosatellites like OPSAT implement online ML for fault detection, isolation, and recovery (FDIR), enabling real-time analysis in resource-constrained environments (Fig. 17) [85].

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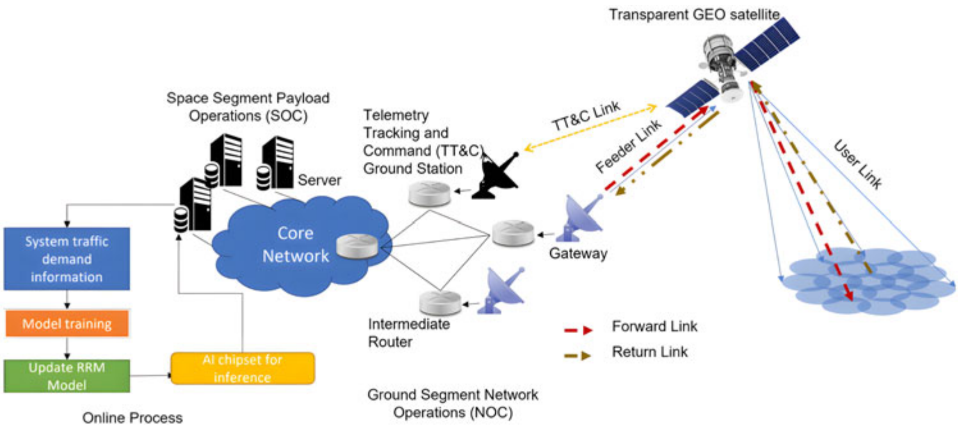

Figure 16. *AI chip implementation in GEO satellite [82].*

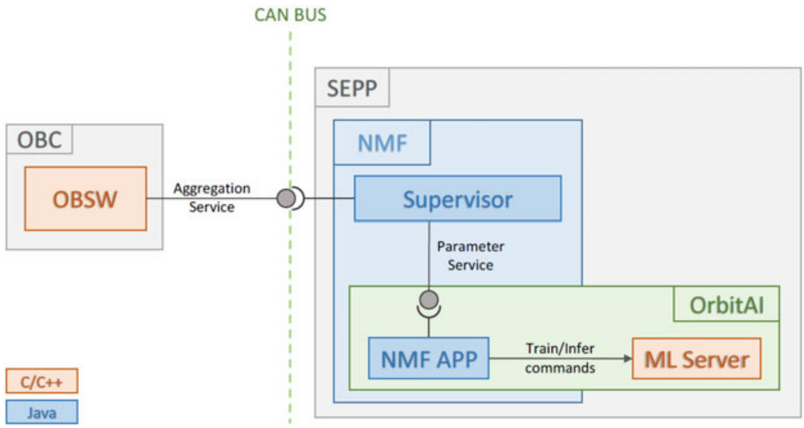

Figure 17. *Orbit-AI app implementation in OPSAT [85].*

High-throughput and navigation systems also leverage ML: very high throughput satellites (VHTS) optimise power/bandwidth using elevation and traffic data [86], while GNSS apply ML for signal processing and anomaly detection [87]. Cross-domain challenges – resource allocation, interference, latency – are addressed via neural networks, SVM, and genetic algorithms, enhancing Quality of Service (QoS) [88, 89].

Data privacy and satellite health are critical considerations: Federated Learning (FedSpace) enables GDPR-compliant distributed training (Fig. 18) [90], while CNNs analyse temperature sensors for real-time health diagnostics, outperforming traditional methods in noise resilience [91].

Satellite data analytics rely on ML for tasks like classification and imagery analysis: SVM, decision trees and random forests handle regression tasks, while CNNs, RNNs and LSTM networks process imagery and fusion (Fig. 19) [92]. Future advancements in machine learning operations (MLOps) and space-grade processors will enable adaptive AI for dynamic space environments [93].

4.3 Deep space, autonomous health monitoring in space

The mental and physical demands of multi-year space missions necessitate enhanced astronaut medical care, and AI shows great promise in improving future crew support systems. By integrating data

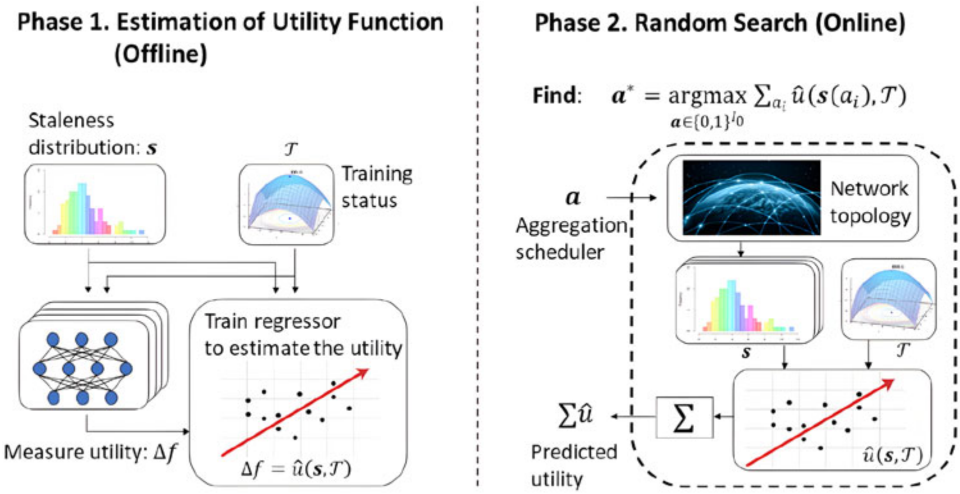

Figure 18. *Overview of aggregation schedular in FedSpace [90].*

Figure 19. *Application of data collected by satellites to monitor construction rate using segmentation [92].*

from sensors monitoring heart rate, skin temperature, exercise and sleep patterns, AI-powered predictive health analytics can provide customised interventions tailored to each astronaut. This holistic approach, combining real-time vital signs, behavioural indicators and environmental conditions, enables sophisticated diagnostics, early risk warnings and personalised treatment plans. For instance, the Crew Interactive Mobile Companion (CIMON) as shown in Fig. 20, an AI robot designed by Airbus, IBM and the German Aerospace Centre, assists astronauts on the International Space Station (ISS). CIMON can navigate the station, document experiments and offer procedural guidance, while also providing emotional support by sensing stress levels and guiding astronauts through therapeutic exercises. Future intelligent systems on the ISS and lunar Gateway will further anticipate astronauts' needs and automate tasks, with AI virtual assistants adapted for psychological support during Mars missions, where communication delays with ground control are significant [94].

Scientific research aboard the ISS is critical for advancing space medicine: NASA's SpaceX Crew-6 recently launched and docked at the ISS, initiating over 200 experiments. These include the Cardinal Heart 2.0 project, which examines whether approved drugs mitigate microgravity-induced changes in

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Figure 20. *CIMON with ESA astronaut Alexander Gerst (Credit: ESA).*

heart-cell function, and microbial studies sampling ISS life-support vents to analyse microorganism behaviour in space. Complementing this, NASA's Biosentinel experiment – deployed on a CubeSat in heliocentric deep space radiation effects, marking the first such study in five decades. To expand research for missions beyond LEO, including lunar and Martian missions, highly automated approaches with AI and ML will be pivotal. NASA's 2021 workshop explored AI's role in advancing space biology and personalised healthcare [95].

AI has significantly transformed expert medical systems, particularly in differential diagnoses. DL advancements enable AI systems to match human experts in diagnosing diseases across radiology and pulmonology. Deep CNNs excel in extracting intrinsic features from raw data, achieving superior results in medical image tasks like classification and segmentation. For instance, OpticNet-71 trained on optical coherence tomography (OCT) images identifies age-related macular degeneration, diabetic macular edema, drusen and choroidal neovascularisation, while CheXNeXt diagnoses 14 diseases from chest radiographs. Semantic segmentation utilises architectures like U-Net for retinal vessel and brain-tumor segmentation. Generative adversarial networks (GANs) further innovate medical imaging: conditional GANs generate fluorescein angiography images from Color Fundus, and RV-GAN specialises in retinal vessel segmentation. These advancements underscore AI's potential to revolutionise clinical support systems [96].

AI in space medicine faces unique challenges: sparse astronaut data for training, limited prospective research in space environments and ethical/legal complexities like managing astronaut-doctor relationships and informed consent. These necessitate specialised approaches and ethical frameworks for effective integration [96].

4.4 Launch vehicles

Recent advancements in AI and ML have significantly enhanced rocket technology reliability and performance. Solid rocket motors (SRMs), critical for launch vehicles and defense missiles, benefit from AI-driven defect detection. Liu et al. [97] pioneered sensor systems using CNNs and LSTM networks to identify inner bore cracks and propellant delamination during testing. Building on defect detection,

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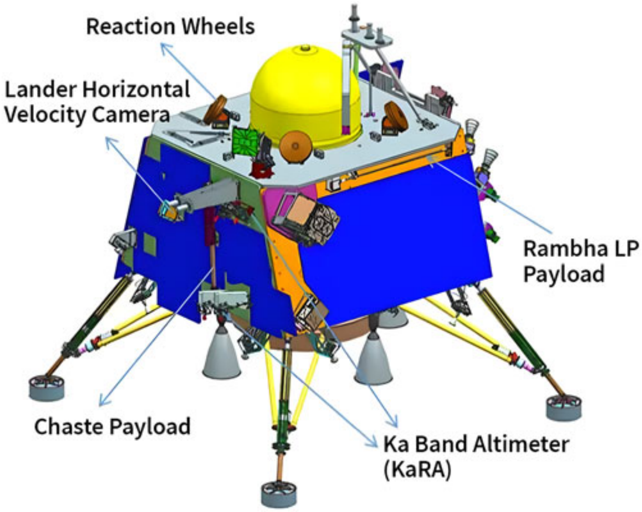

Figure 21. *Chandrayaan-3 (Credit: ISRO).*

ML algorithms address propellant combustion unpredictability: Debus et al. [98] analysed fuel-oxidiser interactions with RF, SVM, K-Nearest Neighbour (KNN) and ANNs, demonstrating RF's superior accuracy over traditional methods.

Hybrid rocket propellant analysis further exemplifies AI's versatility: Surina et al. [99] combined imaging techniques (thresholding, last image subtraction, spatial filtering) with U-Net architectures and Monte Carlo dropout to measure regression rates, enhancing performance insights. For flight performance evaluation, surrogate neural networks (SNNs) simulate hybrid rocket engine (HRE) dynamics, heat transfer and thrust parameters with precision comparable to full-scale simulations [100].

Real-time telemetry optimisation leverages CNNs: Li et al. [101] streamlined rocket status assessment using CNN architectures (input, convolution, pooling, fully connected, output layers) for video data processing. Collectively, these advancements – defect detection, combustion analysis, regression measurement, performance simulation and telemetry – enhance safety, reliability and efficiency in rocketry.

4.5 AI's role in Chandrayaan-3 mission

AI played a pivotal role in enhancing navigation, hazard avoidance, data interpretation and enabling autonomous decision-making in the Chandrayaan-3 mission. Chandrayaan-3 (Fig. 21), the successor to Chandrayaan-2, successfully touched down on the Moon's southern pole on August 23, 2023 [102]. Building on discoveries from Chandrayaan-1 (water detection in the Aitken basin) and Chandrayaan-2 (mineral mapping via orbiter data), AI systems managed critical landing phases by integrating altimeters, velocimeters and cameras to adjust altitude, fire thrusters and scan for obstacles [103–105].

Central to the landing was the terrain relative navigation (TRN) system: using a camera and onboard computer, TRN matched lunar surface images with pre-loaded maps, analysing terrain features, slopes and hazards via image processing and pattern recognition. While exact models are undisclosed, CNNs, Siamese networks or LSTM networks likely enabled feature comparison and sequential data processing during descent [106].

The navigation, guidance, and control (NGC) system dynamically adjusted speed, orientation, and trajectory using TRN inputs and mission objectives. Potential control mechanisms included proportional-integral-derivative (PID) controllers, DQNs trained on Chandrayaan-2 data, DNNs for real-time sensor adjustments or RNNs for sequential data handling.

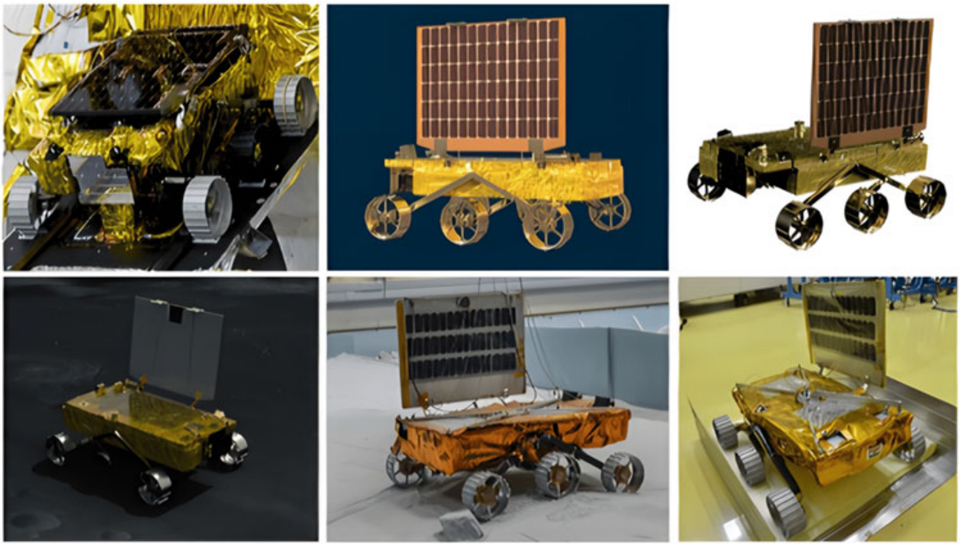

Figure 22. *Pragyan – lunar rover (Credit: ISRO).*

For the Pragyan rover (Fig. 22), AI enabled autonomous navigation: Likely strategies included RL, A*/rapidly exploring random trees (RRT) for path planning, and CNNs for real-time image analysis. Transfer learning may have adapted pre-trained models to lunar conditions. Instruments like the alpha-proton X-ray spectrometer (APXS) and laser-induced breakdown spectroscope (LIBS) utilised AI for geological analysis – CNNs identified features, regression/classification interpreted spectral data and matching algorithms cross-referenced mineral libraries [107].

4.6 Current work by space agencies

Transitioning from exploratory research to practical space applications may seem daunting, but the European Space Agency (ESA) is already utilising AI in its missions. Rovers, for instance, can autonomously navigate obstacles, and data downloads from Mars rovers are now scheduled using AI. AI also supports astronauts aboard the ISS, enhancing their daily operations.

ESA's Hera planetary defense mission exemplifies AI's potential, autonomously navigating through space toward an asteroid by fusing sensor data and making real-time decisions, much like self-driving cars. While most deep-space missions rely on human controllers, Hera's onboard autonomy sets a new standard. Satellites are also gaining more autonomy to perform collision avoidance manoeuvers amidst increasing space debris. In January 2021, ESA and the German Research Centre for Artificial Intelligence (DFKI) launched ESA_Lab@DFKI, focusing on AI systems for satellite autonomy and collision avoidance.

AI also enhances satellite navigation, improving weather forecasting and detecting rogue drones in sensitive airspace. ESA-led projects have applied AI for autonomous situational awareness in ships, and the German Aerospace Centre (DLR) has developed AI methods for space and Earth applications, establishing an Institute of Artificial Intelligence Security in 2021. DLR's AI assistant, CIMON, supports astronauts on the ISS by performing voice-controlled tasks and navigating the station.

NASA also employs AI extensively, with an artificial intelligence group dedicated to supporting scientific analysis, spacecraft operations, mission analysis, deep space network operations and space transportation systems. NASA's cognitive radio technology ptimises communication networks by using 'white noise' areas in communication bands, enhancing the efficiency of limited telecommunication resources. AI has also improved solar research data and facilitated autonomous spacecraft operations, reducing communication delays. NASA's collaboration with Google led to the discovery of two exoplanets by training AI algorithms to analyse Kepler mission data. This success prompted the use of AI in NASA's TESS mission to identify potential exoplanets.

Japan's Japan Aerospace Exploration Agency (JAXA) pioneered AI integration in space missions with its Epsilon rocket, which autonomously performs performance checks, simplifying payload launches. JAXA's 'Int-ball' robot autonomously captures ISS experiment photos, saving astronauts time. The French space agency CNES, in partnership with Clemessy, optimised rocket tank filling using AI neural networks. The UK Space Agency funded AI projects to detect buried archaeological remains via satellite imagery, and the Italian Space Agency co-founded an AI-focused company. These initiatives highlight the transformative potential of AI in space exploration and operations, underscoring the importance of ongoing research, development and international collaboration [108].

5.0 Challenges and legality

Despite advances in AI, its implementation in space faces significant challenges. The integration of AI introduces cybersecurity risks such as signal jamming, satellite command hijacking or physical destruction through adversarial attacks on navigation or control systems. For example, a compromised AI-driven navigation system could misinterpret orbital debris avoidance maneuvers, risking collisions, while manipulated sensor data in robotic rovers might trigger catastrophic drilling operations. Most AI models in space robotics operate via local inference (e.g., onboard Mars rovers or lunar landers) and lack internet connectivity, but threats persist through supply chain vulnerabilities or compromised training data. Robust cybersecurity measures, including radiation-hardened hardware encryption and runtime integrity verification, are critical [109, 110].

While AI excels in repetitive tasks in harsh environments, there is a gap between AI's current perceptual abilities and the complex decision-making required for space missions. To fully realise AI's potential in space, advancements in autonomy, automation, robotic sensing, perception, mobility, manipulation, rendezvous and docking and onboard and ground-based autonomous capabilities are essential. Integrating humans with robots and developing comprehensive data analysis tools will be crucial for expanding human exploration of space.

The balance between human control and AI autonomy will hinge on societal acceptance of automation risks and consensus on the human values and principles to be preserved. Legal challenges also loom, as each jurisdiction will develop its approach to liability, accountability and responsibility in space AI, influenced by existing laws such as criminal, international humanitarian, tort and administrative law. The Liability Convention, which addresses damages from space objects, may need to adapt to autonomous systems – for instance, clarifying fault when an AI-controlled satellite malfunctions due to adversarial training data. These legal issues extend to AI systems supporting space-based services, including GNSS-based emergency response, autonomous vehicles and unmanned aircraft systems.

6.0 Conclusions and future scope

AI and ML have significantly advanced the aerospace industry through predictive maintenance systems using Bi-LSTM, ConvLSTM, CRNNs and VAE models, which analyse sensor data to reduce unplanned maintenance by 25%. In ATM, multi-agent systems optimise flight paths and reduce delays, while XAI enhances transparency in decision-making. Traditional methods like DNNs and genetic algorithms have demonstrated complementary advantages in ATM.

CV applications automate quality control, with models like U-Net identifying cracks and corrosion in real time to maintain industry standards. UAVs employ CNNs and RL techniques such as DQNs and DDPG for trajectory optimisation in dynamic environments. AI-driven UAVs enhance inventory management using PTZ cameras and YOLOv3 for detection/tracking, alongside U-Net architectures for

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barcode scanning. Cooperative spectrum sensing in cognitive drones leverages CNNs to analyse energy matrices, eliminating manual workflows.

These advances in AI and ML have also impacted rocket technology, with ConvLSTM networks and SNNs being used for detecting SRM defects and simulating hybrid engine performance.

Transitioning to space exploration, AI has become a pivotal force in enabling new mission capabilities and scientific discoveries. DQNs enhance real-time decision-making in planetary rovers operating under unpredictable conditions. Chandrayaan-3 utilises a TRN system and RL for the Pragyan rover's autonomous path planning. Satellite operations employ autoencoders for orbit state classification, while AI health monitoring systems like CIMON assist astronauts with daily tasks and psychological support.

Despite these advancements, challenges persist in cybersecurity, legal frameworks and interdisciplinary integration.

AI is set to revolutionise space exploration, unlocking new possibilities and transforming our understanding of the cosmos. Take an example of NASA's Parker Solar Probe, scheduled to reach the Sun's outer atmosphere in December 2024, which will leverage advanced AI systems to endure extreme temperatures up to 2,500 °F (1,370 °C) and collect crucial data using its magnetometer and imaging spectrometer. This mission aims to deepen our knowledge of solar storms and their impact on Earth's communication technologies.

Beyond this, AI will significantly enhance the monitoring of Earth-orbiting satellites and the management of spacecraft on extended missions. By integrating AI with robotics, future missions could deploy autonomous robots to explore distant planets and moons, conduct scientific research independently and relay valuable information back to Earth.

Space travel, exploration and observation involve some of the most complex and dangerous scientific and technical operations ever undertaken, presenting problems that AI excels at solving. Consequently, astronauts, scientists and engineers increasingly rely on ML to address these challenges. From automating spacecraft take-off and landing to steering rockets through space and studying distant planets, AI optimises fuel use and enhances mission efficiency. SpaceX's AI autopilot system allows Falcon 9 rockets to perform autonomous operations, including docking with the ISS. CIMON 2, an AI robot, assists astronauts with hands-free information access and emotional state assessment. NASA's JPL uses AI to model mission parameters and plan future missions, while autonomous systems from SpaceX and the UK Space Agency help avoid collisions with space debris. AI also aids astronomers in mapping the universe, predicting cosmic events and detecting black holes. Projects like the Autonomous Sciencecraft Experiment and SETI@Home demonstrate AI's potential in both Earth observation and the search for extraterrestrial intelligence. These applications highlight AI's transformative impact on space exploration and its role in overcoming the extraordinary challenges of venturing into the final frontier.

The future of AI in aerospace and space exploration will be characterised by the development of intelligent autonomous systems capable of real-time decision-making and adaptive mission planning. These systems will integrate advanced AI architectures, including deep learning and reinforcement learning models, to enable spacecraft, satellites and planetary rovers to operate efficiently and safely in unpredictable environments without continuous human oversight. Such autonomy will be essential for complex missions, allowing vehicles to self-repair, navigate hazards and optimise performance dynamically.

Collaboration between humans and AI will become increasingly vital, especially for long-duration space missions. Research will focus on creating intuitive interfaces and explainable AI (XAI) systems that foster trust and seamless cooperation between astronauts, engineers and AI assistants. These systems will support crew health monitoring, psychological well-being and mission planning, enhancing both operational effectiveness and human factors. Simultaneously, ensuring the resilience and security of AI-driven aerospace systems will be a priority, with advancements in cybersecurity and fail-safe mechanisms designed to protect critical assets from cyber threats and system failures.

Moreover, the scaling of AI to manage large satellite constellations, UAV swarms and distributed sensor networks will require innovative approaches such as federated learning and edge computing to enable decentralised intelligence while preserving data privacy. Ethical, legal and societal considerations will guide the responsible deployment of AI, necessitating collaboration with regulatory bodies to establish standards for transparency, accountability and equitable access. Open, interdisciplinary research and data sharing will accelerate innovation and ensure that AI's transformative potential benefits the global aerospace community, driving sustainable progress and discovery in the coming decades.

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