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The application of artificial intelligence in aerospace engineering

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Abstract. In recent years, there has been considerable interest in applying Artificial Intelligence (AI) in the field of aerospace engineering. However, the existing literature on this topic is not sufficiently comprehensive. This paper is purposed to solve this problem by providing a thorough analysis and overview of the current state of AI in aerospace engineering. The paper is divided into four sections. Firstly, the use of AI in autonomous navigation and flight control is explored, focusing on advanced algorithms and sensor technologies that enable highly autonomous and efficient aircraft navigation. Secondly, the application of AI in image recognition and computer vision is discussed, highlighting its significance in remote sensing and aerospace component quality inspection. The third section examines the integration of AI in unmanned aerial vehicles (UAV), covering the control system and the utilization of machine learning techniques for improved UAV capabilities. Lastly, the paper explores the impact of AI on data analysis and prediction in the aerospace industry, encompassing weather forecasting, resource allocation, and decision-making processes. Finally, this paper gives a general overview of the nowadays application of AI in aerospace engineering.

Keywords: artificial intelligence, aerospace engineering, autonomous navigation, unmanned aerial vehicles.

1. Introduction

Aerospace engineering has witnessed large advancements recently, with a focus on enhancing safety, efficiency, and overall performance of aerospace systems. One area that has garnered considerable attention is the application of Artificial Intelligence (AI) techniques in aerospace engineering. AI has the potential to revolutionize the industry by enabling autonomous systems, optimizing operations, and improving decision-making processes. The research significance of AI in aerospace engineering lies in its ability to address complex problems and improve system performance. AI algorithms can process large volumes of data, analyze complex patterns, and make intelligent decisions in real-time. This capability is particularly valuable in the context of autonomous navigation and flight control, where AI algorithms can enable aircraft to adapt to changing environments, optimize trajectories, and ensure safe and efficient operations. Despite the potential benefits of AI in aerospace engineering, the current state of research and applications in this field is not sufficiently comprehensive. Existing literature lacks a thorough analysis and overview of the advancements, challenges, and future directions of AI in aerospace engineering.

This paper will try to fill this gap by proceeding a comprehensive analysis of the AI situation in aerospace engineering. It will explore the application of AI in various aspects of aerospace engineering, including autonomous navigation, flight control, image recognition, computer vision, unmanned aerial vehicles (UAVs), and data analysis.

By giving the overview of the current situation of AI in aerospace engineering, this paper aims to devote to the existing knowledge and highlight the related paper gaps and future developments. Understanding the limitations and potentials of AI in aerospace engineering will pave the way for further advancements, leading to safer, more efficient, and innovative aerospace systems.

2. Autonomous navigation and flight control

Recently, significant advancements have been made in the usage of AI techniques to address complex challenges encountered in autonomous navigation and flight control. By integrating advanced algorithms and sensor technologies, aircraft can perceive their environment, analyze data, and make precise decisions to achieve highly autonomous and efficient navigation and flight control. These techniques allow aircraft to adapt to varying environmental conditions, handle uncertainties, and optimize their trajectories in real-time. By leveraging AI technologies, autonomous navigation and flight control systems can enhance the overall safety, efficiency, and performance of aerospace operations. The utilization of advanced algorithms and sensor technologies empowers aircraft with the ability to autonomously navigate through complex environments and optimize their trajectories for various mission objectives. This field of research continues to evolve, driving the development of more intelligent and autonomous aircraft systems in the aerospace industry.

2.1. Evolutionary optimization in trajectory optimization problem

Evolutionary algorithms are a type of optimization method that aims to find the global optimum by utilizing heuristic principles, which may draw inspiration from natural paradigms but are not restricted to them, which is helpful to deal with interplanetary trajectory optimization problems. With proper methods, AI can solve the trajectory optimization problem with efficiency. According to Izzo et al, such problems can be classified into three different parts: single-objective problems, multi-objective problems and combination problems [1].

In single objective problems, two primary methods are Differential Evolution (DE), which is a relatively straightforward form of a Genetic Algorithm that is useful for optimizing non-linear and non-differentiable functions in continuous spaces, and Particle Swarm Optimization (PSO), an algorithm for searching and problem-solving that is inspired by biological processes. As shown in the experiment by Vasile et al., one single algorithm in real-world scenarios doesn't show high efficiency [2]. Thus, it is recommended to test effectiveness of more algorithm concurrently and try to integrate multiple meta-heuristics into a single approach. For example, Englander et al. was able to optimize their automated mission design, which involved a series of interplanetary transfers and multiple gravity assist manoeuvres, by merging Differential Evolution (DE) and Particle Swarm Optimization (PSO) together for the best performance [3].

For multi-objective problems, the traditional concept of a single optimal design is replaced by the Pareto front, which represents a collection of solutions that are not dominated by any other solution and reveal the inherent trade-offs between conflicting objectives. Having access to this set of best possible solutions, known as the Pareto-optimal front, is crucial for making well-informed engineering decisions. Population-based algorithms, such as evolutionary algorithms, offer a viable and advantageous approach in this particular scenario. Besides optimizing trajectories, a multi-objective approach has been applied to explore other aspects of guidance and control problems. Vasile and Ricciardi have introduced a memetic multi-objective algorithm that deals with the optimization of multiple objectives simultaneously in the context of the optimal control problem [4]. The effectiveness of the algorithm is evaluated through two specific tasks: optimizing the launch trajectory of a rocket to minimize time and maximize horizontal velocity, and optimizing the ascent maneuver of an orbit to achieve the desired final energy and maneuver time.

When it comes to combination problems, Izzo et al. pointed out that while complexity increased, the optimization of interplanetary trajectories can no longer rely solely on continuous and unconstrained decision variables to achieve effective results [1]. For these problems, more variants and mixtures are required to solve problem according to concrete situations.

2.2. Artificial neural networks in flight control system

By learning from multiple source data, neural networks can make complex decisions and controls, which is beneficial to fly control system. Emami et al. analysed the artificial network-based flight control system with in-depth mathematical way and proposed that there was a wide range of potential applications for neural networks in flight control systems, which can made significant contributions to flight safety and efficiency [5]. In particular, neural networks can be applied to flight control systems for tasks such as flight attitude control, flight trajectory planning, and intelligent flight control system design. At the same time, Intelligent Flight Control Systems consists of into two forms: model-based and model-free types.

Over the past twenty years, the development of model-based neural control, which employs an idealized model of the system during the control design phase, has undergone significant advancements. Three principal methods of model-based neural control are the normal feedback error learning scheme (FELS), the pseudo control strategy (PCS), and the neural back stepping method (NBS). The comparison of the three model-based neural control methods is shown in Table 1.

Table 1. Analysis of different strategies in flight control.

Methods	Advantages	Disadvantages	Applications
Feedback Error Learning Scheme	Continuous learning and adjustment, Improve the system's adaptability and robustness.	Strong dependence on initial states or parameters, Requirment of more training data/computing resources.	Flight attitude control, Flight path control.
Pseudo Control Strategy	Adaptive adjustment of neural network parameters, Optimize and adaptively adjust the system.	Requirment of more computing resources or training data, Prone to local optima.	Strong dependence on initial states/parameters, Requirment of more training data or computing resources.
Neural Back Stepping Method	Continuous learning and adjustment, Effective for nonlinear control problems, Improve the performance and efficiency of the system.	Controlling the aircraft's heading, pitch, and roll.	Aircraft attitude control, Flight path planning, Autonomous navigation.

On the other hand, the model-free approach does not require any prior knowledge of the system dynamics to be incorporated into the control design process. In the traditional model-free method, a single neural network models the entire controller and is trained using error back propagation. However, due to the lack of system dynamics information, this approach makes it difficult to perform mathematical

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analysis on the stability of the system. As a result, this control approach is unsuitable for critical mission, which matches the analysis of Emami et al. [5].

3. Image recognition and computer vision

Image recognition and computer vision methods have gained large progress these years, revolutionizing various industries, including the aerospace sector. These technologies utilize advanced algorithms and machine learning techniques to analyze and interpret visual data, enabling machines to understand and extract meaningful information from images and videos.

In the aerospace field, image recognition and computer vision play a vital role in several applications. Two notable applications are artificial intelligence in remote sensing and computer vision in quality inspection of aerospace components.

3.1. Artificial intelligence in remote sensing

In accordance to the essay by Lary [6], the role of artificial intelligence in remote sensing mainly lies in its ability to efficiently and accurately process remote sensing data, automate object recognition and classification, and detect and predict environmental changes, providing support for environmental management and decision-making. In particular, Artificial intelligence has already been extensively utilized in the field of remote sensing for several purposes. Among the six main directions of AI by Wu, namely, computer vision, natural language processing, robotics, cognitive computing, game theory and ethics, and machine learning [7]. Wang et. al strongly confirmed the importance of machine learning in remote sensing, with a Figure 1. stressing the necessity [8].

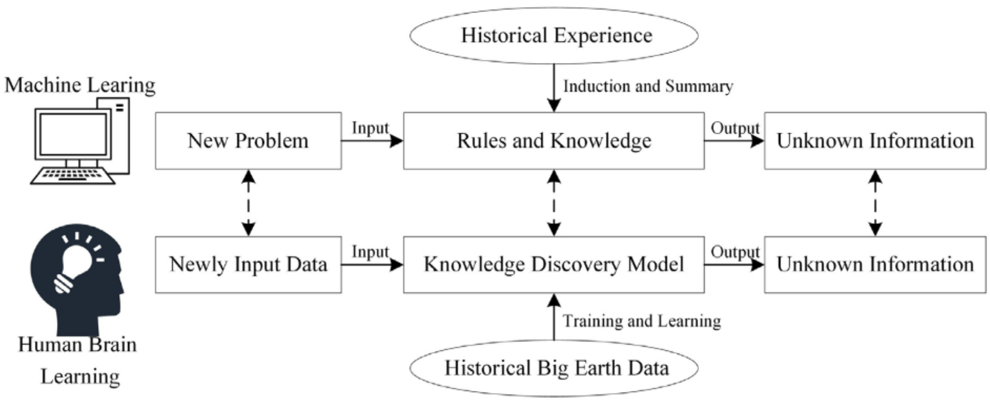

Figure 1. The importance of machine learning in remote sensing.

Through extensive investigation into AI-driven techniques for knowledge discovery, researchers have categorized them into four distinct types based on their developmental stages: (a) rule-based methodologies, (b) data-oriented methodologies, (c) approaches utilizing reinforcement learning, and (d) ensemble methods. Table 2. shows some main algorithms in each approach [8].

Table 2. Methods for discovering knowledge and the algorithms commonly employed.

rule-based methodologies	data-oriented methodologies	reinforcement learning	ensemble approaches
Expert system	k-NN, DTW	Q-learning	Random forest
Decision tree	naive Bayes classifier	Deep Q-learning	AdaBoost
Association rule	SVM, SVR	Q-network	
	ANN,CNN,RNN,LSTM	Deep Q-network	

With the appropriate application of these approaches in remote sensing, AI had advantages in the three aspects of remote sensing: (1) When it comes to remote sensing data processing, artificial intelligence techniques can be employed to achieve efficient and accurate data processing and interpretation through methods such as image classification, feature extraction, and object detection. (2) In terms of object recognition and classification, AI can be utilized to automatically identify and classify objects, such as vegetation cover, land use, and building extraction, through training models and algorithms. (3) Regarding environmental change detection and prediction, AI can analyze and model remote sensing data using machine learning algorithms to detect and predict environmental changes, such as climate change and natural disasters.

3.2. Computer vision in quality inspection of aerospace components

Computer vision, also known as machine vision, is a discipline that studies the use of cameras and computers to recognize, track, and measure targets, replacing the human eye.

There is a growing need for intelligent visual inspection systems in the aerospace industry to ensure the quality of its components. Machine learning, particularly deep learning, as well as the improvement in computer vision have made significant progress in recent years, leading to various attempts to develop automatic and semi-automatic solutions for this industry sector. The quality inspection of aerospace components can be classified into two parts: the internal components and the external components.

When it comes to the internal components, Carlos et al. have developed a system for detecting debris within the channels or passages of avionic components throughout the manufacturing process [9]. The system is designed to identify three distinct types of little fragments: machining swarfs, foundry sand, and metal dust. With help of computer vision and machine learning algorithm, the system solved the problems of insufficient lighting conditions, significant differences in the appearance of the little fragments and difference in the texture of the internal surface of the components. As a result, the system is capable of accurately categorizing video sequences with an average precision of 90.7%, achieving the highest accuracy rates of 95.4% for the empty class and 94.7% for the sand class, which shows the high efficiency of AI in inspection of internal components of aerospace components.

Computer vision and image recognition have many applications in aerospace external components, and here it is used as an example for crack detection in aerospace components. The utilization of digital image technology allows for monitoring of component fatigue and fractures while mechanical parts are in operation, which is useful for detecting shallow cracks and assessing if the measurements impact the lifespan and safety of the components. Xiao et al. have developed an efficient evaluation system for detecting surface cracks on components using procession of the digital image methodology [10]. The typical image acquisition system is shown in Figure 2. Xiao demonstrates that the methodology offers the benefits of precise detailed image processing, allowing for rapid and relatively precise detection of surface crack shortages.

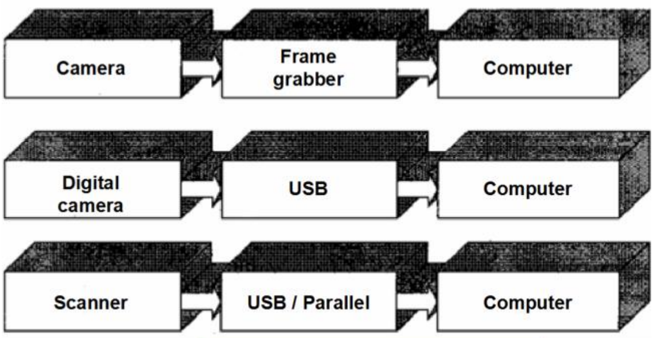

Figure 2. Typical image acquisition system.

Computer vision and image recognition technologies offer significant benefits for the detection of external and internal components in aerospace electronics. These technologies enable automated and efficient detection, improving detection accuracy while reducing costs associated with manual inspection. High-precision image processing and analysis techniques contribute to accurate results while minimizing the risk of human error. The speed and efficiency of these technologies can also help to save time and resources. Overall, the application of computer vision and image recognition technologies in aerospace component inspection promises to offer more efficient, accurate, and cost-effective solutions for researchers and practitioners in this field.

4. Unmanned aerial vehicles

Unmanned aerial vehicles (UAV) have revolutionized the aerospace industry by leveraging the power of artificial intelligence. These intelligent systems equipped with advanced Artificial Intelligent algorithms and technologies enable autonomous operations, precise navigation, and efficient data collection.

In this section, mainly two key aspects will be explored: the control system of unmanned aerial vehicles and the application of machine learning in unmanned aerial vehicles. The control system of unmanned aerial vehicles ensures safe and efficient operation, incorporating hardware and software solutions for navigation and maneuverability. Machine learning techniques enhance UAV capabilities, enabling them to learn from data and make intelligent decisions.

4.1. Control system of unmanned aerial vehicles

Newly developed unmanned aerial vehicles that integrate novel systematic design, construction techniques, sensors, and algorithms will be refined and utilized for a wide range of purposes. Shokirov et al. have pointed out that to accomplish this, an ideal laboratory setup should include equipment for creating and testing models (as depicted in Figure 3) [11]. This would entail utilizing both hardware that relies on an actual digital control system and corresponding software represented by mathematical representation of flight dynamics and dedicated control software for optimal efficacy.

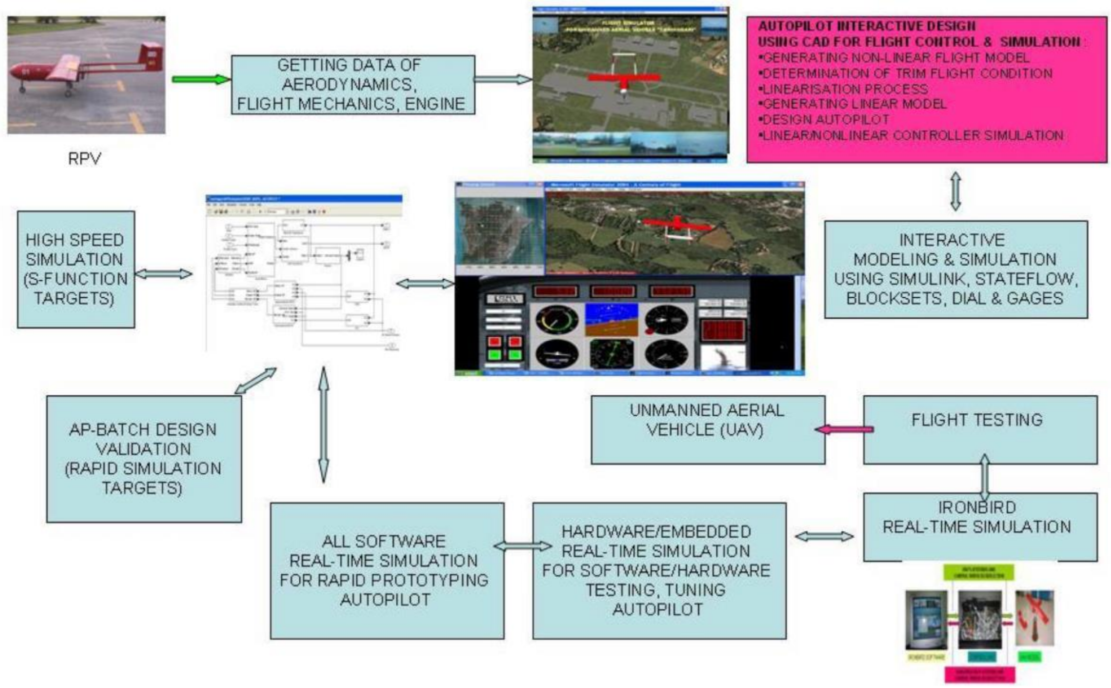

Figure 3. A related computer models.

4.2. Machine learning in applications of unmanned aerial vehicles

Concrete applications of machine learning in unmanned aerial vehicles abound, ensuring the significance of artificial intelligence in UAVs. Both supervised and unsupervised machine learning are useful by terms of optimizing UAV in a lot of aspects.

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One recent typical example of the application of supervised machine learning in UAV is in paper [12]. The authors explore the most effective approach to deploy aerial base stations for the purpose of reducing the workload on ground-based stations while decreasing the energy consumption of the drones. Their proposed solution is deemed to be "ML-assisted" because it involves predicting network congestion and temporarily placing UAVs in strategic locations, as opposed to constantly changing their positions. The prediction of wireless traffic is achieved using a probabilistic model known as Gaussian mixture model (GMM). The results of the numerical analysis indicate that the ML-assisted method is superior to the traditional approach in terms of reducing the mobility and power required for downlink communications.

Unsupervised algorithms also play an important role in the anomaly detection of the unmanned aerial vehicle. Unmanned aerial vehicle networks are highly susceptible to malfunctions and anomalies that may arise during drone operations. To prevent such situations, it is advisable to utilize data collected by drone sensors to monitor the level of flight safety. Anomaly detection is a common approach used to identify data samples that deviate from the expected normal behavior of the system. Bozcan and Kayacan have put forward an unsupervised algorithm that can discover unusual things occurring within the normal situation [13]. The deep learning (DL) architecture proposed by the authors is trained using aerial images and GPS data from a bird's eye view to accomplish this procedure. Titouna et al. have introduced an algorithm for anomaly detection that is capable of recognizing and isolating malfunctioning UAVs. The approach uses Kullback-Leibler Divergence to detect problems rooted in external sensor data such as humidity levels and wind speed [14]. In addition, an artificial neural network (ANN) is utilized to classify internal sensor data. The results of the numerical analysis indicate that the proposed approach achieves an acceptable level of accuracy.

5. Data analysis and prediction

AI techniques have transformed data analysis and prediction in the aerospace industry. In weather forecasting, machine learning algorithms analyze meteorological data, satellite imagery, and historical patterns to provide accurate predictions, improving aviation safety and efficiency. Resource allocation problems benefit from AI techniques, optimizing aircraft routing, fuel consumption, and crew scheduling. By leveraging data analysis and predictive modeling, AI enhances decision-making, safety, and resource management. These advancements drive the aerospace industry forward, enabling more effective data-driven operations in aviation and space exploration.

5.1. AI techniques in weather forecasting

Artificial Intelligence has experienced rapid development and has been extensively utilized across various domains in recent times. A commonly shared concern is how to effectively integrate AI, big data, and machine learning methodology in order to construct prediction models and enhance forecast precision. To achieve this aim, the Tempisk Apollo approach was introduced by Earth Risk in order to generate temperature probability forecasts with greater reliability [15]. This approach relies on numerical outputs from ECMWF and uses an ensemble framework consisting of multiple AI models.

What's more, plenty of related compositions have appeared to develop artificial intelligence in the weather forecasting field, which is a huge improvement to the whole betterment. For instance, the Weather Forecasting contest, which is one of the AI Challenger 2018 Global Experimental Contests, attracted over a thousand teams and participants from various countries. Despite being given only a few meteorological data for training and adjusting, some patterns developed during the competition showed impressive real-time forecasting capabilities for t2, rh2, and w10, thanks to advanced AI algorithms, effective model combinations, and appropriate data processing techniques. Notably, two teams increased the accuracy of t2 forecasts by 24.2% and 17.0% respectively, which is compared with the most reliable AnEn forecast available. This shows the high accuracy when artificial intelligence is used in the data analysis and prediction of weather forecasting.

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5.2. AI techniques in resource allocation problem

The satellite communications sector has prioritized the automation of resource management strategies. With a significant increase in data demand and the introduction of adaptable communications payloads capable of operating and reconfiguring numerous beams in orbit, the industry is poised for significant transformation. The growing complexity in dimensions and operations emphasizes the necessity for AI-driven dynamic algorithms that can make optimal decisions regarding resource allocation, replacing previous rigid policies.

In the specific context of dynamic resource management in multi-beam High Throughput Satellites (HTS), the article presents a comparative analysis of various recently proposed algorithms under practical operating conditions for a specific problem [16]. The task involves assigning power to each beam in a multi-beam HTS. The algorithms evaluated in this study include Genetic Algorithms, Simulated Annealing, Particle Swarm Optimization, Deep Reinforcement Learning, and hybrid approaches. The multi-beam operation scenario is created using demand data from a satellite operator, a comprehensive radio-frequency chain model, and constraints related to hardware and time during HTS operation. The research findings demonstrate that the Deep Reinforcement Learning (DRL) algorithm is the fastest and most effective in terms of service performance, while the hybrid algorithm combining Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) exhibits superior overall effectiveness. Additionally, the GA algorithm displays the highest level of robustness and is suitable for scenarios where user behavior frequently changes.

To sum up, the problem of resource allocation in multi-beam communication satellites is a complex and well-researched problem that is NP-hard and non-convex. Moreover, the problem's complexity is compounded by the increasing number of optimization variables, which adds another layer of difficulty. Consequently, traditional optimization methods often require relaxations or significant computing resources, leading to inefficient performance during real-time operations. Artificial Intelligence presents a promising solution to address these issues.

6. Conclusion

In conclusion, this paper has provided a comprehensive analysis of the current state of Artificial Intelligence (AI) in aerospace engineering, focusing on four key areas: autonomous navigation and flight control, image recognition and computer vision, unmanned aerial vehicles (UAVs), and data analysis and prediction.

Firstly, this paper explored the application of AI in autonomous navigation and flight control. The advantages of AI in this area include enhanced safety through real-time data analysis and decision-making, adaptive trajectory optimization, and improved efficiency. However, challenges such as algorithm interpretability and certification processes need to be addressed to ensure the reliability and trustworthiness of AI-powered systems. Then, the use of AI in image recognition and computer vision is discussed. AI technologies have greatly improved aerospace component quality inspection and remote sensing capabilities. These advancements have led to increased accuracy, efficiency, and reduced human error in these critical tasks. However, challenges such as robustness in varying environmental conditions and the need for large-scale training datasets remain. Besides, we also explored the integration of AI in unmanned aerial vehicles (UAVs). AI algorithms and machine learning techniques have enabled UAVs to operate autonomously, navigate precisely, and collect data efficiently. This has opened up new possibilities for applications such as aerial surveillance, delivery services, and environmental monitoring. However, challenges related to regulatory frameworks and the safe integration of UAVs into existing airspace systems need to be addressed. Lastly, the fourth section focused on the impact of AI on data analysis and prediction in the aerospace industry. AI algorithms have improved weather forecasting accuracy, resource allocation efficiency, and decision-making processes. The ability to analyze vast amounts of data and extract valuable insights has led to improved operational efficiency and cost savings. However, challenges related to data quality, interpretability, and ethical considerations need to be tackled.

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In summary, the application of AI in aerospace engineering offers numerous advantages in terms of safety, efficiency, and innovation. However, it is crucial to address challenges such as interpretability, certification, robustness, and regulatory frameworks.

Future research should focus on overcoming these limitations to fully leverage the potential of AI in the aerospace industry. With continued advancements and collaboration, AI technologies will play a crucial role in shaping the future of aerospace engineering, leading to safer, more efficient, and intelligent aerospace systems.

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