Machine Learning Adaptation in Aerospace Engineering: A Critical Review

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ABSTRACT

Artificial intelligence and machine learning techniques can revolutionize the aerospace industry by utilizing available data in machine learning models through a wide range of applications. This review presents a thorough and detailed outlook of recent trends and developments in machine learning architectures related to the aerospace industry, such as autonomous flight and UAVs, predictive maintenance, optimization, simulation, modeling, and satellite systems. Although this field has made incredible advancements, there are several challenges, such as data shortages, model robustness, and ethical concerns. Future directions are also highlighted in this review, such as machine learning based on physics information, hybrid modeling, and digital twins. This review shines a light on the potential of machine learning in aerospace engineering and industry to improve efficiency, safety, and autonomy in aerospace. In addition, it shows the need for interdisciplinary research to understand and produce robust models and trustworthy, certifiable systems.

Keywords*— Machine learning; Deep learning; Aerospace engineering; Data–driven modeling; Neural networks.*

I. INTRODUCTION

The exponential increase in computer’s computational capabilities, sensing techniques, data storage and acquisition has an incredible and direct impact in engineering applications, especially aerospace engineering. Spacecraft, satellites, aircrafts and unmanned aerial systems can generate a huge amount of data through their different sensors. The availability of such data gained an interest by different researchers to implement it in decision making, design and operation optimization in aerospace application and by harnessing the power of artificial intelligence and machine learning techniques [1–3]. Current advances in deep learning, reinforcement learning, and hybrid data-driven methods have revealed promising results in areas such as autonomous flight, predictive maintenance, aerodynamic optimization, and space system operations [4–9].

Machine learning techniques coupled with AI capabilities are capable to identify complex nonlinear relationships directly from data, potentially reducing computational cost and enabling real-time or near-real-time predictions compared to the traditional physics-based as well as the numerical techniques. Hence, machine learning-based surrogate models, intelligent controllers, and data-driven diagnostic tools have emerged as attractive complements to conventional aerospace analysis frameworks such as computational fluid dynamics, finite element methods, and model-based control techniques [5, 9]. Still, the practical integration of machine learning into aerospace system needs more understanding and more research to push it beyond its limitations.

Aerospace systems operate under extreme safety, reliability, and certification constraints, where failures can lead to catastrophic consequences and regulatory approval processes are often more demanding than the technological development itself. Aerospace engineering systems should be reliable and work properly under any extreme condition as well as, maintain the long life operation with minimum malfunction. The defining characteristic of aerospace systems compared to other systems in term of the usage of machine learning via data driven techniques, is the costly experimental data obtained from full scale modeling or flight tests and this is a significant constraint on the adaptation of machine learning in aerospace applications.

To overcome these challenges, current research has increasingly explored physics-informed learning, hybrid modeling, digital twin concepts, and human - AI collaborative systems as pathways to bridge the gap between data-driven intelligence and physics-based aerospace engineering. These approaches aim to improve generality, enhance trustworthiness, and support verification and validation processes required for safety-critical aerospace systems [4, 10, 11]. Nevertheless, the maturity of these techniques varies significantly across applications, and their readiness for operational deployment need further development and research dedicated efforts in multidisciplinary fields.

Current review articles on machine learning in aerospace tend to highlight algorithmic development or provide broad overviews of AI techniques with limited critical analysis of their applicability, limitations, and certification readiness within aerospace contexts. As a result, there remains a need for a domain-focused review that not only summarizes recent advances, but also critically evaluates how machine learning techniques are being adapted to meet aerospace-specific constraints, identifies recurring limitations across applications, and highlights realistic pathways toward operational integration as well as, the ethical implication of using such a new technique.

The objective of this paper is to critically examine recent developments in machine learning and deep learning as applied to aerospace engineering, with particular emphasis on autonomous systems, predictive maintenance, design optimization, safety and risk management, flight modeling and simulation, and space systems. Instead of presenting a purely descriptive survey, this work aims to synthesize existing studies, identify dominant methodological trends, assess their technological readiness, and discuss the key barriers that currently limit large-scale adaptation as well as, provides the ethical perspective associated with the use of such new techniques. By doing so, the review seeks to provide aerospace researchers, practitioners, and policy - makers with an insight of where machine learning delivers tangible value, where its limitations remain critical, and how future research can better align data-driven intelligence with the extreme requirements of aerospace engineering.

II. Machine Learning Techniques

Machine learning consists of different techniques that can be used to create models and train them from available data sets. Depending on the quality of the data and how rich (big and smart) it is, different methods can be used for training the model [9, 12]. Generally, these techniques can be classified into supervised machine learning, unsupervised, semi-supervised, reinforcement, and hybrid machine learning techniques [9-14].

II. 1 Supervised Learning

In this type of learning, the input and output relations are known, so the training involves the model training on a labeled data set. This technique is commonly used for regression and classification tasks in the aerospace industry. Widely used algorithms include [9-12]:

- Linear regression and logistic regression.
- Support vector machines (SVM).
- Decision trees and random forest.
- Artificial neural networks (ANNs).
- Deep learning such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

II.2 Unsupervised Learning

This type of learning is used when the relation between input and output is unknown or when labeled data are incomplete or unavailable. The model is trained to discover the structure or hidden patterns in the data set [9, 12-14]. Some of the common algorithms are:

- Gaussian mixture models.
- Auto-encoders.
- K-means clustering.
- Principal component analysis.

II.3 Reinforcement Learning

This technique uses feedback on the trained model to make a sequence of decisions and interactions Wang & Ma [1]. The common algorithms are:

- Deep Q-networks (DQNs).
- Q-learning.
- Proximal policy optimization (PPO).
- Actor-critic methods.

II.4 Physics-Based and Hybrids

This type combines the use of models that are physics-based with data-driven models Karniadakis et al. [4]. Some examples of this technique are:

- Fluid dynamics: Navier-Stokes constraints embedded with NNs.
- Combination of CFD results with machine learning predictions.

- Transfer learning: training the model in simulations.

III. Aerospace Applications

III.1 Autonomous Flight Systems and Unmanned Aerial Vehicles

UAVs have advanced significantly through machine learning integration and the rise of artificial intelligence. Machine learning can be implemented in many areas such as environmental awareness and perception, localization and navigation, decision making, control systems, and cooperative UAV systems.

Giusti et al. [15] implemented a deep neural network machine learning technique to visualize the direction of a quad-rotor drone. The model was trained via a real-world large data set. Gandhi et al. [16] created a big data set from crashing a UAV drone 11,500 times and then used a deep neural network to train the model to fly and navigate. Berkenkamp et al. [17] presented a classical reinforcement machine learning technique to optimize safety policies and grant safety certificates based on the performance of the model. Hwangbo et al. [18] used a reinforcement learning approach via a neural network to train and control a quad-rotor drone. The study presents the performance of the trained model in simulation and experimentally via a real drone. The measurement of its stability was done under tough conditions (initial air velocity of 5 m/s).

Chaplot et al. [19] proposed a machine learning model based on a neural network method to solve the localization problem (guessing the location of an autonomous device). The model effectiveness was challenged using different conditions and environments, such as 2D and 3D and utilizing realistic maps. The model faced some limitations with dynamic lighting. Loquercio et al. [20] implemented a conventional neural network to train a drone to fly safely in city streets. The model evaluates different factors, such as navigation, collision, and obstacle avoidance. The data was collected in an outdoor environment and used to train the model.

Zhao et al. [21] inspected and proposed a deep reinforcement learning technique to solve the problem of path planning for UAV base stations while executing search tasks. The proposed model can reduce the decision-making process and find an optimal path in the shortest time. The trained model considered various factors, such as training speed, task completion rate, and obstacle avoidance rate. Guo and Liu [22] utilized deep reinforcement machine learning for the navigation control of UAVs. The model operates and uses a 3D map environment to search for an optimal path. The proposed model needs only 160 rounds to complete its task of path planning and obstacle avoidance.

An incredible progress has been made and reported by researchers regarding the implementation of machine learning to UAVs and autonomous flight systems. However, in many cases it is constraint in a controlled environment or simulation or still in the experimental phase setups. The most promising techniques for this application are deep learning and reinforcement learning. Those techniques showed good performance in navigation, perception and control tasks. However, their dependency on extensive training data raises a major concern regarding safety and robustness. Especially, reinforcement learning technique often lack formal stability guarantees and require unsafe exploration strategies that are incompatible with civil aviation regulations. Moreover, the generalization of trained models across varying environmental conditions, sensor uncertainties, and hardware configurations remains insufficiently addressed. Consequently, while machine learning autonomy illustrate high potential for military, research, and low-risk UAV operations, its direct applicability to safety-critical aerospace systems remains limited without the integration of physics-based constraints, formal verification, and fail-safe architectures.

III.2 Predictive and Periodic Maintenance

Hardware failure and malfunction are inevitable in every industry. It is especially important, most dangerous, and safety-related in aerospace applications. Machine learning integration with the aerospace industry is rapidly increasing, especially in the predictive and periodic maintenance area. The availability of data sets can be a huge benefit for improving safety, cost reduction, downtime reduction, and implementing better strategies. The common discussed topics in this section contain monitoring structural health, features and sensor fusion, industrial predictive maintenance, anomaly detection, and estimation of remaining useful life.

Malhotra et al. [23] presented a machine learning model based on long-short term memory (LSTM) network techniques to identify the unknown health pattern and to detect anomalies. The model utilizes different data sets, such as space shuttle, power demand, and multi-sensor engine. Zheng et al. [24] demonstrated the use of a deep learning approach to estimate the remaining useful life. The model uses the long-short term memory technique with three different data sets. The model performed to illustrate the hidden patterns, operating conditions, fault, and degradation. Hundman et al. [25] illustrated the use of a recurrent neural network (specifically, long-short term memory network) to detect spacecraft anomalies.

Guo et al. [26] presented a new diagnosis technique for rotating machinery based on machine learning–convolutional neural networks. The effectiveness of the model was compared to experimental tests of a rotor with different fault modes. Tabatabaeian et al. [27] presented four different machine learning models trained via a deep learning technique. The trained models were used to evaluate the damage in composite structure (barely visible impact damage). The models reached an accuracy of 96.2% and 98.36% and can be used as a monitoring tool for structural health.

Ferreira et al. [28] implemented a Bayesian recoup data-driven technique to recompense the lack of experimental data. The trained model uses a deep convolutional neural network to evaluate the structure damage. Maragatharaj et al. [29] explored the efficiency of a machine learning method via the K-NN technique (K-nearest neighbors) to investigate an engine's reliability and remaining useful life. The method was also used to enhance engine design optimization, predict a better understanding of engine behavior, and optimize efficient flight operation.

Predictive maintenance considered one of the most important and crucial application in aerospace engineering and a good prospect for implementing machine learning techniques. Recurrent neural networks and deep learning models have revealed strong capabilities in detection of anomalies, fault diagnosis and detection, and remaining useful life estimation using sensor and operational data. Nevertheless, quite a lot of limitations recur, mainly regarding data quality, dataset imbalance, and operational variability across aircraft fleets. Many studies depend on curated benchmark datasets that do not fully capture real-world degradation patterns, sensor drift, or maintenance-induced biases. Furthermore, the interpretability of deep learning-based health monitoring models remains a main concern and a barrier for maintenance decision-making and regulatory policies. Thus, while predictive maintenance systems are closer to operational deployment compared to other machine learning aerospace applications, their long-term reliability and certification require improved precision, standardized and smart datasets, and robust validation under real operational conditions.

III.3 Design Optimization

In the aerospace industry, design optimization has always been a complex task, time-consuming process, and costly. Furthermore, it is multidisciplinary for aerospace systems. Hence, the use of machine learning is a rising field to aid in this matter and can increase efficiency, reduce cost, and show a new approach in the design concept. The most common applications for this section contain structural optimization, aerodynamic shape optimization, multidisciplinary design optimization, space exploration design, uncertainty qualification, generative model integration, inverse design, and topology optimization.

Banga et al. [30] presented the use of a deep learning technique coupled with a 3D encoder–decoder convolutional neural network approach to optimize a 3D topology. The model is used to optimize the computational strategy. The proposed model reduces the computational time by 40% and achieves structural accuracy of about 96%. Zhang et al. [31] presented the use of a convolutional neural network architecture to estimate the lift coefficient of various shapes of airfoils. The model is used to predict the lift coefficient for unseen airfoil shapes using the proposed convolutional neural network technique.

Bertoni et al. [32] investigated the ability to implement machine learning to build a model with an automated decision support environment. The proposed model can create a surrogate model that can be used for airspace design applications. The model harnesses the data and creates hundreds of design configurations that can be helpful for engineers during the design phase. Yamasaki et al. [33] demonstrated topology design by using a deep regenerative model approach. The data-driven technique was used to find the best formula for topology optimization since it is a non-linear problem with various factors affecting its design.

Shin et al. [34] implemented different machine learning techniques, such as K-nearest neighbors (KNN), variational auto-encoder (VAE), and random forest (RF), to estimate the appropriate combination of aircraft initial design parameters. One of the advantages of such a method is its ability to deal with incomplete data. The missing data can be guessed using the machine learning model. The study reveals that the variational auto-encoder (VAE) mode tends to be more accurate than the other models. Xie et al. [35] presented the use of machine learning by coupling the use of high dimensionality reinforcement learning, non-linear and time delay in the physical data, and their use in complex flow modeling systems.

Chen et al. [36] implemented a deep reinforcement learning technique to investigate the performance of an airfoil. The technique consists of constructing a machine learning framework coupled with a CFD program to optimize aerodynamic performance, such as the lift-drag ratio. The study showed an enhancement of 83.5% and 30% for the drag-lift ratios. Liao et al. [37] investigated a new concept for shape design using topology design. The new concept (AITD), artificial intelligence topology design, was implemented and compared to conventional design. The study shows the potential of using this concept for designing hypersonic aircraft and advancing technology with better performance. Artificial intelligence can provide a new perspective regarding the design of aircraft, especially in hypersonic applications.

Yeh and Du [38] investigated a new surrogate-based machine learning model to explore rapid decision-making in designing eVTOL aircraft (electrical vertical takeoff and landing). The proposed model uses regGAN (regression generative adversarial network) architecture. This new model runs the regression coupled with both an adversarial binary cross-entropy loss and a mean squared error loss function. Furthermore, the model uses inverse mapping for its surrogate machine learning model. The study shows that the surrogate model with the mean squared error can reach 99.5% accuracy. It is noted that the used samples were 400 for training, whereas the other models need at least 800 training samples.

Xu et al. [39] proposed a new model for aircraft trajectory optimization. This new machine learning model combined lateral optimization with vertical optimization. The main objective is to reduce the operation cost. The proposed model shows a substantial decrease in fuel consumption for different cases. As well, it shows a promising path for future research in this direction by implementing more complex machine learning models. Minaev et al. [40] developed an algorithm to predict the aerodynamic coefficient of an airfoil using a neural network machine learning technique. The model shows a good prediction of the coefficients as a function of the angle of attack. The model can be utilized as a surrogate model for the CFD optimization technique. The model is hoped to be applicable to a transonic flow regime to depict the behavior of an airfoil in such conditions and to be used as a tool to design large endurance UAVs.

Another major breakthrough and progress has been made by implementing machine learning techniques in design optimization. Especially, in the reduction of computational cost, time and accelerating multidisciplinary aerospace design processes. Surrogate models, generative approaches, and reinforcement learning approach have been effectively applied to aerodynamic optimization, structural design, and trajectory planning. However, the majority of reported improvements are problem-specific and heavily dependent on the fidelity and representativeness of the training data, often derived from numerical simulations rather than experimental validation. This dependence limits and constrains the capability of trained models when applied to novel configurations or off-design conditions and new environments. Additionally, optimization objectives for the most cases are simplified, neglecting manufacturability, certification constraints, and operational uncertainties. Therefore, ML-based optimization currently are used mainly as a complementary tool to traditional physics-based methods rather than a standalone replacement, highlighting the need for hybrid frameworks that integrate physical consistency, uncertainty quantification, and design interpretability.

III.4 Risk Management and Safety

Minimizing accidents, incidents, and mitigating hazards are key components in safety and risk management in the aerospace industry. The complexity of such tasks and the growing use of artificial intelligence can open new ways to deal with this type of problem via utilizing machine learning tools to give a new perspective and insights. The common applications that can be contained in this section are anomaly detection, prediction of accidents and incidents, modeling of pilot's behavior, human factors and behavior, management of air traffic, decision making, safety management systems, and unmanned aerial systems.

Oehling and Barry [41] presented the possibility of using machine learning techniques in airline safety. The investigation was based on the usage of existing flight data which can be traced to the 1970s. The method is to use the unsupervised machine learning technique to observe and analyze the flight data. The study shows that airlines can use this approach with their big data sets to reduce the occurrences of undetected safety issues by analyzing 1.2 million flights. Midtfjord and Huseby [42] developed a machine learning model based on the XGBoost algorithm to evaluate safety threats on the runway of Norwegian airports. The model uses weather conditions data sets and safety reports to train the model.

Dong et al. [43] developed a deep learning model to evaluate safety concerns in aviation and improve transportation. The trained data set was about 200,000 incident reports. Then the model was trained to recognize the primary and contributing factors using the long-short term memory (LSTM) technique. Rey et al. [44] presented an analysis based on data-driven machine learning to illustrate the link between recorded data and the risk associated with potential accidents. The trained model shows the existence of a link between some defined events and the identified factors. Additionally, more advanced machine learning models can be implemented to be able to understand such a complex and dynamic task.

Rodríguez-Sanz et al. [45] illustrated a dynamic machine learning model to predict the trajectory of aircraft. The proposed model is supposed to predict the trajectory and traffic forecasting from 1 to 6 days before operation (pre-tactical phase). The study shows an increase in prediction of about 80% in most cases. Sui et al. [46] implemented a deep reinforcement machine learning technique to present tactical conflict resolution strategies for air traffic management. The model utilizes different factors, such as altitude, heading, and speed adjustments to sort out the conflict.

Haryanti and Komarudin [47] implemented a data-driven method to investigate the events that lead to aircraft accidents. A machine learning model was built to prevent such accidents. The model uses different architectures, such as decision trees, random forests, SVM, and Naïve Bayes. The best model shows an accuracy of 94.29% using the random forest algorithm, followed by a decision tree of 91.43% and 83% using SVM. Zhuang et al. [48] implemented the use of machine learning with a deep learning approach to investigate the interaction between pilots and aircraft under complex flight situations. The model considered many risk factors (46) with different relations (419) to analyze the accident records. The study presents an analytical tool that can enhance safety in flight training, as well as enhance overall reliability.

Risk management and safety analysis in aerospace are another huge application that can benefit of the power of machine learning techniques and can offers valuable opportunities for extracting insights from large-scale operational and incident datasets. Data-driven methods have revealed effectiveness in identifying hidden risk patterns, predicting safety threats, and supporting decision-making in air traffic management and maintenance operations. Nevertheless, safety-critical deployment of such models encounters considerable challenges and limitations, predominantly regarding data completeness, reporting biases, and causal interpretability. Various studies focus on retrospective analysis rather than real-time operational integration, limiting their practical impact. Furthermore, the opaque nature of complex machine learning models conflicts with the transparency and traceability required by safety management systems and regulatory authorities. Consequently, while ML-based safety analysis can improve situational awareness and risk identification, its role should be viewed as a decision-support tool rather than an autonomous safety authority until issues of explainability (interpretability), accountability, and validation are sufficiently addressed.

III.5 Flight Modeling and Simulation

Training pilots, testing systems, and granting certifications are very important and crucial in the aerospace industry. Machine learning techniques can improve efficiency, adaptability, and intelligent behavior in such conditions. The common applications that can be listed in this section are flight dynamic modeling, pilot behavior modeling, simulation in realism and fidelity, simulation of UAVs in real-time, pilot decision making, modeling of flight conditions, and pilot's response modeling.

Bertoni et al. [32] explored the use of machine learning as a surrogate model to utilize qualitative data. The model aims to assist engineers in the early stage of the design. Lei et al. [49] presented a novel method to incorporate a machine learning technique as an opponent for air combat training. The model uses a radial neural network learning technique to train the data set, then the model makes real-time predictions for the flight and fight situations of simulated opponent fighters.

Yu et al. [50] simulated aircraft dynamics and performance using a machine learning neural network accompanied by a physics-based learning technique. The simulated model uses a Boeing 747–100 aircraft for its demonstration. The study shows the physics-based learning approach for the machine learning model is superior to the conventional numerical methods. Zhou et al. [51] presented a machine learning model with a deep learning technique to predict the time of flight departure. The model utilizes the neural network approach with the influence of different factors related to flight operation. The study shows that such a model can be used for airport scheduling and decision-making.

Källström et al. [52] presented a machine learning model to aid pilots in decision-making. The model uses complex conditions for its training. Wang and Ma [53] investigated the aero-elastic phenomena in different flight situations using a machine learning model with a deep neural network approach. The model was constructed using Python and TensorFlow coupled with a deep learning technique. The model is used to predict flutter Mach number as well as panel motion states.

Gerling et al. [54] evaluated the use of a machine learning model using a neural network technique on the performance of Bayesian optimal experimental design. The study shows that using the reinforcement learning technique leads to improved performance by 9.07% in comparison with random design and the enhancement was 6.47% in comparison with the state-of-the-art approach. Silvestre et al. [55] proposed a machine learning model based on a deep learning technique to predict the time of arrival for passenger flights. The model utilizes the 4D trajectory of the flight and weather data sets at the specific airport. The model achieves a mean absolute error of 2.65 min over the entire tests.

Risk management and safety analysis are another sector in aerospace engineering that can be integrated in machine learning techniques and gain a huge insight from available data set and full scale operations. Data-driven methods have been valuable in identifying hidden risk patterns, prediction of safety issues, and scaling the decision-making in air traffic control and management, as well as, maintenance operations. Nevertheless, safety-critical sector of such models confronted with considerable challenges, predominantly regarding data completeness, reporting biases, and causal interpretability. Numerous studies focus on retrospective analysis rather than real-time operational integration, limiting their practical impact. Moreover, the opaque nature of complex machine learning models conflicts with the transparency and traceability required by safety management systems, policy makers and regulatory authorities. As a result, while ML-based safety analysis can improve the awareness and risk management, its role should be viewed as a decision-support tool rather than an autonomous safety authority until issues of explainability, accountability, and validation are adequately addressed. In some cases, the ethical issues also should be addressed to resolve any conflict with the policies and any regulation.

III.6 Space Systems and Satellites

Space missions are tremendously complex and require intelligent systems that must be reliable and autonomous due to their operation in harsh conditions. Scientists and engineers can use machine learning techniques to accomplish such goals. The most common applications that can be listed in this section are health and fault monitoring of satellites, trajectory estimation and optimization, space mission planning, collision avoidance, autonomous navigation, payload optimization, and satellite constellation and management.

Pelletier et al. [56] evaluated the use of convolutional neural network architecture for satellite image–time series and then compared it to other machine learning techniques, such as random forest and recurrent neural network techniques. Peng and Bai [57] explored the use of a machine learning model to enhance orbit prediction accuracy. The model uses publicly available data sets (two-line element and International Laser Ranging Service catalogs). The study shows that the model can significantly improve the physical-based prediction framework.

Yu et al. [58] presented a machine learning model for anomaly detection based on a convolutional neural network combined with a long-short term memory (LSTM) technique. The model also utilizes a generative adversarial network (spatial-temporal). The model can detect different types of anomalies, such as degradation and intermittent anomaly. Saraygord Afshari [59] presented a machine learning model based on a deep learning technique to improve fault detection in satellite attitude control systems. The proposed model uses a long-short term memory technique. The study shows high accuracy in fault detection, hence leading to enhanced system reliability and performance.

Space systems and satellite operations are another application of aerospace industry and can exhibit strong potential for machine learning integration, due to the need for autonomy, fault tolerance, and adaptive decision-making in remote and extreme environment and operation. Data-driven methods have been implemented and well documented to anomaly detection, orbit prediction, and mission planning tasks. Nevertheless, many limitation and challenges involved in this application, such as limited onboard computational resources, sparse labeled failure data, and the impossibility of physical intervention pose unique challenges. Several researchers suggested solutions based on ground-based processing or post-mission analysis, limiting their autonomy in real-time space operations. In addition, the long operational lifetimes of space systems raise concerns regarding model degradation and adaptability over time. Thus, while machine learning offers valuable tools for enhancing space system intelligence, its sustainable deployment requires lightweight, adaptive, and verifiable models capable of operating reliably under extreme uncertainty and minimal human supervision.

Research and development are increased rapidly of machine learning applications across different aerospace realms, and this trend has resulted in a highly fragmented body of literature, often characterized by application-specific demonstrations and limited cross-domain comparison. Although separate studies report promising performance within narrowly defined problem settings, it remains challenging to assess the relative maturity, practical impact, and readiness of these models when viewed from a system-level aerospace perspective. To address this gap, this review introduces a set of synthesis tables that merge and critically compare machine learning applications, techniques, models, and constraints across major aerospace divisions and the most interested to the aerospace industry.

Table 1 illustrates a cross-application comparison of machine learning usage across key aerospace domains, including autonomous systems, predictive maintenance, design optimization, safety management, flight simulation, and space systems. The main machine learning methods, primary data sources, demonstrated benefits, and critical limitations are listed. This comparison reveals that while machine learning offers measurable performance improvements in many aerospace tasks, similar challenges such as limited generalization, data bias, and certification barriers recur across multiple domains. The table emphasizes that successful applications tend to rely on constrained, decision-support roles rather than fully autonomous functions, particularly in safety-critical contexts.

Table I. Cross-Application Comparison of Machine Learning in Aerospace

Aerospace Application	Dominant ML Techniques	Primary Data Source	Demonstrated Benefits	Key Limitations
Autonomous flight & UAVs	Deep RL, CNNs, RNNs	Simulation, onboard sensors	Improved autonomy, obstacle avoidance, adaptive control	Unsafe exploration, poor generalization, lack of certification readiness
Predictive maintenance	LSTM, CNN, K-NN, Bayesian models	Sensor data, operational logs	Early fault detection, reduced downtime, cost savings	Data imbalance, sensor drift, limited interpretability
Design optimization	CNNs, surrogate models, GANs, RL	CFD/FEM simulations	Reduced computational cost, accelerated design cycles	Simulation bias, poor extrapolation, limited experimental validation
Risk management & safety	XGBoost, RF, NLP-based DL	Incident reports, flight data	Hidden risk identification, decision support	Reporting bias, lack of causality, regulatory transparency issues
Flight modeling & simulation	PINNs, hybrid NN models	Flight data, physics-based simulations	Fast prediction, nonlinear modeling	Limited validation range, certification barriers
Space systems & satellites	CNNs, LSTM, GANs	Telemetry, orbital data	Autonomous fault detection, improved orbit prediction	Sparse failure data, onboard resource constraints

Table 2 classifies and illustrates machine learning methods corresponding to their typical aerospace applications and matching technology readiness levels (TRLs). It illustrates a clear gap between algorithmic performance reported in academic studies and the maturity required for operational aerospace deployment. Traditional machine learning models reveal higher readiness due to their interpretability and traceability, while deep learning and reinforcement learning approaches remain largely experimental. Hybrid and physics-informed models emerge as a promising compromise, offering improved generalization and physical consistency while remaining closer to certification requirements. This comparison highlights that technological readiness, not predictive accuracy alone, remains the primary bottleneck for large-scale adoption of machine learning in aerospace systems.

TABLE II. MACHINE LEARNING TECHNIQUES VS AEROSPACE TECHNOLOGY READINESS LEVEL (TRL)

ML Technique	Typical Aerospace Use Case	Typical TRL	Readiness Assessment
Linear / classical ML (RF, SVM)	Maintenance diagnostics, safety analysis	TRL 7–9	Mature, already used in operational decision-support tools
Deep learning (CNN, RNN)	Vision, fault detection, surrogate modeling	TRL 4–6	Strong performance, limited certification and explainability
Reinforcement learning	Autonomous control, trajectory planning	TRL 2–4	Mostly experimental, unsafe exploration limits deployment
Physics-informed ML (PINNs)	Aerodynamics, aeroelasticity, simulation	TRL 3–5	Promising but computationally intensive
Generative models (GAN, VAE)	Design space exploration, inverse design	TRL 2–4	Useful for concept design, not production-ready
Hybrid ML–physics models	Digital twins, simulation acceleration	TRL 4–6	Most promising path toward certification

Table 3 links fundamental aerospace constraints to their direct impact on machine learning adoption and summaries the analogous methodological adaptations required to enable safe and reliable deployment. Limitations like safety-critical operation, regulatory certification, data scarcity, and long system lifecycles impose exceptional demands that are usually absent in other AI-driven industries. The table depicts that showing these limitations necessitates shifts toward explainable models, physics-informed learning, constrained optimization, and lightweight implementations. By explicitly connecting aerospace realities with machine learning research directions, this combination offers a roadmap and understanding for addressing future developments with the practical needs of aerospace engineering and aerospace industry and other related applications that directly linked to machine learning and AI- development.

TABLE III. AEROSPACE CONSTRAINTS VS REQUIRED ML ADAPTATIONS

Aerospace Constraint	Impact on ML Adoption	Required Adaptation
Safety-critical operation	No tolerance for unsafe learning	Safe RL, constrained optimization
Certification (FAA/EASA)	Black-box models rejected	Explainable AI, traceable training
Data scarcity	Limited labeled failure data	Transfer learning, synthetic data
Wide operating envelope	Poor extrapolation risk	Physics-informed models
Long system lifespan	Model degradation over time	Online learning, model updating
Limited onboard resources	High computational cost	Lightweight / TinyML architectures

IV. CHALLENGES AND LIMITATIONS

Machine learning techniques can be very useful and give a new perspective. But, they can have some challenges and deal with a few limitations, such as the quality and availability of data, trustworthiness, model interpretability, robustness, computational constraints, regulatory issues, ethical issues, and adversarial vulnerabilities. Papernot et al. [60] presented the adversarial vulnerabilities and misclassifications in deep neural network architectures. Hamid et al. [61] explored the ethical implications of machine learning and AI in general. The ethical conundrum can be included in specific biases, specific issues of fairness, data transparency, and data privacy and protection. The study aims to raise awareness of ethical values while using AI and machine learning tools.

Barbierato and Gatti [62] presented the concern about machine learning and the nature of the “Black Box” model, which means that the model can’t give a clear explanation of its decision-making process. Hence, there are many concerns about transparency which can be problematic.

V. FUTURE DIRECTIONS

The evolution and future of the aerospace industry and engineering can be shaped by machine learning. This section highlights the future directions that can benefit and redefine this sector of industry:

- Machine learning based on physics information learning.
- Federated learning.
- Hybrid intelligence (AI–Human collaboration).
- Digital twin (via AI-driven design).
- Advancement in AI regulation, ethics, and standardization.
- Quantum machine learning.

Tuegel et al. [63] proposed the use of a digital twin to predict local damage in aircraft structure, material evaluation, and structural integrity. Grieves and Vickers [64] presented the concept of a digital twin, where two systems co-existed, one the physical system and the second the virtual system. Raissi et al. [65] demonstrated the use of a physics-informed model via a neural network machine learning technique. The model uses continuous-time and discrete-time models. Benedetti et al. [66] presented the use of a machine learning application with hybrid-quantum systems. Banbury et al. [67] demonstrated the use of low-power machine learning hardware (tiny machine learning).

VI. CONCLUSIONS

In this paper a critical and thorough examination has been executed to illustrate the role of machine learning across major aerospace engineering applications, including autonomous flight systems, predictive maintenance, design optimization, safety and risk management, flight modeling and simulation, and space systems. The analysis has emphasized the unique operational, regulatory, and safety constraints that fundamentally shape how machine learning can be developed and deployed within this field, also give a peak on some of the ethical concerns that might face this new approach.

The synthesis illustrated in Table 1 depicts that, while machine learning methods have achieved notable performance gains across many aerospace sectors, their successful use is highly uneven. Applications such as predictive maintenance and operational decision support exhibit relatively higher maturity due to their reliance on historical data and their non-intrusive integration into existing workflows. In comparison, autonomous control and reinforcement learning–based systems remain largely confined to simulation environments, where safety, generalization, and certification challenges are less restrictive. This discrepancy describes that algorithmic capability alone is inadequate to determine practical viability in aerospace sector.

Table 2 further demonstrates that technology readiness, rather than methodological sophistication, is currently the dominant limiting factor for machine learning adoption in aerospace applications. Traditional and interpretable machine learning models demonstrate higher readiness levels due to their traceability and validation compatibility, whereas deep learning and reinforcement learning methods largely mostly confined to experimental setups or prototype stages. Hybrid and physics-informed machine learning frameworks materialize as the most promising pathway forward, offering a balance between predictive capability and compliance with physical laws and certification requirements. In addition to the reduction in the processing time since it can provide a feedback based in physical laws to compare to and provide a sort of bench marks.

The constraint of data - driven approach illustrated in Table 3 reinforces that aerospace-specific challenges such as safety-critical operation, limited labeled data, long system lifetimes, and regulatory certification necessitate targeted adaptations of conventional machine learning methods. These include the incorporation of physical priors, explainability mechanisms, uncertainty quantification, and lightweight architectures applicable for onboard research and deployment. Without such adaptations, many machine learning models risk remaining academically attractive yet operationally impractical and irrelevant to the aerospace industry.

Overall, this paper is an attempt to provide a roadmap to the future impact of machine learning in aerospace engineering. Also, to push toward less dependency on the development of increasingly complex algorithms and more on the alignment of data-driven intelligence with aerospace engineering principles, certification frameworks, and system-level validation practices. Future research efforts should therefore prioritize physics-informed and hybrid modeling, standardized benchmarking datasets, transparent validation methodologies, and closer collaboration between aerospace engineers, AI researchers, and regulatory authorities. By doing so, machine learning can evolve from an exploratory research tool into a reliable and certifiable component of next-generation aerospace systems and benefit the aerospace industry. Finally, more research needs to be done on the ethical implication of using this new technology and its impact on how to optimize its usage in the future.

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