Research Paper

Advancing Aircraft Maintenance Through Artificial Intelligence: A Comprehensive Review and Future Perspective

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ABSTRACT

Objectives

This paper identifies trends in AI for aviation maintenance. Aiming to uncover untapped benefits, find research gaps, and provide insight into the current state of research and active applications.

Methods

The method of research is a manual review of research papers, following the structured PRISMA method. Research papers are collected and filtered, before key data points are extracted through reading and keyword search. Papers selected were required to be related specifically to aviation maintenance, written in English, and published in the current landscape of AI, with increasing adoption of generative AI (year >= 2018).

Findings

Findings reveal that AI research geared towards aviation is an emerging topic, with a general year-over-year increase in the number of research papers published. The research reveals several findings: Nuanced topics such as ethical considerations in the use of AI in aviation are yet to be understood completely, and require further exploration, with relatively few papers (n = 29) focusing on explainability and even fewer (n = 3) focusing primarily on the development of xAI; The study of practical applications of AI in maintenance, and research into complex systems that utilise AI-driven subsystems, such as Computer Vision, Digital Twins and Robotic Inspection, have already started industry use and show promise for further enhancements in the future. These systems trend high for research in recent years (n = 14, n = 13, and n = 10, respectively); Few papers research the creation of datasets (n = 2), and a significant number (n = 53) use the C-MAPSS synthetic dataset, suggesting that a gap exists in research and development for datasets specific to aviation maintenance.

Application/Improvements

The paper provides insight on research and trends surrounding aviation maintenance, possible gaps, and possible avenues for further research. There is a risk of bias due to research method limitations.

Keywords: Aviation Aircraft Maintenance, Machine Learning, Industry 4.0, Artificial Intelligence, Predictive Maintenance, RUL, Digital Twin.
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Introduction

Background

Aviation is a large, highly active industry. With a global impact of over $4 trillion and nearly 30000 aircraft in service serving nearly 5 billion passengers and a third of the total world trade value annually (*Fact Sheet - Value of Aviation* 2024). Travel and Tourism combined result in a total impact of $7 Trillion, and resulting in a total of 266 million jobs (Wensveen J 2023). Aviation is undoubtedly a significant industry. Moreover, it is active at all times. Schedules in the industry are strict, and delays have greater consequences as a delay in one process causes cascading delays in other processes. Large amounts of money are moved to achieve the goals of companies in the industry. Total expenses hover around $900 billion (*Fact Sheet - Industry Statistics* 2024).

In the UN's sustainable development goals, the ninth goal relates to industry, innovation and infrastructure. The aviation industry is a part of this. (*Goal 9 Department of Economic and Social Affairs* [no date])

Maintenance plays a large part in the aviation industry, it is one of the top three costs for airlines, after fuel and labour (Wensveen J 2023). However, it is crucial for the reliability of an aircraft and in consequence, the safety of passengers and staff (Ramoso M G D & Cruz R O-D 2025). Proper maintenance ensures smooth operations and keeps the industry functioning.

The work performed during aircraft maintenance is complex, time-critical, and require many personnel and systems to complete. Issues in maintenance can cause financial losses and risk safety of equipment, and in worse cases, human lives (Rajee Olaganathan 2024). Improvements in maintenance, through modern technologies, can help improve safety of air travel, as well as reduce total costs. Innovative technologies can positively affect the future of aviation.

In terms of innovation, Artificial Intelligence (AI) has become a major topic of interest in recent years. Investment in AI has increased significantly and large-scale models have increased from a total of 4 models in 2020 to 284 total models in 2024 (Giattino C, et al. 2023). As AI has progressed rapidly, many different possible applications have been developed or proposed. AI and its impact can be significant, and the aviation industry is no exception.

This paper analyses research work done on the use of AI in aircraft maintenance, diagnostics, prognosis, and related topics. Utilization of rapidly emerging technologies and methods is vital in increasing the safety and reliability of aviation systems, and this paper attempts to progress towards such endeavours.

1.1. Problem Statement

There has been an increased awareness in aircraft safety due to recent high-profile aircraft accidents, and although the accident rate has decreased over the past few decades, confidence in aircraft safety among the general public has decreased (Are planes crashing more often? 2025; Yoder J 2025). Covid-19 has also had a significant effect on aviation, with a sharp decrease in operations starting from the year 2020 causing revenue losses (Dube K, Nhamo G & Chikodzi D 2021, 2021). At this point in time, the industry should be researching methods to increase safety and decrease costs.

Aircraft maintenance is a major area of importance in the aviation industry and directly relates to aircraft safety. Research in this area can reduce disasters and save lives (Insley J & Turkoglu C 2020), as nearly 20% of all maintenance-related accidents result in fatalities (Khan F N, et al. 2020). Methods and practices that can help reduce this number should be a focus of future research. Improvements in the aircraft maintenance process can also save money and reduce delays, which is a significant issue as delays have accounted for a total of 5.3 million hours lost between January 2019 and February 2023.

As AI is an emerging technology, there is much to be explored in how it can improve aircraft maintenance processes. Due to recent advances in AI technology, the breadth of possible applications has expanded greatly and research on the topic can yield new and exciting possibilities for the future (Imran M A U, et al. 2024). An increased understanding of existing literature, gaps, and possible research areas can bring improvements in the aviation industry through enhanced technology use and better processes.

An existing issue impeding progress in enhancing aircraft maintenance through the use of AI is information access. As with emerging technologies, there are many different possible methods and algorithms to achieve similar tasks, and as such, a review of research done up to this point is useful for other researchers to further delve into the topic and identify areas where research is required, and find (through correlation) different use-cases for emerging technologies.

1.2. Research Objectives

The purpose of this research is to perform a systemic literature review on existing research done under this topic. The review will help in:

1. Identify current AI techniques and their applications in aviation systems (including predictive maintenance, fault detection, and decision support systems).
2. Examine the types of datasets, data sources, and algorithms used to train and implement AI models in maintenance operations, highlighting strengths and limitations.
3. Explore ongoing and emerging trends, research gaps, and innovative approaches that could shape the future of AI in aircraft maintenance.

1.3. Research Questions

1. What AI technologies and models have been applied to aviation processes, and which maintenance tasks do they enhance or automate?
2. What types of data, data sources, and algorithms are commonly used for AI implementation in aircraft maintenance, and what limitations or challenges are associated with these data?
3. What future research directions, innovations, or technological trends are anticipated to drive the next generation of AI applications in the aviation maintenance sector?

1.4. Contribution of the Study

The study attempts a broad review of a large number of papers (n = 284;[link of papers reviewed]). The study cross-maps different AI technologies, with aircraft components, and maintenance tasks. The study also provides a very recent, modern view (2018 – 2025) of the research environment.

1.5. Significance of the Study

The study can help in identifying areas of research that have been covered, and areas that are lacking in research. The study could also compile existing research conclusions and help in developing an understanding of prominent research topics and their results.

Ultimately, the study could provide directions to on which research would yield value to the topic.

1.6. Methodology Overview

The research would follow the PRISMA 2020 Framework (Page M J, et al. 2021), adhering to the guidelines provided through the checklist in the framework.

2. Literature Review

This literature review highlights the following aspects:

- The history of aviation maintenance
- How AI supports maintenance
- Current and emerging AI maintenance technologies

2.1. History and Recent Advances

Historically, aircraft maintenance started as basic reactive maintenance. Any issues that occurred in an aircraft were dealt with once they became apparent and started to affect the aircraft's functionality. Throughout the years, maintenance paradigms shifted from reactive maintenance to time-based preventive maintenance, where pars were inspected and fixed according to schedules. Which further evolved to reliability-centred maintenance, where parts inspection considered the reliability of each individual part and how close they were to failure. These paradigms shifted now with the use of AI, through predictive maintenance. (Tamm N 2025)

Reactive maintenance solves issues once a failure has occurred; this method is cheap and easy to follow (*Reliability centered maintenance cost modeling: Lost opportunity cost* 2015). however, reactive maintenance can be catastrophic for critical equipment and can cause serious consequences as failures are allowed to happen (Shehadeh H K 2024). Preventive maintenance attempts to predict when equipment would require maintenance. This type of maintenance is geared towards discovering and solving issues before failures. However, preventive maintenance relies on waiting over a certain period of time to perform maintenance on equipment. Although much better than reactive maintenance, this type of maintenance does not attempt to accurately judge the condition of each piece of equipment, allowing for manufacturing defects and technical errors to cause failures (Lee C, Cao Y & Ng K H 2017).

Preventive maintenance led to condition-based maintenance, where equipment is monitored in real-time to find errors. This was a leap forward in maintenance paradigms, allowing for much improved maintenance, this method still lacked in the face of unexpected failures (MoghadasNian S 2025).

Modern advances in technology, such as rapid digitalization, AI, Industry 4.0, and big data, have led to significant progress in aviation maintenance (Agustian E S & Pratama Z A 2024a). Using big-data to enable data-informed decision making has allowed for the emergence of predictive maintenance, a maintenance strategy that attempts to predict future conditions and identify when failure would occur. Predictive maintenance relies on the various sensors onboard aircraft, as well as historical data and statistics to find the lifespan of various parts (Stanton I, et al. 2023).

2.2. The Role of AI in Predictive Maintenance

AI is well-suited for maintenance tasks as it enables foresight, enabling systems to analyse patterns and determine future conditions allows for predictive maintenance to enhance efficiency through time and cost savings as well as increase safety for air travel (M M 2023).

AI achieves these through data analysis: vast amount of data are gathered from on-board monitoring systems and sensors, which are used in tandem with historical data collected over many years, to identify patterns that may not be obvious to human observers (M M 2023). Modern algorithms in AI can utilize complex data sources including image and video data to perform predictions that were previously impossible to perform (Smith M L, Smith L N & Hansen M F 2021).

AI prediction data, in addition to other data gathered by an AI system, can be used to optimize maintenance schedules. Performing inspection on equipment that does not require maintenance can be a costly action, and using AI to optimize maintenance schedules can allow for reduced delays and increased savings by preventing over-inspections (Mitta N & Ranjan R 2024).

The volume and complexity of the data collected by AI systems would be impossible to process by humans. However, when this data is processed through AI, it can provide insights for decision makers to make changes and improve processes in an organization (Duan Y, Edwards J S & Dwivedi Y K 2019).

Overall, AI technology enables systems to handle and process large amounts of data, both real-time input data and historical statistics and trends to anticipate equipment failures, detect anomalies is aircraft systems, optimize maintenance work and schedules, and ultimately, perform maintenance proactively instead of reactively. This technology makes possible a further increased standard of safety and efficiency and over time, reduces costs for aviation organizations.

2.3. Applications of AI

2.3.1 Data Analytics

Data analytics are the foundation of all AI applications, including aircraft systems, fleet management systems, and performance analysis systems. AI algorithms process large amounts of data from various sources into information and actionable insights for organizations to empower decision making and improve processes. AI systems inform maintenance and inspection processes, scheduling, and inventory management.

In real-time analysis, AI systems stream information from an aircraft's vast array of sensors to analyse its condition. Outside of the aircraft, AI systems help in understanding incidents, aid in both managerial and technical tasks, and gather data for utilization in other systems such as virtual maintenance.

2.3.2 Predictive Maintenance and Early Fault Detection

The most impactful change brought on by AI is the ability to perform predictive maintenance. This method of aircraft maintenance involves using AI algorithms to analyse real-time data streamed from the vast number of sensors in an aircraft. The algorithms process the data and attempt to identify subtle patterns and anomalies indicative of future issues and malfunctions. This early detection of issues is more cost effective to solve, and more importantly, early detection can help prevent escalation of issues and mitigate loss or harm.

2.3.3 Fault Analysis

In the case where a fault does occur, AI can be used to perform diagnosis. AI algorithms can be applied to process data surrounding the fault to find the most probable source of the issue. This use of AI greatly reduces troubleshooting time. AI is used extensively in fault detection systems (Li J, King S & Jennions I 2023; Zhao Y, et al. 2022).

2.3.4 Automated Inspection and Robotics

Automated Inspection is a use of AI slightly different from the previously discussed uses. Here, AI is used in through robotic and image analysis to help during inspection. Automated and AI aided inspections allow for greater precision and efficiency than human-only inspections by employing AI analysis during inspection. AI can be used to analyse image and video data during visual inspections to detect anomalies, cracks, corrosion, wear and tear, and other subtle signs of potential issues. Humans performing these inspections might miss subtle indicators of issues or take far longer to identify issues compared to AI. Robotic drones are another way method of automated inspection that provides benefits beyond the capabilities of human-only inspections: autonomous drones allow reaching and analysing difficult to reach areas of an aircraft. This can greatly reduce inspection times as humans would require specialized equipment and possibly require dismantling large parts of an aircraft to reach such areas. These efficiencies result in reduced costs and maintenance time.

Another benefit of automation in inspection is that autonomous systems are not susceptible to fatigue, oversight, and variability in skill. AI inspections are consistent and repeatable, reducing the likelihood of overlooked issues and allowing for a higher quality of inspection and increasing safety overall.

2.3.5 Logistics Optimizations

The predictive capabilities provided by AI can help in inventory management. AI can be used to forecast the demand for spare parts, allowing for organizations to prevent overstocking and yet, at the same time, avoid shortage of equipment. AI can also be used in logistics to optimize the allocation of resources, predicting in advance where equipment and labour would be required, helping with operational efficiency. Maintenance schedules can also be generated using AI to reduce the impact of maintenance of flight schedules, and prevent over-maintenance which would cause unnecessary delays and incur avoidable costs. AI has been considered in decision support systems for airlines (Geske A M, Herold D M & Kummer S 2024; Saraf A P, et al. [no date]) and Airworthiness management systems (Raoofi T & Yasar S 2023) The use of prediction using AI can to optimize logistics and schedules can prevent delays and related issues which could have a cascading effect on aviation operations. Reinforcement learning is used for the development of aircraft maintenance schedules (Widmer S, Shaukat S & Wu C-L 2023).

2.3.6 Learning and Education

AI can also help in the training and teaching process for technicians, pilots, and other aviation workers. There is literature mentioning possible future use of Intelligent Assistants (Kirwan B 2024; Yang S, et al. 2021) in pilot learning and to aid in enhancing safety during aircraft use. There are also possible uses of AI in Air traffic management, documentation, and aviation education (Kabashkin I, Misnevs B & Zervina O 2023).

2.4. Key AI Technologies

2.4.1 Machine Learning

One of the foundational technologies in AI is Machine Learning (ML). ML is a class of algorithms that ingest data and find patterns. These algorithms train on existing datasets, and, once trained, allow analysis of new data using that trained model.

2.4.2 Generative AI

Generative AI is an emerging technology that can assist aviation in various ways. Technicians can use generative AI to troubleshoot problems. When an AI has access to historical data, it can act as a knowledge base for workers. It can be used to summarize manuals and technical documentation and act as a virtual assistant to technicians troubleshooting an issue, augmenting maintenance and inspection tasks. It can also act as an administrative assistant, automating documentation and related tasks to reduce workload and minimize errors. Generative AI is used in predictive maintenance and to generate synthetic data for training and analysis.

2.4.3 Explainable AI

Using explainable AI is the preferred method for maintenance as it explains the how the AI reaches its conclusions in a human-readable format. This transparency builds trust in a system's decisions and helps regulatory bodies understand the decision-making process of the AI. Both reasons are required when dealing with systems that affect human lives (Shukla B, Fan I-S & Jennions I 2020).

2.4.4 Big Data

Big data is a concept in computer science, that simply relates to the collection and processing of large amounts of data. ML algorithms require large amounts of data to train, generally increasing in accuracy with more data available. This means that AI and big data go hand in hand, in cases where one concept is deployed, the other is often deployed as well.

2.4.5 Computer Vision

AI can be used in applications where the input data is an image or video stream. Here, AI is used to detect object or aspects of objects. Computer vision enables several types of systems: Autonomous robots can use computer vision to navigate and operate in different environments, humans can use cameras to analyse objects, and computer vision can be integrated into larger AI systems that perform more complex tasks.

2.4.6 Digital Twin

Digital twin technology is the concept of recreating a digital representation of a system or object (such as an aircraft) in virtual space. This technology uses data from the real-world object to maintain an accurate digital representation which can provide greater insight into the condition of the object. Simulations can provide data on how the object would perform in different environment or if an issue occurs.

2.4.7 Health Management Systems

Systems that provide thorough analysis of health conditions of aircraft, and equipment installed on them. These systems implement prediction and continuous diagnosis of data from sensors to realize predictive maintenance in aircraft. Health management systems monitor aircraft detect early errors and inform crew and other systems as needed.

2.5. Weaknesses of AI Systems in Aviation

Regarding weaknesses, there is a prominent trend in research identifying weak documentation as a source of issues in both maintenance and AI development (Agustian E S & Pratama Z A 2024b; Avers K B, et al. 2012; Zeldam S G ten 2018). There is a lack of focus on improving the documentation and maintenance processes using AI, instead the focus seems to be on the maintenance itself. A lack of good training datasets (Stanton I, et al. 2023) contributes to slower progress.

3. Methodology

This section presents the PRISMA method. A systemic review method to report information from the existing body of research on the use of AI in aviation maintenance.

3.1. The PRISMA Method

This paper follows the PRISMA 2020 method to perform a systemic literature review. The method provides a checklist of requirements that are needed for the review, organized into seven sections:

1. Title
2. Abstract
3. Introduction
4. Methods
5. Results
6. Discussion
7. Conclusion
8. Future Work

Title, Abstract, and Introduction sections are self-explanatory. The methods section describes the how studies would be selected, data would be processed, and methods that would be used to synthesize the data. The results section shows how many studies were selected, what the results of those studies were, and any meta info regarding the studies. The discussion section interprets the results and how they relate to the research objectives and questions presented.

3.2. Eligibility Criteria

The studies for this review are required to be current to the AI landscape, as a result, only studies published after 2018 are considered. All research is required to be in English, and the subject of the study should be a computer science-related subject.

- Published after 2018
- In English
- Under Computer Science, Engineering, or related field

Additionally, papers may be rejected if they are unreadable or written in any language other than English. Papers that do not deal with the subject of AI or aviation maintenance will also not be considered. Lastly, all papers must match a minimum level of quality, and sensationalized, non-scientific, or low-quality papers will be removed from the study.

- Full text of paper unobtainable
- Non-English papers.
- Papers that do not deal with AI or aviation, or deal with aviation manufacturing, maintenance of unmanned aviation, or airline operations rather than maintenance.

- Articles written in a non-neutral tone, editorialized, containing significant grammar mistakes, or those without proper sources for any figures presented.

3.3. Information Source

The review uses the Semantic Scholar, MDPI, and IEEE Xplore databases.

3.4. Search Strategy

Keywords in this study were established by reading through articles found using initial searches on Google Scholar. All studies are required to be related to aircraft or the aviation industry in some way. The studies must include 'Artificial Intelligence', or 'Machine Learning' (which falls under AI but papers might omit that keyword), and the mention of 'Maintenance'.

As the databases selected have different interfaces, different Boolean keyword searches were used. For IEEE Xplore, the following search was used:

Title: Aircraft OR
Title: Aviation
AND
Maintenance
AND
Artificial Intelligence
OR Machine
Learning

In the case of the MDPI database, the following two Boolean keyword searches were used:

Query 1:

Title: Aircraft OR
Title: Aviation
AND
Maintenance
AND
Artificial Intelligence

Query 2:

Title: Aircraft OR
Title: Aviation
AND
Maintenance
AND
Machine Learning

For Semantic Scholar, the website does not support Boolean Searches (*Semantic Scholar* [no date]). As a result, the following two search terms were used:

Term 1:

artificial
intelligence in
aviation maintenance

Term 2:

machine learning
in aviation
maintenance

3.5. Selection Process

To aid in the study identification process, the program 'Zotero' will be used. The selection process will follow the steps below in order:

1. All articles would be identified by their names and authors, and sorted into their source (Google Scholar, Science Direct, etc.).
2. Early screening would be performed to remove articles with titles that do not align with the research topic.
3. The article titles, authors, and years will be compared to find and remove duplicates.
4. Another round of screening will be performed using article abstracts to further pare down the number of studies.
5. The article full text will be searched for and saved. Any articles without full text will be removed.
6. Any articles not in English will be removed.
7. Articles that do not match the subject matter of the research will be removed.
8. Articles will be read through and any articles that do not meet quality standards will be removed.

All remaining articles will be used in the research.

3.6. Data Collection Process

Data will be collected manually for this report. Each paper would be read and data points would be extracted and synthesized. To assist in collection, the reference manager Zotero would be used to catalogue articles, and its web browser plugin would be used to quickly collect articles from web searches.

3.7. Data Items

The synthesis method will analyse aspects of each research paper, such as:

- The topic of study: Maintenance, Fault detection, scheduling, or some other area?
- The technology used in the research: Machine learning, deep learning, expert systems, etc.
- General trends discovered throughout the research.

3.8. Study Risk of Bias Assessment

There is a significant risk of bias in the studies, due to the large amount of research papers and the broad topic of research. The limited number of databases could result in missing relevant papers, as only IEEE Xplore, MDPI, and Semantic Scholar were queried for research papers. If there are relevant papers that are not catalogued in one of these databases, they have not been part of the research.

Another bias is introduced through the nature of the search. If there are relevant papers that do use different wording from the search query, they would also be missed from the search and not be part of the research.

Another concern is the possibility of low-quality papers. There is a higher likelihood of low quality papers being included as part of the research due to the large number of papers in the research. This is slightly mitigated by using high quality databases such as the three used in this research.

4. Results

4.1. Study Selection

The PRISMA flow diagram is illustrated in Fig. 1. The diagram shows results from several sources filtered in the following order:

- Date filter
- Deduplication
- Filter by subject matter
- Papers without available full text
- Papers not in English

Resulting in a final total of 284 papers.

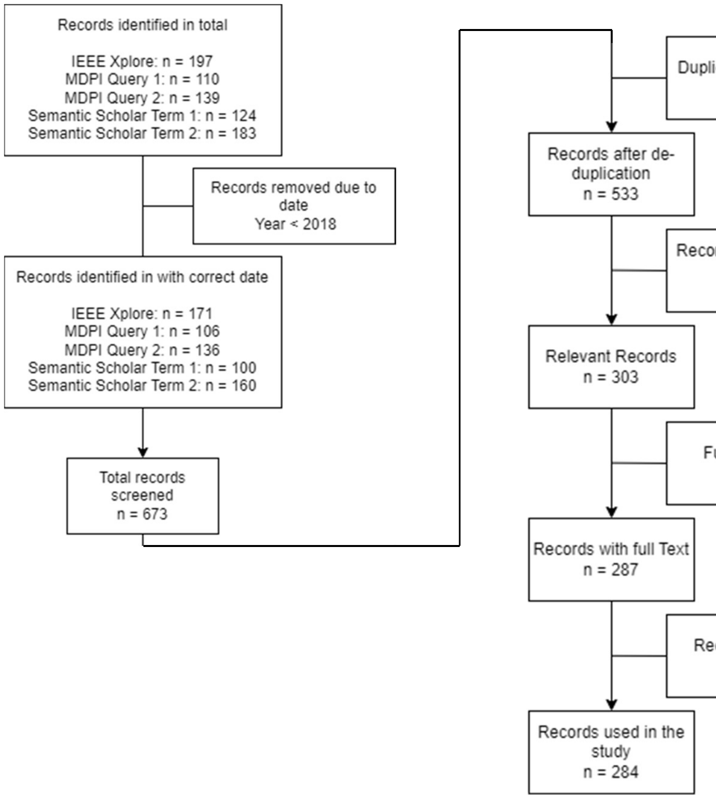


Fig. 1. PRISMA flow diagram

4.2. Structure of the Data

4.2.1 Types of Studies

The papers in this review are categorized into:

- Academic Reviews: Literature reviews and analysis papers
- Datasets: Papers that demonstrate a dataset
- Proposed Framework: Papers that contain information about

conceptual frameworks related ideas
- Proposed Methods: Papers that propose some sort of method of integrating AI into aviation maintenance.
- Study: Papers that provide an overview or research about a broad topic.

4.2.2 Topics

Topics define the aspect of the aviation maintenance the paper most relates to. In cases where a paper could encompass many topics, the most appropriate one is chosen. Some topics, such as 'predictive maintenance', are given lower priority, as nearly all papers touch on that subject.

4.2.3 Relevant Aspects of Maintenance

For papers that focus on a single component of the aircraft, this section simply states that part. In other cases, where a paper mentions multiple parts, the aspect might be 'General Aircraft'. 'Overall Aviation System' means that the ideas in the paper affect more than a single plane.

4.2.4 Technology

The type of technology a paper deals with can vary greatly. 'Machine Learning', 'General AI', and to a lesser extent, 'Deep Learning' are a catch-all term where a paper described some general AI solution.

4.3. Analysis

4.3.1 Publication Count by Year

The number of publications per year show a clear upward trend, with a consistent increase in the number of publications year-over-year. This is a key insight regarding the rapid advancement of the use of AI in aviation maintenance.

Year of Publication	Count of Publications
2018	10
2019	16
2020	21
2021	23
2022	29
2023	43
2024	76
2025	66

Table 1. Total number of relevant papers published per year

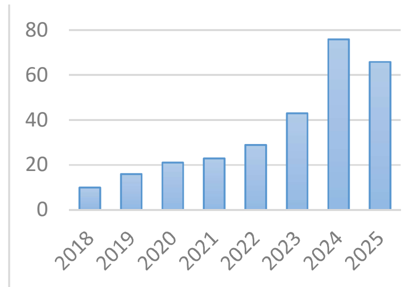


Fig. 2. Papers published as a bar graph

4.3.2 Most Common Themes

The number of papers that mention a specific theme in maintenance can be used to determine the popularity of the different ideas in this field. Below are the most common keywords found in the papers.

Theme	No. of Papers
Predictive Maintenance (Or Variations)	55
Machine Learning (Or Variations)	53
Remaining Useful Life (Or Variations)	51
Artificial Intelligence (Or Variations)	35
Deep Learning	32
Prognosis/Prognostics and Health Management (Or Variations)	24
Aircraft Maintenance	21
Fault Diagnosis	19
Long Short-Term Memory (Or Variations)	17
Aircraft Engine OR Aircraft Engine (AE)	16
Digital Twin (Or Variations)	15
Aviation Safety	12
Neural Networks (Or Variations)	12

Table 2. Common themes in papers

4.3.3 Distribution of Types

The majority of papers propose methods (Table 2.). This does, however, display the lack of datasets available

	Type	No. of Papers

Academic Review	25
Dataset	2
Proposed Framework	21
Proposed Method	187
Study	49
Total	284

Table 3. Types of papers

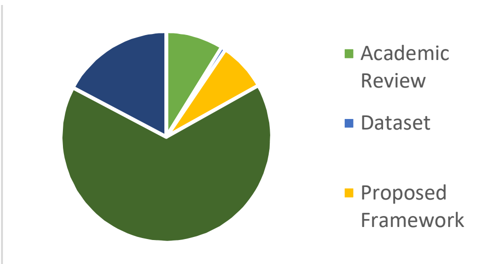


Fig. 3. Pie chart of paper types

4.3.4 Most Common Topics

Most papers seem to share similar topics (Table 4). This suggests there might be a lack of research in some areas.

Topic	No. of Papers
Remaining Useful Life	36
Data Management and Analysis	29
Application/Implementation Analysis	24
Defect Detection	23
Maintenance Prediction	22
Fault Diagnosis	21
Health Monitoring	16
Fault Prediction	16
Prognostics and Health Management	14
Model Analysis/Comparison	13
Fault Detection	9
Anomaly Detection	6
Condition Monitoring	6
Performance and Evaluation	5
Simulated Prediction Model	5
Maintenance Scheduling	5
Component Analysis	5
Condition-Based Maintenance	4
Technology and Systems Review	3
Process Optimization	3
Training Data	3
Maintenance Assistance	2
Maintenance Strategy	2
Component Management	2
Diagnostics	2
Maintenance Safety	2
Fleet Management	2
Digitization	1
Image Analysis	1
Aircraft Lifecycle Management	1
Equipment Maintenance	1

Table 4. Number of papers per topic

4.3.5 Most Common Aspects of Maintenance

The bias, shown in Table 5, is much greater than previous categories. It seems that the vast majority of research is focused towards aircraft engines.

Aspect	No. of Papers
Aircraft Engines	76
Overall Aviation System	58
Flight/Maintenance Data	25
General Aircraft	25
Aircraft Structure	17
Maintenance Support	14
Aircraft Skin/Exterior	14
Aircraft Electrical System	10
Fleet Maintenance	9
Aircraft Fuel System	6
Aircraft Hydraulic System	5
Aircraft Landing Gear	4
Several	3
Aircraft Electromechanical System	2
Helicopter Maintenance	2
Aircraft Engine Exhaust	2
Aircraft Fuselage	2
Aircraft Bearings	2
Aircraft Engines and Aircraft Hydraulic System	1
Aviation Oil	1

Aircraft Brake System	1
Aircraft Radio Equipment	1
Aviation Regulations	1
Aircraft Environmental Control System	1
Glass Canopy	1
Aircraft Mechanical System	1

Table 5. Number of papers per aspect/

4.3.6 Most Common Technology

In regards to the type of technology that is the primary focus of each of the research papers, the literature is heavily biased, with the vast majority of papers dealing with general machine learning or general deep learning, as shown in Table 6. The reason for such a bias is due to the categorization of papers involving multiple different technologies: papers with multiple technologies are categorized under a more general, common technology (for example, papers dealing with neural networks and other non-neural network machine learning technologies are categorized under machine learning).

Technology	No. of Papers
Machine Learning	87
Deep Learning	66
Neural Networks	20
Computer Vision	14
Digital Twin	13
Robotic Inspection	10
Data Processing	9
Natural Language Processing	8
Generic AI	7
Extended Reality	6
Explainable AI	5
Extreme Learning Machine	5
Decision Support System	5
Generative AI	4
Federated Machine Learning	4
AI and Internet of Things	4
General AI	4
Genetic Algorithm	1
Gaussian Mixture Model and Hidden Markov Model	1
Belief Rule Based	1
Bayesian Inference	1
Simulation	1
Automation	1
Supervised Learning	1
Reinforcement Learning	1
Class Adaptive TL Network	1
Non-Destructive Testing	1
Gradient Boosting	1
Modelling and Simulation	1
Multiple Instance Learning	1

Table 6. Number of papers per technology

4.4. Synthesis Overview

4.4.1 Overview of Research

The statistics present which aspects of aviation maintenance draw the most research. Regarding the contents of the research, there are typically several different AI algorithms implemented and compared in each paper. For example, if a typical paper (Type = Proposed Method, Topic = Remaining Useful Life, Aspect = Aircraft Engines, Technology = Machine learning) is taken from the list, the following fit:

- (Sharma V, Dagar R & Sharanya S 2024) "A XGBoost Optimized Ensemble Model for Remaining useful Life Prediction of Aircraft Turbofan Engines". The paper proposes predicting RUL through extreme gradient boosting. The paper evaluates the approach as well. The paper utilizes NASA's C-MAPSS dataset, which is a synthetic dataset found commonly through the literature.
- (Kimollo M & Liu X 2024) "Aircraft Engine Remaining Useful Life (RUL) Prediction Using Machine Learning". The paper uses Long Short-Term Memory to binarily classify whether an engine will break

within a month. The paper also tests a convolutional Neural Network to great success. The paper uses NASA's C-MAPPS dataset as well.

Other focuses in the review were found to be around Defect Detection. For the tasks revolving around routine maintenance and checkup, it seems there is a large focus on attempting to create AI that can complete them. For the fourteen papers on Aircraft Skin/Exterior, eleven primarily deal with Defect Detection. Papers such as (Khan A A, Prakash V & Jaiswal K 2025), (Plastropoulos A, et al. 2024), and (Connolly L, et al. 2024) use UAV and either YOLO or CNN to inspect aircraft surface damage.

Yet another correlation is between the Aircraft's Structure and Health Monitoring. There is some research around monitoring the health of an aircraft's structure using AI. (Kolozis P, et al. 2025) proposes transmitting ultrasonic waves through an aircraft's structure and processing the wave's results through a Neural Network to deduce the internal condition of the structure.

4.4.2 Algorithms

In general, the data suggests the deep learning algorithms, such as variations on the Long Short-Term Memory algorithm, are being used to great successes. Ensemble models also provide significant benefit, as well as extreme gradient boosting. Neural Networks are also utilized for varied tasks such as detecting corrosion (Le M & Su Luong V 2024) or Structural Stress Prediction (Jia W & Chen Q 2024).

As aircraft engines see the bulk of the work being put into this field, there have been many different algorithms utilized in different tasks for engines alone:

- Extreme Machine Learning
- Deep Equilibrium Model
- Implicit Function Theorem
- Monte Carlo Dropout
- Support Vector Machine
- K-Nearest Neighbours
- Random Forest
- Linear Regression
- Support Vector Regression

All have been used for RUL alone. Other algorithms used for the engine are:

- U-Net Architecture
- Generative Adversarial Network
- Convolutional Neural Networks
- Restricted Boltzmann Machines
- Weighted Least-Squares

4.4.3 Datasets

The primary dataset for the vast majority of the papers, is NASA's C-MAPSS dataset. Which seems to be a synthetic dataset which seems to be very popular.

4.5. Research Synthesis

4.5.1 Classification of AI Methods

Machine learning is a general field under AI that encompasses all methods of developing systems that learn and improve automatically. The term forms an umbrella under which many AI technologies are classified (Sarker I H 2021):

- Classification Analysis
- Regression Analysis
- Cluster Analysis
- Dimensionality Reduction
- Association Rule Learning
- Reinforcement Learning
- Neural Networks

The technologies described in the research can be classified into each of these categories, as shown in Table 7.

4.5.2 Overrepresentation of Deep Learning

The deep learning method is overrepresented in the literature. The method is characterized, as opposed to other machine learning methods, by:

- No requirement of manual feature: Deep learning methods perform feature selection automatically within the neural network. This removes a data preprocessing step during training (Dargan S, et al. 2020).
- Improved performance as training data grows: Deep learning performance increases as the amount of data increases, whereas other machine learning methods may plateau after a

certain point, illustrated in Fig. 4. (Sarker I H 2021).

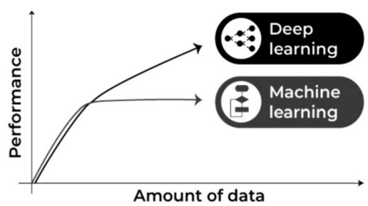


Fig. 4. Comparison of deep learning and machine learning (Sarker I H 2021)

4.5.3 Datasets

The majority of papers that cite an external data source, cite NASA's C-MAPSS (n = 53). The dataset is generated by monitoring a simulated aircraft engine performing a number of flights, with persistent faults being introduced to naturally age the engine (*C-MAPSS Aircraft Engine Simulator Data - NASA Open Data Portal* [no date]). Other papers (n = 3) cited datasets acquired from Kaggle, and several acquired gathered data to create custom datasets.

Two papers (Sumari A D W, et al. 2025; Yang H & Desell T 2022) involved the creation of datasets, one created a dataset from gathered flight data logs, and the other developed image data for maintenance assistance robots.

The research outlines a clear lack of variety in datasets, and shows that there is very limited machine learning research performed using real-world data.

Type of Learning	Category	Technology	Comments
Supervised Learning	Classification Analysis	XGBoost	A type specific of gradient boosting algorithm
		Belief Rule-Based	A rule-based classification with the ability to handle uncertainty
		Gradient boosting	
		Bayesian Inference	A statistical method used in classification algorithms

4.5.4 The Regulatory Environment in Aviation

A relatively small number of papers touch on the topic of explainability (n = 29), a chief concern for regulation and safety. Three papers focus primarily on the development of explainable AI, which is a low number as there are significant issues regarding the use of AI in aviation (Azyus A F, Wijaya S K & Kurniawan B 2025):

- The majority of AI algorithms lack transparency
- Bias in existing practices could train AI systems on false data and result in imperfect or insecure solutions.
- Some AI algorithms can seem to perform non-deterministically, causing difficulties in assessment and certification
- AI may cause security vulnerabilities if advanced and continuous security measures are not put in place.

These issues require further research to ensure real-world readiness of AI systems.

The vast majority of professionals in the aviation industry have expressed a need for the regulation of AI, as currently there exist cases where AI is not well regulated (*Ethics for Artificial Intelligence in Aviation - Aviation Professionals Survey Results 2024/2025 EASA* 2025).

Type of Learning	Category	Technology	Comments
Unsupervised	Cluster Analysis	Gaussian Mixture Model	
Supervised or Unsupervised	Neural Network	Deep Learning	A significantly large category under Neural Networks that uses deeply layered networks for improved results
		Class adaptive TL network	
	General	Computer	The use of AI in image-based data

Type of Learning	Category	Technology	Comments
	Machine Learning	Vision	
		Explainable AI	AI with the ability to provide reasoning for decisions made.
		Generative AI	AI used to generate new data by identifying patterns in training data
		Federated Machine Learning	Performing machine learning collectively from several devices
		Genetic Algorithm	A mimicry of natural selection as a method of learning
		Supervised Learning	Learning based on labeled training data to infer output from a given input
		Reinforcement Learning	Learning using automated evaluation
		Multiple Instance Learning	A type of supervised learning where data is grouped into bags
	Application of Machine Learning	Digital Twin	
		Robotic Inspection	
		Natural Language Processing	
		Extended Reality	
		Decision Support System	
		Internet of Things	
		Simulation	
		Automation	
		Non-Destructive Testing	
		Modelling and Simulation	

Table 7. Table categorizing the technologies

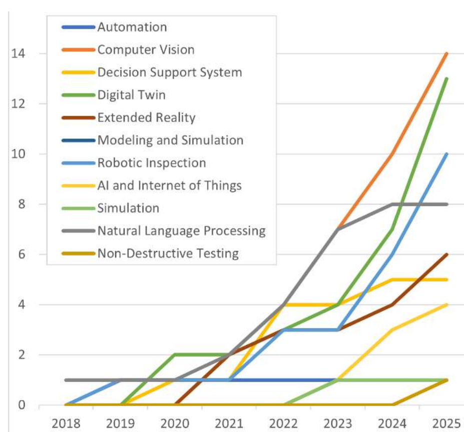
4.5.5 Practicality

The overall sentiment regarding the practicality of the various AI methods in the real-world are positive. Several papers attempted to verify proposed methods using digital or physical simulations with positive outcomes, however, there is a lack of long-term real-world data to verify the exact effectiveness of the methods.

4.5.6 Possible Future Trends and Constraints

Emerging trends among research about topics and applications in AI indicate that computer vision, digital twins, and robotic inspection have seen a rise in popularity in recent years (Fig. 5.).

Fig. 5. Number of papers of select topics over time



4.5.6.1 Computer Vision

The implementation of computer vision faces some unique constraints:

- Security is a particularly important issue in computer vision, as the input data can be highly sensitive.

- Vision sensors can be delicate, combined with the harsh environments outside aircraft result in computer vision requiring particularly robust hardware in aviation.

4.5.6.2 Digital Twins

The development of digital twins for health prognosis is a method that faces fewer constraints. Digital twins can be installed alongside existing technologies, and as such, require little regulatory intervention. The technology can also use diagnostic data to feed into the twin in order to correct deviations and improve the model's accuracy over time. The most significant constraint for digital twins is their performance. In order to provide realistic results, digital twins need to act as close to the physical twin as possible, which is a challenge when modelling complex physics such as fluid dynamics and fracture mechanics. As a result, digital twin technology relies on the availability of high-performance hardware and the performance of integrated AI algorithms.

4.5.6.3 Robotic Inspection

The other trending research topic, robotic inspection, is a practical implementation of computer vision. A robotic system utilizes computer vision for both inspection of objects and to map the environment in order to maneuver the robot. This method, as a result of employing computer vision, faces similar constraints. Additionally, robotic inspection requires ensuring a robot does not cause harm, requiring the system to perform self-correction, keep distant from equipment or hazardous objects, and most importantly, ensure no human comes to harm from its movement. These requirements limit the environments for a robotic system, and require significant precautions to ensure that the system does not cause harm.

4.5.7 Identified Gaps

The widescale use of NASA's C-MAPSS dataset can cause issues in theory. As it is a synthesized dataset, any biases in the set will reflect on all studies that utilize it. There need to be more datasets for researchers to use, as this would mitigate any possible 'Achilles' heel' situations.

Another issue seems to be the focus on aircraft engines. There needs to be a balance among different parts of an aircraft for healthy progress to occur. Currently, the significant attention given to single, albeit very important, part, could cause other safety-critical areas to be ignored.

The five papers in explainable AI suggest that this is an area that requires focus. As all commercial aviation follow strict rules and regulations, there would undoubtedly be interest in AI that can help others understand complex aviation systems in the near future.

There is little research that aims to empower the engineer working on the aircraft. Although there is research revolving Augmented Reality and smart peripherals, there is little research on advancing the tools available to the engineer. Technology such as UAVs and automatic detection are useful but until unsupervised autonomous systems can be created, there will always be a need for a human to ensure the safety of the passengers and crew.

5. Discussion

5.1. Summary

The research conducted in this paper shows that, in regards to AI in aviation, there is a significant focus on the use of deep learning; the majority of research as been aimed towards aircraft engines; and that the main research topic is to estimate the remaining useful life. Prediction of faults is preferred over the detection of faults, though there is interest in the research of fault detection specifically on aircraft structure and skin.

5.2. Objectives

The research has addressed the initial objectives:

- Current AI techniques and methods have been identified, including how popular different methods are in the current research environment.

- Limitations in the datasets used for training of these techniques were found, and discovered that research could be enhance with more data.
- The vast majority of AI methods use deep learning, and other than the chief focus of health prediction of aircraft engines, there are emerging trends of the use computer vision, robotics, and digital twin technology.

5.3. Key Challenges

These results demonstrate that despite the large number of possibilities for the use of AI, the majority of research has focused on a small portion, and there are few novel implementations of AI in maintenance. Very few papers focus on fault analysis, maintenance logistics, and the use of generative AI in such an application. The low focus on explainable AI is also a concern as deep learning algorithms are difficult to regulate.

Some other topics of concern are the lack of freely available datasets, especially datasets containing real-world data; security constraints in the use of AI; lack of data on the performance of different AI methods in the real-world; and the currently in-process regulatory framework for the use of AI in aviation.

5.4. Limitations and Potential Future Research

This research, although large, has a potentially limited scope due to the search strategy. Additionally, the synthesis of a wide variety of research papers results in a shallower, more broad and general conclusions. Future research could evaluate the use of a specific subset of AI in aviation. As this paper finds that there is a significant amount of research on aircraft engines, and deep learning, future research could focus on the evaluation of different deep learning techniques for aircraft engines; whether there is a lack of research in other aspects of aircraft; or comparisons between deep learning and other approaches to aviation maintenance.

6. Conclusion

This paper covers the current atmosphere around AI in the aviation sector. The papers gathered demonstrate where aviation maintenance resources are being pooled, and what the latest research has accomplished. At the moment, it is clear that the field is full of interesting ideas due to the recent advances in AI.

7. Appendix A

7.1. Figures

7.2. Tables

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