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Aircraft Fault Detection using Artificial Intelligence: A Review

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Abstract:- Aircraft is one of the famous traveling mediums to travel from one country to another. Aircraft can carry more than 300 passengers on one trip. Many passengers have died in airplane accidents in history. The leading cause of these accidents is the internal and external defects of the aircraft. Most errors can be early detected. With the improvement of technology, there are many advanced techniques that people have invented to automate fault detection. Among them, artificial intelligence takes a higher place than other techniques. Because these techniques are straightforward to use and understand, they save time and cost. This research paper discusses existing solutions for aircraft fault detection using AI and the techniques that they used in their research papers. Additionally, proposing a new solution for aircraft fire detection.

Keywords:- *Artificial Intelligence, Deep Learning, Machine Learning.*

I. INTRODUCTION

Aircraft is a type of vehicle that is used to travel through the air by gaining power from the air. In the modern world, most people use aircraft to travel from one country to another country. There is a high capacity in an aircraft. Airbus A380 has 525 passengers capacity [1]. There are many types of aircraft. They are amphibious, helicopters, cargo planes, flight jets, gliders, etc.

Aircraft is a collection of many mechanical parts. The power plant, empennage, landing gear, fuselage, and wings are the main parts of aircraft. There are many faults that can be occurred in these mechanical parts. A small fault can be affected to a major breakdown of the system. Therefore, safety is a major concern of the aircraft. In 1985 [2], the crash of Japan airlines flight 123 reported 520 deaths of passengers and cabin crew members. The description of types of faults are as follows,

Table 1 Description Of Fault Types

Fault Type	Description
Design errors	Manufacturing companies are responsible for these types of errors. Components of aircraft are manufactured by correctly, but there are design errors. These small errors can be affected the whole components of the aircraft.
Maintenance errors	Almost 12% of aircraft accidents are caused by maintenance errors. Aeroperu Flight 603 [2], Japan airline flight 123 and chalks flight 101 are some of the famous flight accidents that are caused by maintenance errors.
Hydraulic failures	Hydraulic failure means the pilots lost control of the airplane to turn left, right, and climb. This is a rare fault because there are three or more hydraulic systems in bigger aircraft and small aircraft has manual control systems.
Aircraft engine faults	This is a rare fault because there are multiple engines in an aircraft. Engines are one of the most complicated systems of aircraft. A 250-horsepower airplane engine lost power during flight as a result of the propeller's excessive speed.
Manufacturing faults	Manufacturing failures occurred when the aircraft is manufactured differently that its original design. Example: 1957 MCNbs [2] Island RCN Banshee crash.
Aircraft wing faults	Wings are the heart of the aircraft. Because wings are very helpful to fly through the air. This is an uncommon fault, but these types of failures can lead to major disasters.
Pilot error	Tenerife disaster is one of the best examples of pilot error. All 583 [2] passengers and cabin crew members died in this accident. The main reason for this accident is the pilot had begun the takeoff run without getting air traffic control clearance.
Communication failure	The appropriate connection between air traffic control units is a key requirement. If the flight lost the connection, it will be a major issue for the entire process.

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Aircraft technicians play a major role to ensure aircraft safety. Nowadays, most techniques that they use have manual processes. Aircraft technicians detect these errors using their own knowledge. Aircraft skin inspection is one of the primary faults detection techniques. Sometimes this traditional prediction might be right or wrong. Therefore, if we can introduce a technological environment to detect these failures before much damage will be helped to increase the accuracy of the result and increase the performance of the aircraft. Small failures can be led to critical accidents, and they will be directly affected human life. Aircraft Safety is a key requirement.

II. AIRCRAFT AND ARTIFICAIL INTELLIGENCE

The aviation industry has been developing day by day because of advanced technologies. In 1950, the introduction of the jet engine [3] is one of the turning points of advanced technologies. Among them, artificial intelligence is getting a high rank because this technology is very advanced, easy to use and understand, and saves money and time. From 1950 to the present, there are many improvements that can be seen in aircraft maintenance, aircraft manufacturing, traffic management, etc. Most of the researchers mentioned that it is very easy to use machine learning because of the abundance of data in the aviation sector.

Artificial intelligence is the intelligence provided by machines [4]. Those machines have been trained to think like a human by using artificial intelligence techniques. There are many AI techniques in the world today. The description of techniques of artificial intelligence is as follows.

Table 2 Description of Techniques

Technique	Description
Machine Learning	Machine learning is a key technique in AI. Machine learning is an application that provides the ability to learn and improve system requirements by using data and algorithms. Batta Mahesh [6] defined machine learning as a technique that is used to give some guidance to handle big data in a useful manner.
Natural Language Processing	Natural language is an interaction between computer and human language which is created to process natural language. Most people use NLP for text conversation and audio conversation. This technique uses algorithms to identify the exact hidden patterns of the data and convert those data into a format that is helped to understand by the computers.
Automation and Robotics	Automation is a process that is used software and other technology to process human work. Robotics is a field that combines computer science and engineering to build robots to perform human work. There are three types of automation. They are industrial automation, software automation, and process automation.
Machine Vision	Machines can detect visual information and analyze those for future work. Cameras can capture visual information and convert those data to digital data. Voice recognition is the best example of computer vision. This technique can capture complex data and use it effective way.

There are many existing solutions that are already using AI techniques. Self-piloted airplanes are one of the famous improvements of airplanes using aircraft intelligence. This product uses a vision-based automated system to process the aircraft during landing, taxi, and take-off. This system is developed by artificial intelligence algorithms using 500 flight details dataset. Natural language processing is used for virtual assistance. Aircraft researchers mentioned that 70% of aircraft accidents [5] are caused by human factors errors. Self-piloted artificial intelligence can eliminate these errors because AI has advanced machine learning algorithms.

It is a well-known fact that improper or neglected airplane maintenance has contributed to some of the worst aviation accidents. Even last year, aircraft maintenance was the biggest cause of domestic flight delays. The revenue streams of airline operators are significantly impacted by several existing approaches to aircraft maintenance. For instance, in 2017, airlines spent a combined $76 billion on maintenance[5], repair, and overhaul, or around 11% of all operating expenses. Based on information from various types of sensors, businesses like Airbus are already using and implementing intelligent AI-based maintenance solutions for their aircraft.

The digital twins' approach is deemed a wonderful fit for air traffic control applications. By automation routine actions during peak hours, controllers may concentrate on moves that are crucial for safety. The ultimate objectives of an AI-based air traffic management solution would be increased operational effectiveness, weak separation trajectory prediction, and automation of air traffic control. According to the experts, AI will make it easier for air traffic controllers to handle the complexity of adding new vehicles as well as the expected increase in air traffic. With better predictive capabilities, it will assure secure, safe, and highly effective airspace management, leading to fewer delays and fewer gas emissions because less fuel will be spent.

III. RELATED WORKS

Many studies have been conducted at aircraft fault detection using various AI approaches and machine learning algorithms. The following work represents the existing works of aircraft fault detection.

Xuyum F. et al [7] identified that there are large noise and complex data in Aircraft Communication Addressing and Reporting System (ACARS) data. Therefore, it is very hard to detect faults effectively. They introduced a novel method for aircraft engine fault detection. These researchers used a convolutional neural network (CNN) and supportive vector machine (SVM) algorithms. And CFM56-7B26 engine data is used to validate the effectiveness of data. This team clearly mentioned that their proposed solution requires less time and fewer parameters more than existing solutions. The highest accuracy that they achieved is 96.16%. Their future target is to use Quick Access Recorder (QAR) data for aircraft failure detection.

Caizhi L. et al [8] mentioned that aircraft skin is very important to recognize the flight and safety performance of the aircraft. They identified existing solutions have very low accuracy levels. This research team used the convolutional neural network to introduce a signal classification model for aircraft skin detection. They used four optimization algorithms. They are, SGD, momentum, RMSprop, and Adam. But Adam's optimization algorithm showed the best accuracy levels for this signal classification. This method offers a fresh approach to the detection of aircraft skin because it can recognize the probe picture, ultrasonic A-scan signal, and, track and assess the kind of the change's region.

Brian M. et al [9], proposed a data-driven algorithm for full automated aircraft sensor failure detection. A time series of typical behavior is used in the proposed machine learning method to mimic the evolution of the relevant measures by a linear time-invariant system. A Kalman observer is used to keep a distinct real-time estimate of the measurement of interest given additional information from related sensors. An anomaly is identified by the sustained difference between the measurements and the estimate. The amount of variation required to identify a sensor defect is calculated using a decision tree, which is informed by integrating additional sensor measurement information. By using it to three test systems demonstrating different forms of sensor defects, including data from actual commercial flights, an unstable aerodynamics model with dynamic stall, and a model for longitudinal flight dynamics induced by air turbulence, they validated the methodology.

Changrui et al [10], identified existing aircraft skin fault detection as a low-efficiency level. Because of that, they proposed a YOLO4 object detection algorithm for aircraft skin failure detection. Lightweight design with YOLO4 improved 10% of detection speed. MobileNetV3 is used for the feature extraction method of the network. From the basic YOLO algorithm to the sophisticated YOLO4, the YOLO series has been created. Because it can train and detect on a single GPU and strikes a reasonable balance between speed and detection accuracy, YOLO4 is more useful for engineering applications.

Murat Bronz et al [11] recognized the real-time challenges of small-scale fixed-wing UAVs. It has been shown that real-time fault detection is feasible under conditions of noisy measurements, communication barriers, and wrapped wing structures. They used eleven flight logos for this fault detection. This team proposed a data-driven supportive vector machine algorithm for classifying the behaviors of aircraft. They faced an overfitting problem because of limited data. The highest accuracy that they achieved is 95%.

Maren D. Dangust et al [12] introduced a new technique for reducing the volume of logs of aircraft warning and failure messages that are kept by the central maintenance system. The suggested model integrated a bidirectional gated recurrent network auto-encoder that cooperated to offer the right connection failure or warning signs associated with removing that aircraft LRU aiding in the recognition of aberrant patterns. Aircraft central maintenance system (ACMS) data was used for their prediction. AE-CNN-BGRU model is indicated in the evaluation result. Their future goal is to study this AE-CNN-BGRU architecture for translating time data to graphical displays that make use of recurrence graphs.

Qin Liu et al [13] identified that nowadays researchers are giving their focus on making aircraft more energy efficient, reliable, environment friendly, and low maintenance costs. They defined More Electric Aircraft (MEA) as the best solution for this focus. They proposed real-time failure detection and isolation system for MEA. They used an FPGA-based neural network method for this prediction. The highest accuracy that they achieved is 99.5%. Their future goal is to introduce multiple fault detection systems for aircraft.

P A Mallikarjuna et al [14] recognized that the gearbox is one of the important parts of aircraft engines. Any slight gearbox damage can result in the aircraft engine breaking down. Consequently, it is important to research fault diagnosis in the gearbox system. In order to categorize the status of the gearbox as excellent or bad, two deep learning models Long Short-Term Memory (LSTM) and Bi-Directional Long Short-Term Memory (BLSTM) are proposed in this study. These models are applied to time and frequency-domain data on aircraft gearbox vibration. The effectiveness of the suggested models is assessed using a dataset on airplane gearbox vibration that is available to the public. The findings demonstrated that precision produced by LSTM and BLSTM is very reliable and applicable in the time domain as compared to the frequency domain in health monitoring of aircraft gearbox systems.

Renee S. & Douglas L. [15] diagnosed that the pitot-static system, which consists of two ports outside of the aircraft and provides crucial airspeed information, is susceptible to interference and malfunctions because of its location. An airplane can be taught to autonomously identify mistakes in faulty sensors and learn to repair them if it has access to the redundant sensor output. In this work, they created a unique machine learning method for identifying sensor failures in

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aircraft and forecasting using an online paradigm, to gather data. The status of the pitot-static system is categorized using the autocorrelation of the incoming pressure data.

Ranting et al [16] discovered that the ultrasonic-guided wave transducer arrays can be used for the detection and localization of structural damage in a stiffened skin-to-stringer composite panel typical of modern aircraft construction. However, it is quite challenging to apply wave scattering theories to this section due to the geometrical and material complexity. This research team used a convolutional neural network and a 1D-CNN algorithm for their application. Based on the training data that has been learned, the DL approach automatically chooses the most sensitive wave characteristics. Additionally, the network's generalization skills enable the detection of damage that may differ from the training instances.

Table 3 Comparative Study Of Reseracher Works

Research paper name and year	**Author**	**Type of dataset**	**Type of failure**	**Technique**	**Algorithms and accuracy**
Aircraft [7] engine fault detection based on grouped convolutional denoising autoencoders (2018)	Xuyum Fu Hui Luo Shisheng Zhong Lin Lin	Aircraft Communication Addressing and Reporting System (ACARS) data of CFM56-7B26	Aircraft engine failures	Feature vectors techniques with supportive vector machine and convolutional neural network (CNN) algorithm are mainly used.	SVM: Error DAE+SVM: 76.86% Partial dimension CDAE: 89.82% Full dimension CDAE: 95.18% Novel method(propose): 96.16%
Recognition [8] of the internal situation of aircraft skin based on deep learning (2021)	Caizhi Li Xiaolong Wei Hanyi Guo Weifeng He Xin Wu Hanjun Xu Xinyu Liu	500 pictures are collected of different shooting distances and different shooting angles.	Internal failures using aircraft skin-based detection	Optimization algorithms and convolutional neural networks	Improved SSD: 96.5% SSD: 95.1% YOLOv3: 95.7% Faster R-CNN: 97.7%
Physics-informed machine [9] learning for sensor fault detection with flight test data (2020)	Brain M. De silva Jared Callaham Jonathan Jonker Nicholas Goebel Jennifier Klemisch Darren Mc Donald Nathan Kutz Steven L. Brunton Alexsandra Aravlin	21 fights sensor data	Aircraft sensor fault detection	Machine learning techniques with decision tree algorithm	This team recognized five types of faults. The accuracy levels that they achieved for these failures are as follows, Catastrophic failure: 97.32% Slow oscillation: 96.72% Increased noise: 97.30% Slow drift: 97.84% All: 98.18%
Application [10] of light weight YOLOv4 in aircraft skin fault detection (2022)	Changrui Nong Jing Zhang Zhenyu Liu Qungsong Zeng Tianqui Zhang	Not mentioned	Aircraft skin fault detection	YOLOV4 object detection algorithm MobileNetV3 feature extraction method	Mean average precision YOLOV4: 56.75% YOLOV4-ML: 55.26%
Real-time [11] fault detection on small, fixed wing UAVs using machine learning (2020)	Murat Bronz Elgiz Baskaya Daniel Delehaye Stephane Puechmorel	Flight test logs Link: https://github.com/mrtbrnz/fault_detection	Aircraft wing faults	Supportive vector machine (SVM) algorithm	SVM: 95%

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A rare [12] failure detection model for aircraft predictive maintenance using a deep hybrid learning approach (2022)	Maren David Dangut Lan K. Jennions Steve King' Zakwan Skaf	Two datasets are used, 1. Aircraft central maintenance system (ACMS) data. 2.Aircraft maintenance activities data (A330, A320)	Aircraft rare faults	Deep learning techniques using auto-encoder and bidirectional gated recurrent unit network	Accuracy for FIN_4000HA using AE–BGRU and AE–CNN–BGRU model: 99.74% Accuracy for FIN_11HB using AE–BGRU and AE–CNN–BGRU model: 99.93%
Real [13] time FPGA-based hardware neural network for fault detection and isolation in more electric aircraft (2019)	Qin Liu Tian Liang Zhen Huang Venkata Dinavahi	Not mentioned	Electric aircraft fault detection	LSTM based network with different hyper parameters. FPGA-based neural network.	FPGA-based neural network: 99.5%
Aircraft [14] gearbox fault diagnosis system: An approach based on deep learning techniques (2020).	P B Mallikarjuna Sreenatha M Manjunath S Niranjan C Kundur	24 aircraft gearbox vibration datasets	Aircraft gearbox fault detection	Deep learning techniques-based LSTM and BLSTM based models	LSTM in time domain: 98.38% BLSTM in time domain: 99.75% LSTM in frequency domain: 93.25% BLSTM in frequency domain: 93.75%
A machine learning [15] approach to aircraft sensor error detection and correction (2018)	Renee Swischuk Douglas L. Allaire	NASA aircraft dataset	Pitot static system failures	K-nearest neighbors Steepest descent algorithm Sammon's mapping	Not mentioned.
Damage [16] imaging in skin-stringer composite aircraft panel by ultrasonic-guided waves using deep learning with convolutional neural network (2021)	Ranting Cui Guillermo Azuara Francesco Lanza di Scalea Eduardo Barrera	PZT excitation signal dataset	Aircraft skin-based failures	Deep learning convolutional neural networks	Pristine-skin-stringer_Flage model: 99.86% Stringer_cap model: 99.97%

After considering the above table, most researchers gave their focus on aircraft skin fault detection. Because aircraft skin fault inspection is the main fault detection type that is used by aircraft technicians. Aircraft engine fault detection is the second most focused topic. Because the engine is the heart of an aircraft. If there is any failure in the engine, it will be a reason to fail the whole system. Aircraft sensor fault detection is another important topic that most researchers gave their attention. Aircraft sensors are very helpful for pilots to give a report of aircraft conditions. Other focused areas are aircraft gearbox, wings, and rare failure detection.

Most researchers used neural networks for their predictions. Because there is a high complexity of aircraft real-time data. After considering past researchers' works and existing solutions, there is a low level of attention to the use of AI techniques for aircraft fault detection. Because aircraft systems are very difficult to understand, it is very hard to find datasets and there is high noise data in a dataset.

IV. FUTURE WORK

After reviewing the past researchers' works and existing solutions, there are few drawbacks are identified. The main problem that was identified is that there is low attention given by researchers to fire detection systems of aircraft. Fire can occur at any time because of internal and external faults. Therefore, ensuring the aircraft and passengers' safety is a key responsibility. There are five areas where fire and overheat detectors are located. They are, wing and fuselage bleed air ducting, support pylons, wheel wells, APU, and cargo compartments. This system works separately to detect fire.

These systems diagnose fire by using simple concepts. Fire detection systems detect fire when the temperature is higher than a specific temperature. This temperature is measured by the manufacturing company and different aircraft have different temperature levels. Gas detectors are detected by using cameras. Sometimes, fire alarms are switch-on, on without having a fire. This simple concept is not good to diagnose fire.

After considering the existing drawbacks, the proposed solution is to introduce IoT and machine learning-based systems to detect fire at the early stage. The special feature is this system can diagnose fire at any part of the aircraft with less error percentage. There are five places to detect the fire of an aircraft. This IoT-based device is attached to these five places and connects with the system. This proposed fire detection system works together with these five places and measures the required inputs using a sensor of an IoT device and diagnoses the fire at any time. The main advantages of this system are less time is required to predict the result, accuracy is higher than the normal process and less money is required to manufacture this IoT-based device.

V. CONCLUSION

This review paper's main goal is to identify the AI strategies of the aviation industry. After considering past researchers' work and existing solutions, the main thing that I noted is that the aviation industry is getting 50% of the advantages of AI. But they are not getting 100% of effectiveness. There are few fields that are still available to use AI techniques. In my point of view, the aviation industry can get fast develop by using AI.

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