Machine Learning Applications in Aircraft Structural Health Monitoring

Sreehari.Kambrath[1], Immanuel Selvakumar[2]
[1]Assistant Manager, Genpact India Pvt Ltd, Bangalore,Karnataka,India
[2]Professor, Division of Electrical and Electronics Engineering, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India

Abstract— **Structural Health Monitoring (SHM) of aircraft is one of the sophisticated technologies applied that ensures aircraft's serviceability, safety, and reliability. Traditional SHM methods rely on physical models and expert judgement to identify and assess damage. The traditional methods can consume more time and can be expensive. They may be unable to diagnose and detect certain types of damage. Machine learning (ML) is a powerful tool that can be used to automate and improve the accuracy of SHM. ML has emerged as a promising approach for automating the diagnostic and prognostic process of structural internal and external damages in aircraft, leading to improved maintenance practices and enhanced operational safety. This paper depicts the overall findings and challenges involved in SHM, discusses various ML algorithms and methodologies employed in this field, and presents case studies highlighting the effectiveness of ML techniques in detecting and predicting structural defects. The paper also discusses the scientific application of machine learning processes to identify and rectify structural defects and challenges in any aircraft. We shall discuss the different types of ML algorithms that can be facilitated by SHM and some examples of how ML has been applied to manage and improve the health of aircraft.**

Index Terms— **ML, SHM, Reliability, Fatigue, Predictive Maintenance**

1. INTRODUCTION

Aircraft (SHM) has emerged to be of great importance due to the fact that it is directly related to aircraft structural health management. With the aircraft fleets becoming complicated and aged, advanced methods for detecting, diagnosing, and predicting structural damage are in increasing demand. Machine learning has been one of the most promising solutions to meet these challenges and increase effectiveness in aircraft SHM systems. [11],[15],[16]. Machine Learning algorithms offer automated analysis of large volumes of sensor data collected from aircraft structures, enabling the identification of subtle patterns and anomalies indicative of structural defects [12]. By leveraging ML techniques such as classification, regression, anomaly detection, and clustering, aircraft SHM systems can provide real-time assessments of structural integrity, facilitating proactive maintenance and improving operational safety [11].

The machine learning algorithms benefit the aircraft SHM process in many ways over traditional methods [15, 20]. ML models are designed for the learning and reinforcement of historical data based on variable conditions, and they continuously learn and improve their performance. These models can handle complex relationships between various parameters, allowing for more accurate damage detection and prediction [11][25]. Furthermore, ML techniques can complement human expertise by providing data-driven insights and necessary recommendations [16]. Additionally, it presents real time case studies that demonstrate the effectiveness of ML techniques in detecting and predicting structural defects using algorithms [12]. Exploring the intersection of ML and SHM emphasizes this study to contribute to the overall improvement of aircraft structural life and deliver an optimized pathway for maintenance management [13],[18],[26].

Most of the structural components require special attention in SHM practices. Structural components that are susceptible to high loads, fatigue, and environmental factors may experience degradation or failure over time. To address this concern, the field of

SHM pertaining to critical aircraft structural components has developed [18]. The main requirement for aerospace structural health monitoring can thus be defined to originate from the critical need to confirm the integrity of aerospace structures [23]. Aircraft defects related to structures and its failures can lead to catastrophic consequences, jeopardizing passenger safety and causing significant financial losses. The integration of advanced SHM systems, including ML-based approaches, enables continuous monitoring and early detection of structural anomalies, contributing to improved maintenance strategies and enhanced operation.

One area where ML has found application in aircraft SHM is vibration-based monitoring. Gildish et al. (2022) presented a study on helicopter bolt loosening monitoring using vibrations and ML [1]. By analyzing vibration data collected from sensors, ML models were trained to detect and classify bolt loosening conditions, enabling proactive maintenance and preventing potential failures. Gunawan et al. (2018) formulated a technique to enhance the operational reliability by the applying the F-statistic method, and also by blending the techniques in Linear Support Vector Machines [2]. The combination of ML techniques with vibration analysis enhances the accuracy and sensitivity of damage detection algorithms.

Reliability analysis is another significant aspect of SHM systems. Etebu and Shafiee et al. (2018) conducted a reliability analysis of SHM systems, emphasizing the importance of accurate data acquisition and processing for reliable structural health assessment [3]. ML algorithms provide powerful tools to process large volumes of sensor data and extract relevant features for accurate damage identification. Real-time monitoring is essential for timely maintenance and mitigation of structural issues. Laflamme et al. (2021) explored the use of real-time ML techniques for high-rate structural health monitoring [4]. By employing online ML algorithms, the system continuously learns from incoming data, adapting to changing conditions and enabling prompt decision-making. In addition to vibration analysis, ML has been applied to other SHM techniques in aerospace applications. Sundaram et al. (2009) utilized density modeling and extreme value statistics to monitor aircraft engine health, enabling early detection of anomalies and maintenance planning [5]. Ignatovich et al. (2013) focused on fatigue damage and sensor development for Aircraft SHM, employing ML algorithms to analyze data and improve damage prognosis [6]. Furthermore, Karballaeezadeh and Mosavi et al. (2020) proposed smart SHM of flexible pavements using ML methods, demonstrated the capability for extending ML applications beyond aircraft structural life cycle management [7].

A variety of techniques and methods have been worked out for the challenges connected with structural health monitoring and damage identification. Several research papers have made significant contributions in this field, proposing innovative approaches and leveraging machine learning algorithms for enhanced monitoring capabilities. Gildish, Grebshtein, Aperstein, Krushinski, and Makienko et al (2022) introduced a new method for monitoring bolt loosening events occurring in rotorcrafts using vibrations and machine learning [1]. Etebu and Shafiee et.al. (2018) conducted reliability analysis of structural monitoring systems, highlighting the importance in assessing the effectiveness and dependability of these monitoring systems [3]. Hu and Dodson et.al. (2021) explored the utilization of real-time reinforcement learning techniques offering valuable insights into real-time data processing and active decision-making [4]. Kulkarni and Achenbach delve into the realm of fatigue damage prognosis and structural health monitoring, highlighting the significance of predictive techniques in assessing the remaining useful life of fatigue-loaded structures [5]. Ignatov et al. (2013) studied on cyclic stress damages and development of monitoring sensors in aircraft structural parts, with a specific emphasis on the challenges associated with aircraft maintenance and safety [6]. Karballaeezadeh and Mosavi et al. (2020) proposed an intelligent structural health monitoring techniques for inducing flexibility in tracking the health, and by utilizing machine learning methods to enhance monitoring and maintenance strategies [7]. Bos et al. (2015) provides a business perspective on fielding structural health monitoring systems on legacy military aircraft, addressing the economic considerations and benefits of implementing such system [8]. These studies collectively contribute to the optimization of structural health monitoring and damage detection techniques, offering valuable insights and innovative solutions to enhance the safety, reliability, and maintenance of various engineering systems.

The application of ML in SHM systems also presents challenges and considerations. Tanner et al. (2003) presented a systematic health monitoring process system for gas turbine aero-engines, emphasizing the data-fusion requirement with feature extraction, and fault diagnosis algorithms [9]. Le et al. (2022) proposed an ML approach for the auto-detection and testing of non-visible corrosion in aircraft structures using electro-magnetic frequency waves to overcome complex inspection challenges [10].

2. METHODOLOGY

The methodology focusses mainly on several case studies conducted for structural health monitoring of aircraft using ML algorithms based on supervised and unsupervised learning. This mainly include the following steps and is represented in fig.1.

Literature Based Analysis: -This methodology was carried out so as to identify and study and understand the basic properties and application of ML algorithms which in turn produces some effects on the operational characteristics of the SHM parameters. This method merely helps to give a pure theoretical knowledge regarding the study.

Comprehensive and Systematic approach*:* This mainly includes the overall and deeper study conducted regarding the subject along with the theoretical knowledge through continuous reference of research and seminar papers of various eminent scientists and researchers who has presented their work in ML application towards the monitoring of aerospace structures

Thematic Grouping Approach: - In this methodology, case studies are categorized and grouped together based on the applications or subject areas they belong to. This approach allows for a systematic examination of different cases within specific themes or domains, facilitating a deeper understanding of the subject area by identifying common patterns, trends and insights across the grouped cases. Thematic analysis delivers a systematic framework to organize and analyze the real-time cases in order to provide substantial insights and conclusions, which are very well needed for active inferential decision-making within the specified application contexts.

Technology Translation study: - In the context of ML applied in aerospace structural health monitoring, the technology transfer methodology would typically involve the following steps:

1. Identification of the source domain*:* Determine the domain where ML techniques, in this case, aerospace structural health monitoring, have been successfully applied.

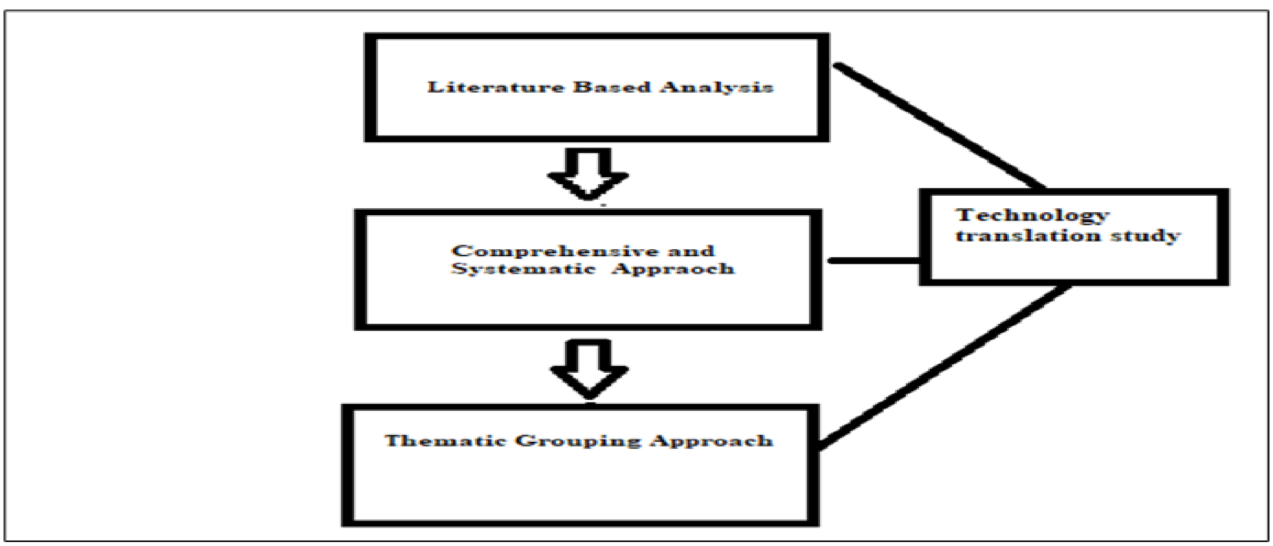

Fig. 1 Methodology of study

2. Understanding the target domain*:* Gain a thorough understanding of the target field or industry where the ML techniques will be transferred or adapted. For example, if ML techniques used in aerospace structural health monitoring are being applied to the healthcare industry, it is crucial to understand the specific challenges and requirements of healthcare-related applications.

3. Knowledge transfer: Extract the relevant knowledge, techniques, algorithms, or models from the source domain (aerospace structural health monitoring) and adapt them to suit the specific needs and challenges of the target domain.

A. Aircraft Structural Health Monitoring

In general health monitoring process is a fast-advancing technology that has the immense capability to change and transform traditional aircraft maintenance operations. SHM uses sensors to monitor the condition of an aircraft's structure and identify any damage or degradation before it causes a failure. This can help to prevent aviation accidents and save lives of the entire crew and passengers.

A wide variety of devices are used, which include strain gauges, accelerometers, and ultrasonic sensors. Each is assigned to perform different functions based on the requirements and field of application. For example, strain gauges are often used to measure the stress levels in an aircraft's structure, while accelerometers are used to measure vibration.

The data from the sensors is collected and processed by a computer. The computer uses algorithms to identify any changes in the data that could indicate damage. If damage is detected, the computer will alert the aircraft's crew so that they can take action to repair the damage. SHM has numerous benefits over the old practices followed in aircraft maintenance. Firstly, SHM can detect damage much earlier than traditional methods. This means that repairs can be made before the damage causes a failure. Secondly, SHM can identify the location of the damage, which can help to speed up the repair process. Thirdly, it is applied to diagnose and track the aircraft structural health of an aircraft's structure for its service operational period, that helps in identification of trends that could indicate critical problems. When technology continues its progression, SHM is likely to become an essential part of aircraft safety.

The technological development of machine learning is a significant factor in improving the structural reliability and safety of aircraft through broader means, especially with the advancements in artificial intelligence [3].

B. ML in Aircraft SHM

The aircraft structural components are equipped with sensors especially with Civil Aircraft structures. Applying the integration of active and passive health monitoring techniques rely upon on SMART induced Layer technology, which was conducted on a fuselage skin panel and surface of wing to monitor the condition and diagnosing the critical structural defects using the ML algorithm [24]. Let’s study some more instances where ML is widely applied.

Helicopter Bolt Loosening Monitoring: - For IAF AH -64 Helicopters there was an issue detected on bolt loosening in the body of the rotorcraft [1]. Bolt loosening has been highlighted as a possible concern to flight safety requiring ongoing visual inspection as well as higher maintenance and repair costs. Automatic fault detection for loosening in helicopter bolts through vibration measurement is challenging and difficult, as the number of such events is small, and the high-energy vibration due to rotating parts hides the soft signs given out by the loosening bolts. The evaluation of collected hums vibration-related data from IAF helicopter fleets was run through a newly developed loosening monitoring technique. The small number of defective cases were addressed with ML-based unsupervised anomaly detection. With the application of harmonic filtering to differentiate the intense vibrations generated by rotating components from the lower-energy vibrations of the structure, the predictive power of health characteristics was greatly increased. The

experimental results of loosening monitoring techniques convey that the process can be applied further to other systems as well, which involve health monitoring.

Damage Classification: This method is mainly used for identifying and categorizing structural defects and damages through certain guided signals are produced by series of piezoelectric sensor network, as well as

NLPCA (Non-Linear Principal Component Analysis) and structured machine learning algorithms. This is depicted in fig.2. As per [11] for the evaluation of this methodology, two structures were built, which are made of a multilayered sandwich CFRP and a composite plate. By applying suitable mechanical loads, the damages were purposefully generated on these structures, which will simulate damage phenomena like skin delamination and cracking physically [11].

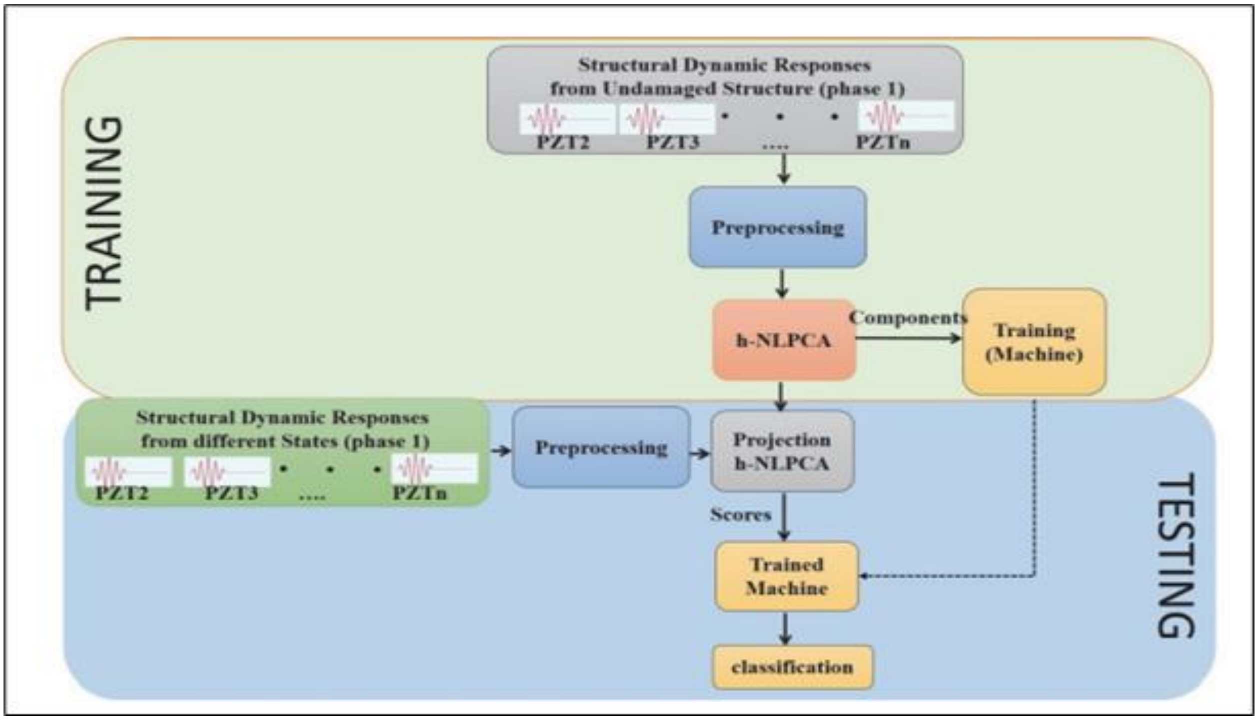

Fig. 2 Damage classification Methodology [11].

Crack detection in Aircraft engines: - For crack detection in aircraft gas turbine engine the CNN is employed widely used as an ML tool [12]. For effective maintenance of an aircraft gas turbine engine, it is important to check for structural cracks and irregular variations, which can be observed through thorough inspection. The deep learning-powered image-processed inspection reports provide sufficient information, which will really help in the assessment of the optimization of repair costs, and in turn, they minimize the complexity of maintenance monitoring through the increased level of accuracy produced by ML classifiers.

The Structural Monitoring mainly involves implementing strategies and techniques on enhancing reliability of structures to ensure accurate and consistent detection, diagnosis, and prognosis of structural health issues. One key aspect of reliability enhancement is the selection and deployment of appropriate sensor technologies. The choice of sensors plays a crucial role in accurately capturing and monitoring structural behavior. Advanced sensors, such as strain gauges, accelerometers, and acoustic emission sensors, have been widely used in SHM applications [1][4][7]. These sensors offer high sensitivity, reliability, and the ability to capture real-time data, enabling effective structural health monitoring.

Data analysis methods are another vital component in reliability enhancement. Advanced machine learning tools have been employed to extract meaningful information from the collected data [2],[5],[9],[12],[14]. These methods enable the identification of damage patterns, the detection of anomalies, and the prediction of structural health degradation. System optimization is also crucial for enhancing reliability in SHM. This includes developing robust algorithms, calibration procedures, and maintenance protocols to ensure accurate and consistent performance of the monitoring system [3][6][10][13].

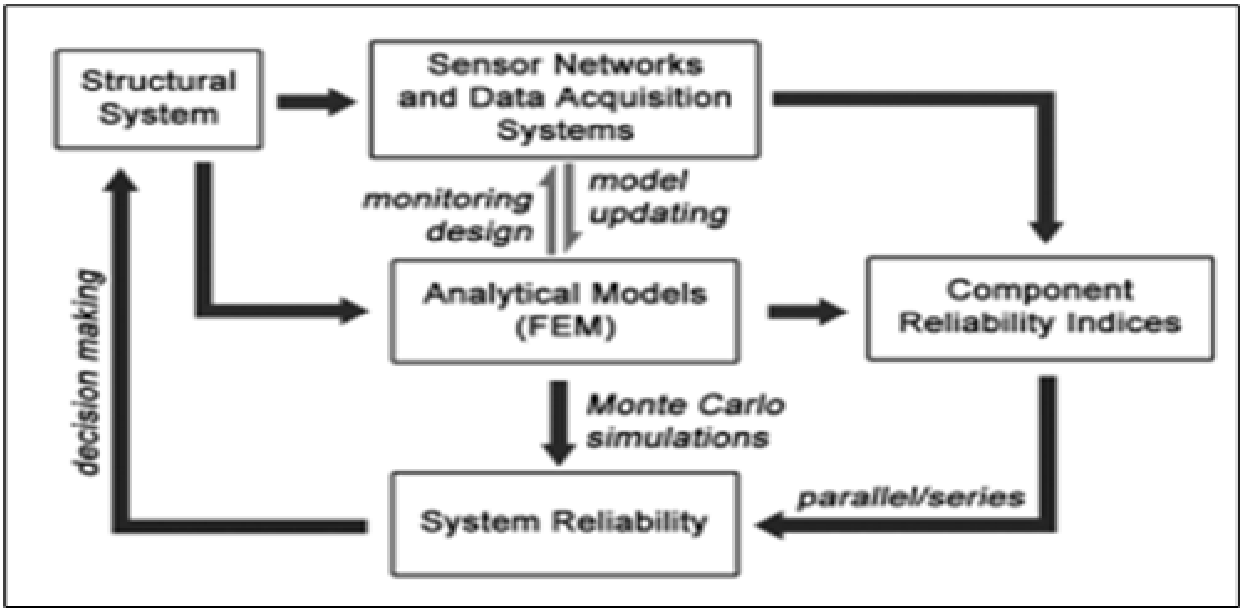

Fig. 3 Basic framework for reliability analysis using SHM.

Reliability analysis tools and methods are utilized to estimate and quantify the parameters of performance and dependability pertained to SHM system [8],[11],[15]. These techniques involve assessing the system's functional capability and its total reliability in detecting and diagnosing structural health issues. Reliability analysis provides insights into system weaknesses, allowing for necessary improvements and optimizations. The framework is as shown in fig. 5. Integration with structural integrity assessment methods further enhances the reliability of SHM systems. By combining SHM data with structural analysis techniques, such as finite element analysis or probabilistic methods, a comprehensive understanding of structural behavior and health can be achieved [16],[19]. This integrated approach enables accurate structural health assessment, prognosis, and decision-making regarding maintenance and repair actions.

A continuous research and development efforts focus on standardization and certification procedures for SHM systems [17],[20],[21]. Standardization ensures consistent practices, reliable performance, and interoperability of SHM systems across different applications and industries. Certification procedures validate the reliability and performance of SHM systems, ensuring they meet specific quality and safety requirements.

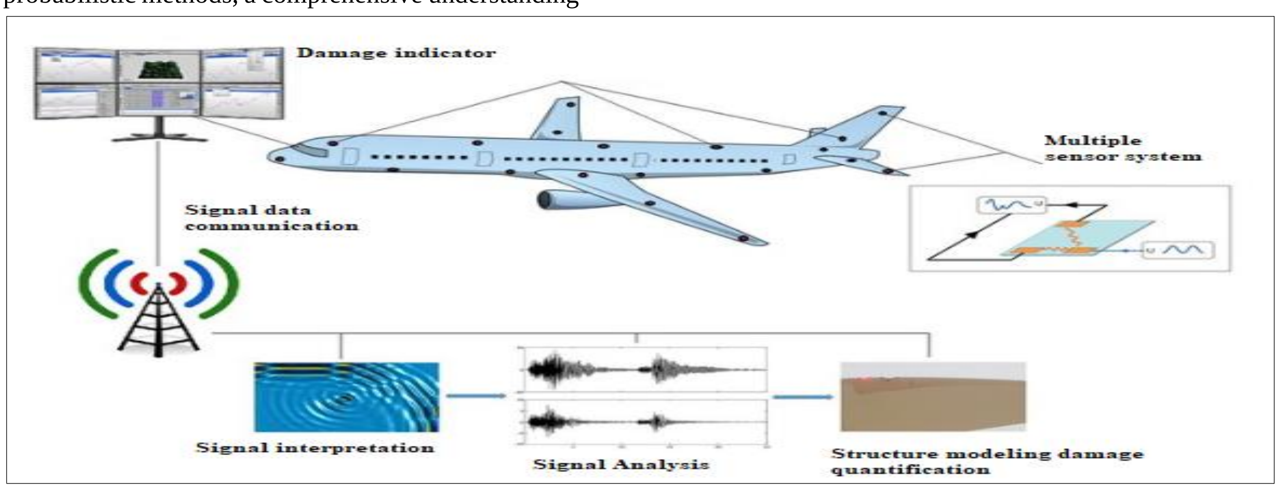

Fig.4 On-line Structural Health Monitoring of Aircraft

On-line Structural Monitoring: - The potential structural defects and damages on the fuselage panels are identified through strain field lines and through signals which are generated by a network of monitoring transducers [17]. The basic process flow is represented in fig. 4.

Fatigue and corrosion detection: These are some of the major critical detections concerned with aircraft structural and powerplant health monitoring that meet the safety standards of the structures. Fatigue damage and corrosion pose significant risks to structural components. In the field of fatigue detection, research has highlighted the importance of monitoring the structural health and prognosis of damages. Kulkarni and Achenbach [5] emphasize the significance of SHM in fatigue. Advanced sensor conceptualized technologies, like strain gauges, acoustic emission and sensors have been used to measure structural responses and identify phenomena due to fatigue [5],[6]. Such sensors record in real-time strain measurements, vibration, and acoustic emissions leading to the identification of locations and monitoring of fatigue crack propagations. Machine learning algorithms combined with the techniques applied for statistical analysis have been used to parse the valuable data from sensor data in order to predict fatigue-related damage [7],[10],[11].

Corrosion detection is equally important in structural health monitoring. Currently, there are the most commonly used non-destructive testing (NDT) methods, which include visual inspection, ultrasonic and electromagnetic testing, and eddy current-based testing, which are used for corrosion detection [8]. The techniques mentioned in fig.5 allows the evaluation of corrosion-related damage, such as material thinning, pitting, or cracking, without causing further harm to the structure. Additionally, the development of corrosion sensors utilizing electrochemical techniques has shown promising results [10],[20].

To enhance the reliability of fatigue and corrosion detection, researchers have integrated advanced sensing technologies with data analysis methods. Deep learning-based image and signal-based processing techniques and supervised ML algorithms have been utilized for the extraction of relevant information from sensor data and to identify fatigue and corrosion patterns [11],[22]. Integration with structural analysis techniques, such as finite element analysis and probabilistic methods, aids in the identification and quantification of fatigue and corrosion effects [8].

Furthermore, specific sensor technologies designed for fatigue and corrosion detection have been developed. These sensors provide real-time monitoring of parameters directly related to fatigue and corrosion, offering targeted and accurate detection capabilities [21]. By combining advanced sensing technologies, data analysis methods, and integration with structural analysis techniques, SHM systems can effectively detect and assess fatigue and corrosion-related damage, enabling proactive maintenance and repair actions to affirm the longevity and safety standards of aerospace structures.

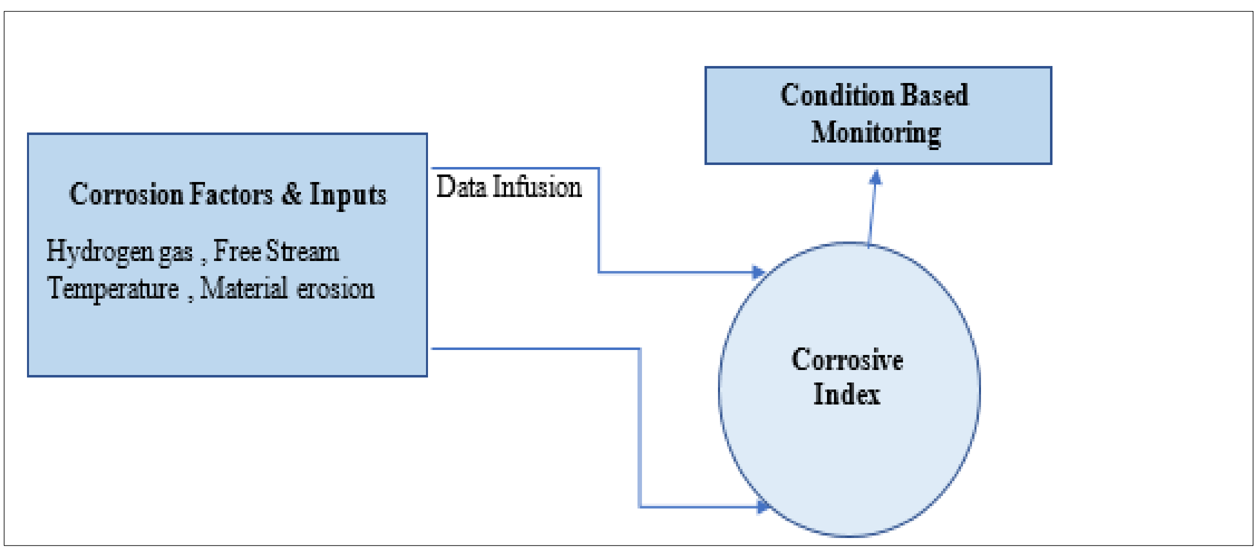

Fig.5 Corrosion detection process through machine learning

3. RESULTS AND DISCUSSION

The studies performed in this work have demonstrated the integration of machine learning in various aspects of SHM, ranging from detection and diagnosis to predictive maintenance. Studies have explored various applications of machine learning, including bolt loosening monitoring in helicopters, improving the reliability of existing methods, and real-time monitoring in concern with diagnostics and detection of damages. Advanced algorithms of ML can be widely applied to fatigue damage prognosis, hidden corrosion detection, damage classification, and smart monitoring of flexible pavements. The development of real-time, high-rate monitoring systems and the utilization of cumulative absolute velocity features have improved the accuracy and efficiency of SHM processes. Moreover, the integration of machine learning with diverse sensor technologies, including acoustic emission sensors and electromagnetic testing, has expanded the capabilities of SHM for different applications.

The utilization of machine learning methods has also led to significant improvements in the reliability and effectiveness of SHM systems. By employing linear support vector machines and hyper-solution SVM classification frameworks, the performance of existing methods has been enhanced, ensuring more accurate and robust results. Additionally, machine learning has enabled the development of predictive models for structural health, enabling proactive maintenance strategies and minimizing potential risks. The integration of SHM systems in legacy aircraft and gas turbine engines has brought about significant benefits, including enhanced safety, optimized maintenance, and extended lifespan of critical components.

According to the precedence research report the fruitful impact created by ML will increase the Aviation market for the next decades as showed in fig.6.[26].

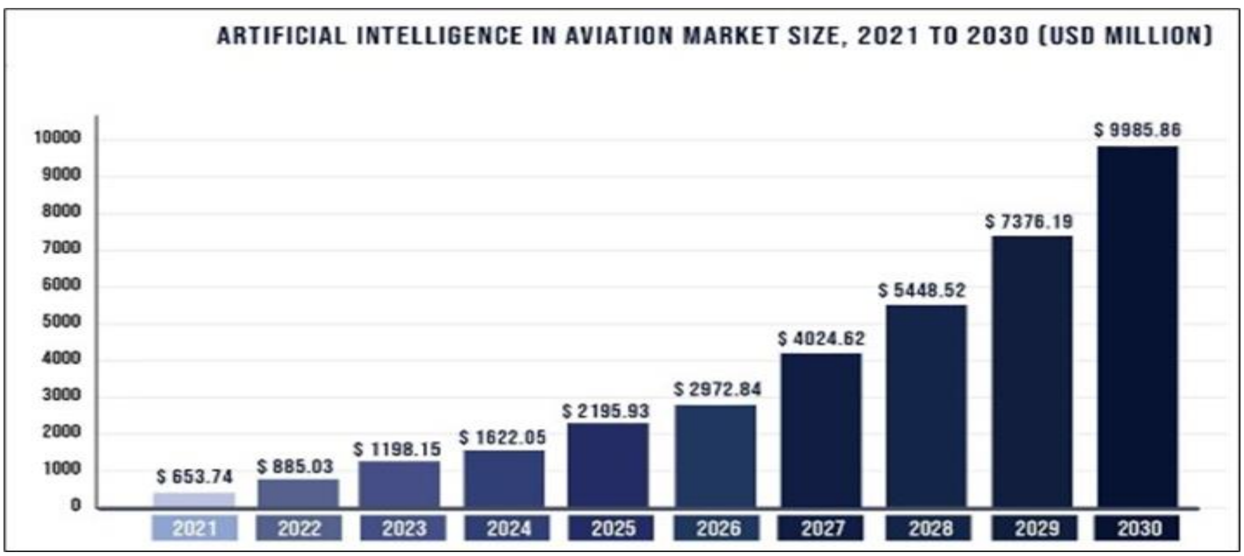

Fig. 6 The global artificial intelligence in aviation market size [26].

4. CONCLUSION

The challenges and opportunities still exist in the field of SHM and machine learning. The effective handling and analysis of large-scale, high-dimensional data remain crucial for accurate modeling and decision-making. The development of advanced algorithms and techniques, along with the exploration of emerging technologies, will further enhance the capabilities of SHM systems. The importance of SHM in aerospace industries and the exploration of emerging technologies and high-dimensional data sources have been emphasized.

Overall, these advancements highlight the potential of machine learning to improve the efficiency, reliability, and effectiveness of SHM systems, contributing to the overall safety and maintenance of structures.

ACKNOWLEDGMENT

I would like to express my appreciation for Karunya Institute of Technology for all the facilities and resources needed to complete this work. My special thanks to colleagues and the research supervisor, whose cooperation and excellent encouragement set me on this work. Last but not least, my family provided all the support, encouragement, and patience that drove me through this work.

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