b) The provision of an objective tool for monitoring and evaluating the effectiveness of remedial measures is facilitated by the implementation of enhanced training programs or modifications to Standard Operating Procedures.

The advantages of FDM are often emphasized in accident investigations. An illustrative instance is the accident involving Gulf Air's A320 aircraft GF072 on August 23, 2000, near Bahrain International Airport [26]. According to the conclusive report of the Accident Investigation Board (AIB), it was determined that the flight data analysis system was experiencing unsatisfactory performance at the time of the accident [27]. The airline's lack of access to flight data analysis resulted in the deprivation of a crucial tool for safety analysis. Upon the retrieval of flight data from the aircraft, a comprehensive analysis of the whole period of the flight, referred to as a timeline, is conducted. Historically, the FDM methodology has included the use of statistical tools for the purpose of data analysis.

The airline uses specialized software to analyze flight data, which identifies instances when certain aspects of the flight data have beyond predetermined thresholds. This strategy is based on established "exceedances," which are predetermined concerns. Events are occasionally described as occurrences in which there is a deviation from the predetermined schedule. The conventional algorithmic approach for identifying exceedance or incidents is analyzing the data for any deviations from the specified limits specified in the flight manual, standard operating procedures (SOPs), and principles of sound airmanship [28]. This methodology relies on the proficiency of human experts in constructing a framework that use pre-determined thresholds to detect known safety issues through the assessment of a restricted set of variables. A solitary event is constituted by many instances that are captured in a consecutive manner.

The process of event detection might be laborious. Nevertheless, the progress in computer methodologies has presented novel opportunities for the analysis and understanding of flight data. The utilization of Machine Learning (ML) methodologies has been crucial in driving progress within the banking and online gambling industries. ML is a subfield of AI that focuses on the creation and advancement of computer systems with the ability to access data, recognize patterns, acquire knowledge, and enhance performance through experiential learning, without requiring direct human intervention. The utilization of computational methodologies holds the promise of substantially augmenting the efficiency and efficacy of the aviation industry.

The aviation industry operates within a limited financial margin. Despite the ongoing expansion of air travel, the aviation industry remains susceptible to external factors, particularly fluctuations in oil prices. Hence, the thorough analysis of flight data has the capacity to optimize flight operations, leading to a reduction in fuel consumption, diminished maintenance and insurance costs, and an enhanced level of safety. However, the traditional statistical techniques employed for analyzing flight data, which rely on pre-established criteria, are inadequate in delivering full information and are also burdensome. This constraint may be mitigated by using machine learning methods. The aforementioned approaches provide the capability to conduct comparisons of flight data parameters over a significant number of flights, hence enabling the identification of novel or unfamiliar patterns. These observed trends may indicate atypical or incongruous conduct in relation to the majority of flights. The examination of outliers is a subject of interest that requires more inquiry.

An illustration of an atypical flight trajectory occurs during the descent phase when the aircraft deviates from the established protocol for a stable approach, specifically by failing to deploy the landing gear by the time the altitude reaches 1000 feet. Another illustration of an atypical flying occurrence may be an extreme inclination of the aircraft's nose during the process of taking off. In conventional approaches to flight data analysis, an aircraft's pitch exceeding a predetermined threshold is indicated by a red flag. However, machine learning algorithms have the capability to identify aberrant pitch deviations, as seen in **Fig 7.**

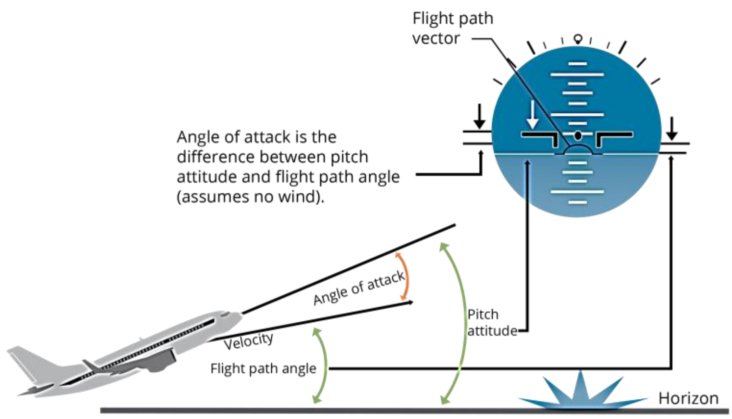

Fig 7. The Angle of Aircraft Pitch During Take-Off

Contemporary machine learning (ML) algorithms are highly suitable for not only classifying flights as safe or unsafe, but also for conducting in-depth analysis of flight particulars and providing comprehensive explanations for the factors contributing to flight unsafety. The advancement of machine learning algorithms has led to increased efficiency in analyzing flight data, making it more appropriate for generating predictions based on such data. The following sections delineate the machine learning strategies that have been used for FDM. The last section of the paper encompasses the conclusion, when the main findings and implications are summarized, and the subsequent discussion of potential avenues for further research.

IV. CONCLUSION AND FUTURE SCOPE

In summary, the aviation industry has seen notable technological progress, namely in the domains of AI and ML. The advancements have significantly influenced many facets of the field, including air traffic management, aircraft upkeep, and analysis of flight data. The use of AI and ML algorithms has significantly enhanced the efficiency and operational capacities within the aviation industry. The potential to transform commercial aviation exists with the development of single-pilot controlled aircraft, aided by digital assistants and remote pilots stationed on the ground. The operational concept known as One-to-Many (OTM) enables a solitary remote pilot to exercise control over several manned and unmanned vehicles, therefore enhancing operational efficiency and yielding cost reductions.

Artificial intelligence (AI) and ML methodologies have been used in the analysis of flight data, particularly within the domain of Flight Data Monitoring (FDM). Historically, the field of FDM has mostly used statistical methodologies to evaluate flight data and identify departures from pre-established thresholds. Nevertheless, the emergence of machine learning algorithms has opened new possibilities for the study of flight data. Machine learning algorithms have the capability to not only categorize flights as either safe or hazardous, but also provide comprehensive analysis into the underlying factors contributing to risky flights. Moreover, the implementation of predictive maintenance (PdM) has emerged as an essential strategic approach within the aviation sector. Using sophisticated analytical tools and machine learning algorithms, the practice of PdM enables the ongoing evaluation of equipment health in real-time. This approach facilitates proactive maintenance strategies, hence enhancing equipment performance and mitigating the likelihood of failures. This methodology improves the effectiveness of preventative maintenance by offering ongoing observations on the real-time state of the equipment, hence mitigating superfluous repair expenses, and reducing machine downtime.

The aviation industry has significant potential for future breakthroughs in AI and ML. The advancement of AI-driven virtual assistants and the incorporation of AI technology into air traffic control systems have the potential to augment operational efficiency and safety measures. Furthermore, the investigation of novel machine learning methodologies, such as deep learning, has the potential to enhance predictive capacities in the domains of aircraft maintenance and flight data analysis. Nevertheless, there exist several issues that require attention and resolution in the next period. The incorporation and verification of extensive datasets for machine learning applications continue to pose a substantial challenge. Furthermore, it is imperative to prioritize the establishment of robust security measures and dependable protocols for AI and ML systems within the aviation industry. This is essential to uphold the safety and overall soundness of aviation operations. The aviation industry has adopted technical advancements in AI and ML, resulting in notable enhancements in efficiency, safety, and operational capacities. The prospective developments in virtual assistants, air traffic control systems, predictive maintenance, and flight data analysis indicate a significant future scope for these technologies in the sector. Nevertheless, it is essential to acknowledge that the effective application of these technologies in the aviation industry will heavily rely on the resolution of obstacles pertaining to data integration, security, and dependability.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding agency is associated with this research.

Ethics Approval and Consent to Participate

The research has consent for Ethical Approval and Consent to participate.

Competing Interests

There are no competing interests.

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