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Abstract

The rapid evolution of modern aircraft systems has generated massive volumes of flight data, creating new opportunities for intelligent safety monitoring, predictive maintenance, and automated fault diagnosis. Machine learning models have emerged as powerful solutions for analysing complex aviation datasets, enabling accurate identification of abnormal flight behaviour and classification of system-level faults. This chapter presents a comprehensive analysis of advanced machine learning approaches for flight anomaly detection and fault classification, covering data acquisition, preprocessing strategies, feature engineering, supervised and unsupervised learning techniques, ensemble algorithms, and deep learning architectures. The chapter explores the capabilities of models such as Random Forest, Gradient Boosting, XGBoost, Convolutional Neural Networks, Long Short-Term Memory networks, Autoencoders, and Transformer-based frameworks for extracting meaningful patterns from multidimensional flight data. Special emphasis is placed on challenges associated with data imbalance, sensor uncertainty, real-time monitoring, model interpretability, and deployment in safety-critical aviation environments. Emerging technologies, including explainable artificial intelligence, digital twins, federated learning, and intelligent predictive maintenance frameworks, are discussed to highlight future research directions. The presented insights contribute toward developing reliable, adaptive, and trustworthy artificial intelligence systems for next-generation aviation safety management.

Keywords: Flight Anomaly Detection, Machine Learning, Fault Classification, Aircraft Health Monitoring, Deep Learning, Predictive Maintenance

Introduction

The aviation industry represents one of the most safety-critical and technologically advanced domains, where continuous monitoring of aircraft performance remains essential for maintaining operational reliability and passenger safety [1]. Modern aircraft have evolved into highly complex cyber-physical systems consisting of interconnected avionics, propulsion units, flight control mechanisms, communication networks, navigation systems, and intelligent monitoring platforms. These systems continuously generate enormous volumes of operational data through onboard sensors, Flight Data Recorders (FDRs), Aircraft Condition Monitoring Systems (ACMS), and other digital platforms. Parameters related to engine performance, altitude, airspeed, fuel consumption, vibration, temperature, pressure, control surface movement, and environmental conditions provide valuable information regarding aircraft health and operational behaviour [2]. The increasing availability of such high-resolution flight data has transformed traditional aviation safety approaches from reactive fault investigation toward proactive monitoring and predictive decision-making. Conventional safety assessment techniques primarily depend on predefined operational limits, manual inspection, and scheduled maintenance activities [3]. Although these methods have contributed significantly to aviation reliability, they often experience limitations when handling complex nonlinear relationships, hidden degradation patterns, and early-stage abnormalities within large-scale flight datasets [4]. The growing complexity of aircraft systems demands intelligent analytical frameworks capable of continuously evaluating operational conditions, identifying deviations from normal behaviour, and providing early warnings regarding potential failures. In this context, machine learning has emerged as a transformative technology that enables automated interpretation of flight data and supports advanced anomaly detection and fault classification mechanisms. The integration of artificial intelligence with aviation data analytics provides significant opportunities for improving aircraft reliability, reducing maintenance costs, minimizing operational risks, and strengthening overall flight safety management [5].

Flight anomaly detection has become a critical research area focused on identifying deviations between expected aircraft behaviour and actual operational performance. Aircraft anomalies can originate from various sources, including mechanical degradation, sensor failures, electrical disturbances, software errors, environmental influences, navigation inaccuracies, and abnormal pilot interactions [6]. Some faults develop gradually due to component aging, material fatigue, or progressive system degradation, whereas other anomalies occur suddenly because of unexpected failures or external disturbances. Early recognition of such abnormal conditions enables timely maintenance intervention and prevents minor operational irregularities from developing into severe safety incidents [7]. Identifying flight anomalies remains a challenging task because aircraft operations naturally involve significant variability during different flight phases. Changes in altitude, velocity, atmospheric conditions, aircraft loading, route characteristics, and pilot inputs create complex operational patterns that must be distinguished from genuine fault conditions [8]. Traditional rule-based monitoring systems generally depend on fixed thresholds established through engineering knowledge and historical experience. These systems perform effectively for clearly defined abnormal conditions but often fail to detect subtle deviations that involve interactions among multiple parameters [9]. Machine learning-based anomaly detection approaches overcome these limitations by learning operational patterns directly from historical flight data and establishing intelligent representations of normal and abnormal behaviour. Such approaches enable automatic discovery of hidden relationships among flight variables and provide enhanced capability for detecting previously unknown anomalies. The development of reliable anomaly detection models therefore represents an important step toward achieving proactive aviation safety management and intelligent aircraft health monitoring [10].