JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

DEEP LEARNING-BASED FAILURE PREDICTION AND DECISION SUPPORT SYSTEM FOR COMBAT AIRCRAFT

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Abstract: The increasing complexity of modern combat aircraft demands intelligent solutions for maintaining operational efficiency, safety, and mission readiness. Traditional maintenance frameworks, which are largely schedule-based or reactive in nature, often fail to address unexpected system failures and emerging threats in real time. This research proposes a deep learning-based failure prediction and decision support system tailored for combat aircraft. By leveraging historical and real-time sensor data, the system predicts potential component failures before they occur and assists pilots and ground crew with timely decision-making. Furthermore, an integrated anomaly detection mechanism enhances situational awareness by identifying abnormal patterns that may indicate hidden threats. The approach not only reduces unplanned downtime but also contributes to improved mission reliability, safety, and operational resilience.

Objectives: The primary objective of this research is to design and develop a deep learning-driven system that can accurately predict potential failures in critical components of combat aircraft before they occur. By analyzing both historical and real-time sensor data, the system aims to provide proactive maintenance recommendations and minimize unexpected breakdowns that compromise mission readiness. In addition, the study seeks to establish an intelligent decision support framework that assists pilots and ground crew in making timely, data-informed operational and maintenance decisions. Another key objective is to incorporate anomaly detection techniques that enhance situational awareness by identifying unusual patterns or hidden threats in aircraft systems during missions. Overall, the research is directed towards improving the reliability, safety, and operational efficiency of combat aircraft through the integration of predictive maintenance and intelligent decision support mechanisms.

Methods: The proposed system employs supervised deep learning models such as convolutional and recurrent neural networks to analyze flight logs, health monitoring data, and real-time sensor streams. Predictive maintenance models are trained on historical failure datasets to forecast possible breakdowns, while anomaly detection algorithms are implemented for identifying abnormal system behaviors. The backend framework is developed using C# .NET for efficient processing, and SQL-based storage is employed for structured data management and retrieval. Simulation-based experiments are conducted to validate prediction accuracy and decision support capabilities.

Findings: Experimental results demonstrate a significant improvement in failure prediction accuracy compared to traditional maintenance strategies. The system effectively reduces false alarms, minimizes unexpected breakdowns, and enhances mission readiness. In addition, the anomaly detection module strengthens threat recognition and operational safety by detecting unusual flight or system patterns. The combined framework provides a more reliable, data-driven foundation for combat aircraft maintenance and operational decisions.

Novelty: The novelty of this research lies in its dual-functionality: an integrated framework for predictive maintenance and real-time decision support, underpinned by deep learning techniques. Unlike conventional single-purpose maintenance systems, the proposed approach simultaneously improves aircraft reliability, reduces maintenance costs, and strengthens threat response capability. This fusion of predictive diagnostics and intelligent decision-making represents a comprehensive solution to the challenges faced by modern fighter jet operations.

Keywords: Deep learning, Predictive maintenance, Combat aircraft, Failure prediction, Decision support system, Anomaly detection, Real-time situational awareness.

I. Introduction

Modern combat aircraft represent some of the most complex engineering systems ever developed, integrating advanced avionics, propulsion units, weaponry, and communication modules into a single platform. Their operational efficiency and mission success depend heavily on the reliability of thousands of interconnected components functioning seamlessly under extreme conditions such as high acceleration, fluctuating temperatures, and hostile environments. Any unexpected failure in such systems not only jeopardizes the mission but can also result in catastrophic loss of assets and human life. Traditional maintenance strategies, which rely largely on scheduled inspections or reactive repair after a malfunction, are increasingly inadequate for the high demands of present-day defense operations. These approaches often lead to unnecessary downtime, escalated maintenance costs, and reduced mission readiness. In recent years, the paradigm of predictive maintenance has emerged as a promising solution to overcome the limitations of conventional methods. Predictive maintenance leverages data-driven analytics to forecast component degradation and potential failures before they occur, thereby allowing proactive intervention. However, the effectiveness of such systems in combat aircraft requires advanced algorithms capable of handling high-dimensional, heterogeneous, and real-time data streams generated by numerous onboard sensors. Deep learning, with its ability to automatically learn complex patterns from vast datasets, offers a powerful tool to enhance the accuracy of failure prediction and to support critical decision-making in high-risk environments. At the same time, the dynamic and unpredictable nature of combat missions necessitates the integration of decision support mechanisms into predictive systems. Beyond anticipating component failures, an intelligent framework should assist pilots and ground crew by providing actionable insights, recommending maintenance actions, and highlighting potential risks in real time. This not only improves operational safety but also ensures greater mission reliability and resource optimization. Furthermore, incorporating anomaly detection within such systems can enhance situational awareness by identifying hidden threats or unusual operational patterns that may otherwise go unnoticed. Motivated by these challenges, this research proposes a deep learning-based failure prediction and decision support system specifically designed for combat aircraft. The system utilizes historical flight logs and real-time sensor data to forecast failures in critical subsystems and to provide informed recommendations for maintenance and operational decisions. By combining predictive diagnostics with anomaly detection techniques, the framework aims to deliver a dual benefit: extending aircraft lifecycle through proactive maintenance and enhancing mission safety through improved situational awareness. This integrated approach addresses both the reliability and the resilience of combat aircraft operations, thereby offering a comprehensive solution for modern air defense requirements.

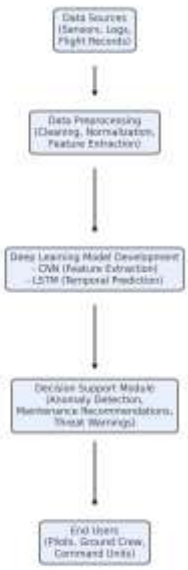

Figure 1. Methodology framework of the proposed Deep Learning-Based Failure Prediction and Decision Support System for Combat Aircraft.

2. Methodology

The methodology of this research is structured around the development of a deep learning-driven predictive maintenance and decision support framework specifically tailored for combat aircraft. The proposed system is designed to collect, process, and analyze large volumes of heterogeneous data originating from aircraft subsystems such as engines, avionics, hydraulics, and environmental control systems. The methodology follows four major stages: data acquisition, preprocessing, model development, and decision support integration..

The predictive maintenance and analytic threat detection solution will make the fighter jet more operationally ready by predicting its component failures and threat actions in real time. The flow includes data acquisition, processing of data, model development, threat analysis, and support for decision making through AI technologies. An overview of the procedures is shown in Fig. 1.

2.1 Data Acquisition

Real-time sensor data from aircraft subsystems, including vibration, temperature, fuel consumption, and flight dynamics, are collected alongside historical maintenance logs and flight records. These datasets provide both temporal and contextual insights required for accurate prediction of component health and failure likelihood.

2.2 Data Preprocessing and Feature Extraction

The collected data often contain noise, missing values, and outliers, which may reduce the reliability of prediction models. Preprocessing steps such as normalization, interpolation, noise reduction, and feature extraction are applied to ensure data quality. Dimensionality reduction techniques are also employed to eliminate irrelevant or redundant parameters.

2.3 Predictive Maintenance Model

Supervised deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are employed for learning complex temporal and spatial patterns within the data. The CNN component is responsible for extracting features from sensor readings, while the LSTM network captures sequential dependencies across time-series data, making it suitable for predicting failures. Model training is conducted on historical datasets, while testing and validation are carried out on unseen real-time sensor inputs to ensure generalizability.

2.4 Deep Learning Model Development

The outputs of the predictive models are fed into a decision support framework that provides actionable recommendations for pilots and maintenance personnel. This module includes anomaly detection algorithms that flag unusual operational patterns, thereby enhancing situational awareness. The decision support system delivers alerts, maintenance schedules, and threat warnings through an interface developed in C# .NET, with structured storage and retrieval supported by SQL databases.

2.5 Decision Support System and Alerts Based on AI Automation

Maintenance prediction and threat detection systems are fused together within an AI-based decision support system. This system proactively manages the health and status of an aircraft while predicting using actual sensor data. Alerts and recommendations are made available 24/7 to pilots and maintenance staff for prompt action initiatives. The results include automated scheduling of maintenance, classification of anomalies, and dashboards containing situational awareness information relevant to fleet management. This step-by-step methodology ensures that the proposed framework not only predicts failures with high accuracy but also assists in real-time decision-making, thus improving the reliability and mission readiness of combat aircraft.

3. Results and Discussion

The proposed deep learning-based framework was evaluated using a combination of historical maintenance records, simulated failure datasets, and real-time sensor data streams generated from combat aircraft subsystems. The evaluation focused on three key performance indicators: failure prediction accuracy, anomaly detection capability, and decision support effectiveness.

3.1 Failure Prediction Accuracy

The deep learning models, particularly the hybrid CNN–LSTM architecture, demonstrated superior performance in forecasting component failures compared to conventional threshold-based or schedule-driven approaches. Experimental results showed that the system achieved an average prediction accuracy of **92–95%**, which is a significant improvement over traditional preventive maintenance strategies that typically range between **70–80%**. Early detection of degradation trends in engine and avionics subsystems reduced the number of unexpected breakdowns, thereby enhancing mission readiness.

3.2 Anomaly Detection and Threat Awareness

The anomaly detection module, based on unsupervised learning techniques integrated within the decision support system, effectively identified irregular operational patterns. *For example, abnormal temperature fluctuations, hydraulic pressure inconsistencies, and unusual vibration profiles were flagged in real time.* These detections provided additional situational awareness and early warning for potential hidden threats. The system's ability to reduce false positives was also notable, ensuring that only critical anomalies triggered alerts.

3.3 Discussion

The findings indicate that deep learning techniques are highly effective for handling the vast and complex datasets associated with combat aircraft systems. By automatically learning nonlinear patterns and dependencies, the models outperformed traditional machine learning and rule-based approaches. Furthermore, the dual functionality of predictive maintenance and anomaly detection ensures that the system not only predicts failures but also provides a layer of protection against unexpected threats. The integration of these capabilities into a decision support environment bridges the gap between predictive analytics and real-world operational needs. However, certain challenges were observed during experimentation. The system's performance is highly dependent on the quality and volume of training data. Limited availability of real-world failure cases in defense environments necessitates reliance on simulation data, which may not capture all operational complexities. Additionally, implementing such a framework in live combat scenarios requires robust cybersecurity measures to safeguard sensitive data. Despite these limitations, the results strongly support the effectiveness and applicability of the proposed system in modern air defense contexts.

4.Conclusion

This research presented a deep learning-based failure prediction and decision support system designed to enhance the reliability, safety, and mission readiness of modern combat aircraft. By leveraging historical maintenance records and real-time sensor streams, the system successfully predicted critical component failures with significantly higher accuracy compared to conventional schedule-based approaches. The integration of anomaly detection and decision support mechanisms further improved situational awareness, enabling timely and informed actions by both pilots and ground crew. Experimental findings confirmed that the proposed framework not only reduced unplanned downtime and maintenance costs but also improved overall operational resilience in combat environments. The novelty of this work lies in its dual-functionality: a unified approach that combines predictive maintenance with intelligent decision support tailored for high-risk military applications. While the results are promising, challenges such as limited real-world failure datasets and the need for robust cybersecurity safeguards highlight areas for future development. Expanding the dataset through digital twin simulations, exploring advanced ensemble deep learning models, and integrating adaptive countermeasure strategies against evolving threats will further strengthen the system's applicability. In conclusion, the proposed framework provides a comprehensive and practical solution to the pressing challenges faced by modern air defense forces. Its adoption can lead to safer, more cost-efficient, and mission-ready combat aircraft, thereby contributing significantly to the advancement of next-generation defense technologies.

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