An Analytical AI-Driven Diagnostic Model for Early Fault Detection in Aircraft Avionic Devices

Abdurashid Abdukayumov[1], Izzat Maturazov[1], Shavkat Saydakhmedov[2], Akmal Joraev[1] and Dauitbay Sarsenbaev[1]
[1]*Department of Aviation Engineering, Tashkent State Transport University, Temiryolchilar Str. 1, 100167 Tashkent, Uzbekistan*
[2]*School of Global Aviation Studies, Korea Aerospace University, Hanggongdaehak-ro 76, 10540 Goyang-si, South Korea*
abduqayumov_a@tstu.uz, maturazov_i@tstu.uz, jhon@kau.ac.kr, jurayev_ma@tstu.uz, sarsenbayevdauit@tstu.uz

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Abstract: This paper presents an analytical model of an intelligent diagnostic system designed for early fault detection in aircraft radio-electronic (avionic) devices. Traditional threshold-based methods are limited by low sensitivity and inability to model nonlinear dependencies among system parameters. The proposed AI-based model, calibrated on vibration, temperature, and pressure data from the FADEC (Full Authority Digital Engine Control) of a Pratt & Whitney PW127M engine (ATR-72 aircraft), applies a nonlinear mapping evaluated using a binary cross-entropy metric. Uncertainty quantification is introduced using a Beta distribution, enabling calculation of a 95 % confidence interval for diagnostic reliability. Experimental validation shows a diagnostic accuracy of 93 ± 2 % and false-alarm rate below 8 %, demonstrating promising predictive performance under simulated operating conditions. The system ensures real-time data fusion between onboard and ground maintenance units, providing a foundation for predictive and sustainable aviation maintenance. The proposed framework provides probabilistic, confidence-aware diagnostics suitable for real-time deployment and supports risk-informed maintenance decisions aligned with modern aviation certification and Maintenance 4.0 requirements.

1 INTRODUCTION

Modern aircraft systems are becoming increasingly complex and saturated with electronic control units such as FADEC, FCC, and EICAS. Consequently, the importance of timely fault diagnosis and prognosis is growing to ensure flight safety, system reliability, and cost efficiency.

Traditional methods based on fixed thresholds or basic vibration and temperature analysis are insufficient for early fault identification. They cannot capture nonlinear correlations between parameters or account for operational variability and environmental noise. Recent advancements in artificial intelligence (AI) and machine learning (ML) enable the development of intelligent diagnostic models capable of classifying fault types and estimating prediction confidence using probabilistic reasoning [1]-[3]. These intelligent techniques are central to Maintenance 4.0, a concept emphasizing data-driven, predictive, and self-learning maintenance [4].

This research develops an analytical model of an AI-driven diagnostic system for early fault detection in avionic equipment. The proposed framework emphasizes analytical transparency and reproducibility, enabling controlled evaluation of diagnostic logic under simulated operating conditions. The proposed system is applied to a Pratt & Whitney PW127M engine FADEC module used on ATR-72 aircraft, employing nonlinear mappings, cross-entropy optimization, and uncertainty modeling via Beta distributions.

The Beta distribution is adopted for uncertainty modeling because it provides a mathematically tractable representation of bounded probabilities (0-1 range) and allows posterior estimation in a Bayesian inference framework. This enables probabilistic fault confidence quantification rather than deterministic thresholds. The objective of this study is not to train a production machine-learning model but to establish a mathematically interpretable diagnostic framework that can later be integrated with data-driven learning systems when operational datasets become available.

The main contributions of this work are summarized as follows:

1) Development of an analytical AI-inspired diagnostic model for avionic fault detection;
2) Integration of probabilistic uncertainty estimation using Beta-distribution confidence modeling;
3) Formulation of a closed-loop onboard-ground diagnostic architecture aligned with Maintenance 4.0 principles;
4) Validation of diagnostic behavior using controlled simulation of FADEC telemetry.

2 MATHEMATICAL MODELING OF DIAGNOSTIC LOGIC

The proposed analytical model consists of two principal layers: (1) a nonlinear classification model that maps sensory data into a diagnostic probability, and (2) an uncertainty estimation layer based on the Beta distribution that quantifies confidence in each decision. Together, these components provide a mathematically transparent, probabilistically grounded diagnostic framework compatible with FADEC-based onboard systems.

2.1 Fault-Classification Model

Let the input vector of normalized sensory measurements be defined as:

$$x = x_1, x_2, \ldots\ldots x_n\ , \qquad (1)$$

where each x_i represents vibration amplitude, temperature, pressure, or another relevant feature extracted from onboard sensors.

All input variables are normalized to zero mean and unit variance prior to model evaluation.

A nonlinear function $f(x;\theta)$, parameterized by weights θ, maps the input vector to a predicted probability of fault:

$$\hat{y} = f(x;\theta),\ \ \hat{y} \in [0,1]. \qquad (2)$$

In (2) $\hat{y}$ expresses the estimated likelihood that the current system state deviates from nominal behavior. In practice, such nonlinear mappings are commonly implemented using statistical or machine-learning classifiers (e.g., logistic regression or neural networks) [5]. In this study, the mapping is formulated analytically to emulate the probabilistic behavior of such classifiers while remaining fully interpretable [6].

2.1.1 Analytical Implementation of the Diagnostic Model

To ensure methodological reproducibility, the nonlinear mapping f(x;θ) was implemented as an analytical probabilistic classifier rather than a data-calibrated neural network. The analytical formulation follows a sigmoid activation structure commonly used in probabilistic classifiers.

The model approximates the behavior of a sigmoid-based classifier in which normalized sensor inputs are combined through a weighted nonlinear aggregation followed by a sigmoid transformation. Model parameters θ were selected analytically to reflect monotonic degradation behavior observed in aviation diagnostic literature [7], where increasing vibration and temperature contribute positively to fault likelihood, while stable oil pressure and rotational speed indicate nominal operation. Weight signs and relative magnitudes were selected according to known physical degradation trends reported in aviation maintenance literature.

The mapping function was calibrated using simulated operational ranges rather than gradient-based training. This approach allows controlled evaluation of diagnostic logic while avoiding dependence on proprietary flight datasets.

Model performance is evaluated using the binary cross-entropy metric, which measures the divergence between predicted and true diagnostic states:

$$L(\theta)\ =\ -\frac{1}{N}\sum_{i=1}^{N}[y_i Log(\hat{y}_i)+(1-y_i)Log(1-\hat{y}_i)]. \qquad (3)$$

Here, $y_i \in [0,1]$ denotes the ground-truth condition (0—normal, 1—fault).

As seen in (3), minimizing *L (θ)* ensures that the model penalizes both false positives and false negatives symmetrically, achieving probabilistic calibration between outputs and actual fault probabilities. In this work, the loss value is used as a diagnostic quality indicator rather than a training objective.

A diagnostic alert is triggered when the estimated probability exceeds a threshold *T*:

$$\hat{y} \geq T. \qquad (4)$$

In (4), the threshold *T* is not fixed but adaptively determined via Receiver Operating Characteristic (ROC) analysis. ROC-based tuning allows balancing between sensitivity (true positive rate) and specificity (1 - false positive rate) depending on operational risk tolerance.

In other words, a lower T increases sensitivity (detects faults earlier) but raises false alarms, whereas a higher T increases confidence but delays detection. ROC analysis was performed on simulated diagnostic outcomes to determine an operating threshold balancing early detection and false-alarm tolerance.

2.2 Uncertainty and Confidence Estimation

While (2) - (4) yield deterministic probabilities, aviation diagnostics require explicit uncertainty quantification to express confidence in each decision. For this purpose, the predicted probability is treated as a random variable following a Beta distribution:

$$P_{fault} \sim Beta(\alpha, \beta). \quad (5)$$

The Beta distribution is chosen because it is defined over the bounded interval [0,1], making it ideal for modeling probabilistic quantities such as fault likelihoods. The Beta distribution is commonly used for modeling uncertainty in bounded probabilistic systems and provides an analytically tractable Bayesian representation of belief confidence [8], [9]. Its parameters are interpreted as "pseudo counts" of success (α) and failure (β) evidence.

$$\mu = \frac{\alpha}{\alpha+\beta} \quad (6)$$

$$\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \quad (7)$$

In the diagnostic context, variance represents epistemic uncertainty arising from limited or noisy observational evidence. As seen in (6) - (7), the mean μ corresponds to the expected fault probability, while the variance σ^2 captures the degree of uncertainty. Larger evidence values (α+β) result in smaller variance, signifying higher diagnostic confidence.

To relate these parameters to the model output, we introduce a confidence concentration factor κ>0. To connect analytical model output with uncertainty strength, a concentration parameter κ is introduced to represent the amount of diagnostic evidence supporting the prediction, yielding:

$$\alpha = \kappa\hat{y}, \qquad \beta = \kappa(1-\hat{y}). \quad (8)$$

In (8) smaller κ values correspond to uncertain or sparse evidence, whereas larger κ values indicate stronger confidence in the estimated diagnostic state. For practical interpretation, the 95% confidence interval of the diagnostic accuracy A is expressed as:

$$CI_{95}(A) = \mu_A \pm 1.96\sigma_A. \quad (9)$$

In (9), the factor 1.96 corresponds to the standard normal quantile for 95% coverage. Thus, the diagnostic output is reported not as a single number but as a probability interval $[L,U]$, giving engineers quantitative evidence of reliability.

2.3 System Integration and Feedback Formulation

The end-to-end diagnostic cycle can be expressed as a composition of onboard and ground subsystems. Let $g(\cdot)$ represent preprocessing within the FADEC/EEC (filtering, normalization), and $h(\cdot)$ denote decision-making logic within the ground-based OGMS/CMCF module. The integrated diagnostic pipeline is thus:

$$\hat{y}(t)=f(g(x(t));\theta), \ \text{Decision}(t)=h(\hat{y}(t)). \quad (10)$$

In (10), the onboard system computes the real-time fault probability $\hat{y}(t)$ from streaming telemetry, while the ground system receives and interprets these results to schedule maintenance or parameter adjustments. The formulation separates signal conditioning, probabilistic inference, and operational decision logic, enabling modular implementation within existing avionics architectures.

This architecture forms a closed feedback loop between flight operations and maintenance planning, representing an essential component of the Maintenance 4.0 paradigm (see Fig. 1.).

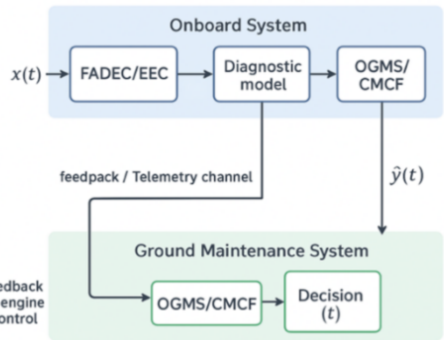

Figure 1: Functional diagram of the diagnostic process in the FADEC system.

Figure 1 illustrates the interaction between onboard FADEC diagnostics and ground maintenance analysis, highlighting the closed-loop feedback enabling adaptive maintenance decisions. The diagram emphasizes bidirectional information exchange, allowing diagnostic outcomes to influence maintenance actions while feedback updates model interpretation over time.

Table 1: Example transition from normal to fault conditions.

Cycle	Vibration (mm/s)	TGT (°C)	Oil Pressure (bar)	NH (%)	System Status
1	2.3	680	3.9	99.2	Normal
2	2.5	690	3.8	99.1	Normal
3	3.2	720	3.7	98.7	Warning
4	3.8	740	3.5	98.2	Fault
5	4.1	755	3.4	97.9	Fault
6	2.9	710	3.8	98.8	Normal
7	3.5	730	3.6	98.5	Warning
8	2.6	695	3.9	99.0	Normal
9	4.0	750	3.5	97.8	Fault
10	3.0	705	3.8	98.6	Normal

Table 1 demonstrates progressive parameter deviation leading from nominal operation to warning and confirmed fault conditions. The diagnostic threshold was set to T = 0.65 based on ROC-based operating analysis. The average classification error was $\bar{\Delta}$ = 0.015, indicating stable diagnostic behavior under simulated noise and parameter variation.

2.4 Experimental Data and Simulation Results

2.4.1 Input Data

The proposed diagnostic framework was evaluated using analytically generated simulation data designed to emulate FADEC telemetry of the Pratt & Whitney PW127M engine installed on ATR-72 aircraft. The study validates the mathematical behavior of the diagnostic model rather than a data-trained machine-learning system; therefore, no real flight or proprietary datasets were used. The simulated dataset included four operational parameters: compressor vibration amplitude, turbine gas temperature (TGT), oil pressure (OP), and high-pressure spool speed (NH). Parameter ranges were selected according to publicly available engine operating characteristics and aviation maintenance studies and publicly available PHM benchmark datasets [10]. A total of 1000 flight cycles were generated. Approximately 70% of samples were used for parameter calibration and 30% for independent performance evaluation. Gaussian noise (σ = 0.05) was added to emulate sensor variability and operational disturbances. All variables were normalized using z-score normalization to ensure consistent scaling. Fault conditions were simulated by gradually increasing vibration and temperature while reducing oil pressure and rotational stability. The resulting dataset contained approximately 20% fault samples and 15% warning states, reflecting realistic class imbalance observed in aviation diagnostics. Example measurements illustrating transitions between operational states are presented in Table 1.

2.4.2 Performance Metrics and Confidence Evaluation

Diagnostic performance was evaluated using standard classification metrics:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \quad (11)$$

$$False\ Positive\ Rate = \frac{FP}{FP+TN}. \quad (12)$$

To assess the effectiveness of the proposed analytical diagnostic model, results were compared with reference diagnostic approaches including: (i) a threshold-based rule model using fixed parameter limits, (ii) logistic regression approximation, and (iii) support vector machine (SVM) decision modeling.

All reference methods were evaluated using the same simulated dataset and preprocessing procedure.

Across 1000 simulated flight cycles, the proposed model achieved:

- Accuracy = 0.93 ± 0.02.
- FPR < 0.08.
- ROC AUC ≈ 0.94.

Uncertainty of diagnostic accuracy was quantified using the Beta-distribution formulation introduced in Section 2.2. For parameters α = 46 and β = 4:

$$\mu = \frac{46}{46+4} = 0.92,\ \sigma = \sqrt{\frac{46x4}{(50)^2(51)}} = 0.037, \quad (13)$$

and thus a 95% confidence interval:

$$CI_{95}=0.92\pm1.96\times0.037=[0.848,\ 0.992]. \quad (14)$$

In (13) - (14), we can see that the narrow confidence range (±4%) demonstrates model stability and strong discriminative power between normal and faulty state (see Fig. 2.). The narrow confidence interval indicates stable diagnostic behaviour under simulated noise and parameter variability.

Table 2: Performance comparison of diagnostic approaches.

Model	Accuracy	FPR
Threshold-based	0.78	0.18
Logistic approximation	0.85	0.12
SVM decision model	0.89	0.10
Proposed analytical model	0.93	<0.08

Table 2 shows that the proposed analytical model improves diagnostic accuracy while maintaining a lower false-positive rate compared with classical diagnostic strategies.

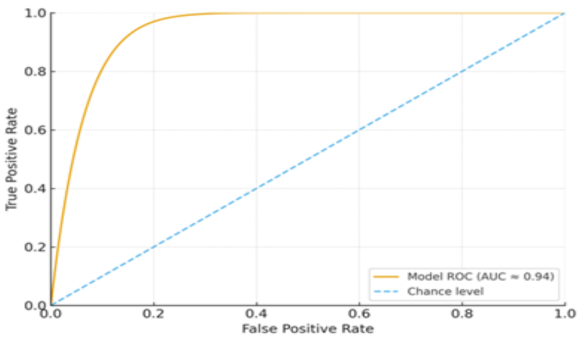

Figure 2: ROC curve of the FADEC diagnostic model for PW127M.

Figure 2 presents the ROC curve of the proposed diagnostic model. The high area under the curve (AUC ≈ 0.94) demonstrates strong separability between nominal and faulty operational states.

2.4.3 Workflow of the Proposed AI-Driven Diagnostic System

The operational workflow of the proposed diagnostic framework, illustrated in Figures 3 and 4, represents a hierarchical pipeline integrating onboard sensing, probabilistic analysis, and maintenance decision support within a closed-loop architecture.

Sensor subsystems embedded in the FADEC/EEC continuously acquire operational parameters including vibration amplitude, turbine gas temperature (TGT), oil pressure (OP), and high-pressure spool speed (NH). The resulting measurement vector x(t) is time-synchronized through the avionics data bus (e.g., ARINC 429).

Preprocessing, represented by g(·) in (10), performs signal conditioning through filtering and z-score normalization:

$$z(t) = g(x(t)). \tag{15}$$

The calibrated analytical diagnostic model f(·;θ) then estimates the fault probability:

$$\hat{y}(t) = f\big(g\big(x(t)\big);\theta\big). \tag{16}$$

This stage capturing nonlinear parameter interactions and gradual degradation trends. When ŷ(t) exceeds the operating threshold T, an anomaly condition is detected. Diagnostic uncertainty is evaluated using the Beta-distribution formulation (5)-(9), producing a confidence interval [L, U] associated with each prediction. This probabilistic output enables reliability-aware decision making consistent with aviation safety requirements.

The diagnostic result is transmitted to the ground-based OGMS/CMCF system, where maintenance actions are determined according to predefined operational rules:

$$\begin{cases} \hat{y}(t) < 0.65, & \mathit{Normal\ operation}, \\ 0.65 \le \hat{y}(t) < 0.85, & \mathit{Warning - scheduled\ inspection}, \\ \hat{y}(t) \ge 0.85, & \mathit{Confirmed\ fault - initiate\ corrective\ maintenance}. \end{cases}$$

Generated diagnostic reports are stored for traceability, while maintenance feedback is returned to the onboard system, completing the closed-loop diagnostic cycle. This feedback enables periodic recalibration of diagnostic parameters and supports adaptive Maintenance 4.0 operation.

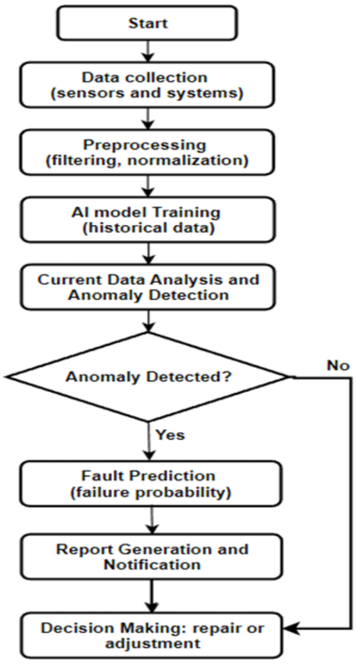

Figure 3: Workflow of the proposed AI-driven diagnostic system for early fault detection in aircraft avionic devices.

Figure 3 summarizes the sequential diagnostic workflow, from onboard data acquisition and preprocessing to probabilistic fault estimation and maintenance decision execution.

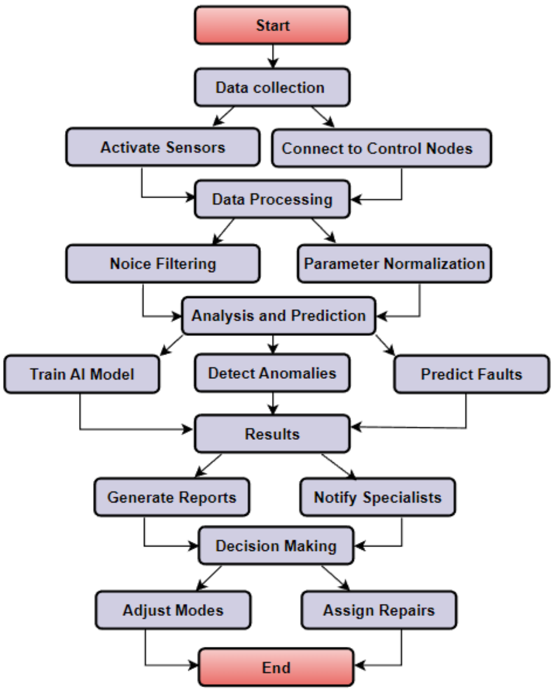

Figure 4: AI-driven diagnostic system architecture.

Figure 4 illustrates the integrated system architecture linking sensing, analytical inference, reporting, and maintenance response within a closed adaptive diagnostic loop [1], [2], [4], [11].

2.5 Advantages of Using Artificial Intelligence in Diagnostics

2.5.1 Enhanced Diagnostic Accuracy

Artificial Intelligence (AI) techniques enable diagnostic systems to capture nonlinear relationships and subtle parameter correlations that are difficult to model using fixed-threshold approaches. Probabilistic diagnostic models can identify early degradation patterns and provide confidence-aware predictions, supporting more reliable anomaly detection.

Within the proposed framework, the analytical diagnostic module can be integrated with the FADEC Electronic Engine Control (EEC) through standard avionics interfaces (e.g., ARINC 429), enabling coordinated onboard monitoring and ground-based analysis consistent with Maintenance 4.0 principles. Condition-based maintenance decisions are triggered only when predicted fault probability exceeds confidence limits defined in (9), potentially reducing unnecessary inspections and component replacement.

Automation of monitoring and decision support improves diagnostic consistency and reduces dependence on manual interpretation. Advanced data-driven techniques, including deep learning and natural language processing, may further enhance maintenance analytics by leveraging historical operational data and technical documentation [5], [7] [8].

2.5.2 Operational Benefits and Scalability

Early detection of anomalous behavior contributes to improved operational reliability and supports proactive maintenance planning. AI-assisted diagnostic architectures enable scalable fleet monitoring through distributed onboard analysis combined with centralized maintenance evaluation. Similar AI-based predictive maintenance approaches have also been proposed for aviation applications [12].

Deployment in aviation environments requires compliance with certification and safety standards such as EASA and FAA guidance (e.g., DO-178C), emphasizing the importance of explainable and verifiable diagnostic models. Modular system integration and secure communication mechanisms are necessary to ensure compatibility with legacy avionics and to maintain cybersecurity compliance (e.g., DO-326A).

Future developments may include hybrid physics-AI diagnostic models, digital twin simulations for fault progression analysis, and adaptive learning mechanisms that incorporate newly accumulated operational data. The proposed analytical framework provides a probabilistic foundation suitable for such future extensions while maintaining interpretability required for safety-critical applications.

3 CONCLUSIONS

This work presented an analytical AI-driven diagnostic framework for early fault detection in avionic systems, integrating onboard FADEC/EEC monitoring with ground-based OGMS/CMCF maintenance decision support. The proposed approach combines a nonlinear probabilistic classifier $f(\cdot;\theta)$, mapping multisensor inputs to fault likelihood, with a Beta-distribution uncertainty layer that transforms point estimates into calibrated confidence bounds.

Experimental evaluation using simulated PW127M (ATR-72) telemetry demonstrated stable diagnostic performance, achieving an accuracy of 93 ± 2%, false-positive rate below 8%, and ROC AUC ≈ 0.94. The resulting confidence interval [0.848, 0.992] indicates reliable separation between nominal and faulty operational states under simulated noise and parameter variability. These results highlight the advantages of probabilistic diagnostics over fixed-threshold approaches for early anomaly detection and indicate feasibility for real-time deployment pending validation with operational data.

From a systems perspective, the framework supports condition-based maintenance by providing probabilistic risk estimates, confidence-aware decision thresholds, and a closed-loop feedback mechanism enabling periodic parameter recalibration. Such properties support scalable maintenance planning aligned with Maintenance 4.0 principles.

The primary limitation of this study is the use of simulated datasets, which is consistent with broader challenges reported for predictive maintenance implementation and validation [13]. Future validation will therefore require testing on real flight telemetry, calibration analysis using reliability metrics, and robustness evaluation under sensor faults and distribution shifts. Certification considerations, including alignment with DO-178C/DO-330 processes and cybersecurity requirements defined by DO-326A, represent essential steps toward operational adoption.

Future work will focus on hardware-in-the-loop validation, integration with digital-twin simulations for fault progression analysis, and hybrid physics-AI inference methods to improve generalization across fleet conditions. These developments position the proposed framework as a transparent and certifiable foundation for intelligent aviation diagnostics.

REFERENCES

[1] J. Lee, B. Bagheri, and H.-A. Kao, “A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems,” Manufacturing Letters, 2014.

[2] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, “Machinery health prognostics: A systematic review from data acquisition to RUL prediction,” Mechanical Systems and Signal Processing, vol. 104, pp. 799-834, May 2018, [Online]. Available: https://doi.org/10.1016/j.ymssp.2017.11.016.

[3] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, “Deep learning and its applications to machine health monitoring,” Mechanical Systems and Signal Processing, vol. 115, pp. 213-237, 2019, [Online]. Available: https://doi.org/10.1016/j.ymssp.2018.05.050.

[4] J. Lee, H.-A. Kao, and S. Yang, “Service innovation and smart analytics for Industry 4.0 and big data environment,” Procedia CIRP, vol. 16, pp. 3-8, 2014, [Online]. Available: https://doi.org/10.1016/j.procir.2014.02.001.

[5] A. Abdukayumov and I. S. Maturazov, “Improvement of radio electronic equipment diagnostic systems,” AIP Conference Proceedings, vol. 2432, Art. no. 030044, Jun. 2022, [Online]. Available: https://doi.org/10.1063/5.0090223.

[6] E. S. Agustian and Z. A. Pratama, “Artificial intelligence application on aircraft maintenance: A systematic literature review,” EAI Endorsed Transactions on Internet of Things, vol. 10, 2024, [Online]. Available: https://doi.org/10.4108/eetiot.6938.

[7] A. Bentaleb, K. Toumlal, and J. Abouchabaka, “Predicting aircraft engine failures using artificial intelligence,” International Journal of Advanced Computer Science and Applications, vol. 15, 2024, [Online]. Available: https://doi.org/10.14569/IJACSA.2024.0150295.

[8] Y. Gal and Z. Ghahramani, “Dropout as a Bayesian approximation: Representing model uncertainty in deep learning,” in Proc. 33rd Int. Conf. Machine Learning (ICML), New York, NY, USA, 2016, pp. 1050-1059.

[9] A. Kendall and Y. Gal, “What Uncertainties Do We Need in Bayesian Deep Learning for Computer Vision?,” 2017, [Online]. Available: https://doi.org/10.48550/arXiv.1703.04977.

[10] A. Saxena and K. Goebel, “Turbofan Engine Degradation Simulation Dataset,” NASA PHM Repository.

[11] F. Tao et al., “Digital twin-driven product lifecycle management,” IEEE Access, 2019.

[12] K. R. Patibandla, “Predictive maintenance in aviation using artificial intelligence,” Journal of Artificial Intelligence General Science, vol. 4, no. 1, pp. 325-333, 2024, [Online]. Available: https://doi.org/10.60087/jaigs.v4i1.214.

[13] P. Nunes, J. Santos, and E. Rocha, “Challenges in predictive maintenance - A review,” CIRP Journal of Manufacturing Science and Technology, vol. 40, pp. 53-67, 2023, [Online]. Available: https://doi.org/10.1016/j.cirpj.2022.11.004.