

Harris Hawks Optimized Mamba-Transformer Framework for Intelligent Aircraft Engine Fault Diagnosis

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ABSTRACT: Accurate and early Aircraft Engine Fault Diagnosis (AEFD) is important for improving flight safety, reducing maintenance costs, and preventing unexpected engine failures. However, the engine is exposed to continuous mechanical and thermal stresses, it disposed to various types of faults and performance degradation. To overcome these problems, this paper proposes a Harris Hawks Optimized Mamba-Transformer (HHO-Mamba-Transformer) framework for intelligent AEFD. Proposed Mamba-Transformer model, where the Mamba module efficiently captures long-range temporal dependencies in aircraft engine operating conditions, whereas the Transformer module learns important global relationships and interactions between the extracted features. The HHO algorithm is developed to optimize the Mamba-Transformer parameters, thereby improving learning efficiency, convergence, and diagnostic performance. Experimental evaluation is implemented in Python software using NASA C-MAPSS-1 Turbofan Engine Degradation Dataset with 98.9% of accuracy, recall, F1-score and 99% of precision for accurate detection of AEFD. The novelty in this paper is the proposed HHO-Mamba-Transformer framework provides an intelligent, adaptive, and efficient solution for AEFD.

Keywords: Aircraft Engine Fault Diagnosis, Harris Hawks Optimization, Mamba, Transformer

1. Introduction

Aircraft engine is a critical component that ensures the safe, stable, and reliable operation of an aircraft [1]. The aircraft engines operate for extended periods under high loads and demanding conditions, regular monitoring and maintenance are important [2]. Engine maintenance therefore represents a major part of overall aircraft maintenance, and timely fault detection is important for preventing unexpected failures, reducing maintenance costs, and ensuring flight safety [3-4]. Furthermore, accurate diagnosis requires a widespread understanding of the machines structure, operating conditions, and possible failure modes [5]. However, in real-world situations, expert engineers not always available, as they occupied with other tasks to have expertise

in a particular component [6-7]. Researchers have developed various methods to diagnosis the aircraft engine fault.

2. Literature Survey

For AEFD several techniques have been established by Machine Learning (ML) as well as Deep Learning (DL) methods. In [8] Wu et al (2024) have proposed One Dimensional – Convolutional Neural Network-Bidirectional Long short Term Memory (1D-CNN-BiLSTM) with Convolutional Block Attention Module (CBAM) to improve the identification of different engine fault conditions in AEFD. It automatically extracts local patterns from sensor and engine-condition signals. However, it is relatively complex architecture overfit when the available aircraft engine fault dataset is small.

Consequently, in [9] Kurdi et al (2026) have presented Geographic Information Systems (GIS) through Deep Neural Networks (DNN) path optimization for aircraft. DNN-based trajectory optimization reduces unnecessary movements. Nevertheless, incomplete geographic information negatively affects trajectory planning. Additionally, in [10] Shen et al (2025) have developed a Gray Wolf Optimizer (GWO) with 1D-CNN model for aero-engine fault diagnosis. GWO reduces the dependence on trial-and-error selection of CNN hyperparameters. Nonetheless, finding the optimal CNN parameters through GWO increases the overall training time. Furthermore, in [11] Wu et al (2025) have invented Transformer-based model for aero-engine gas-path fault diagnosis by learning the complex relationships between gas-path measurements and engine operating parameters. However, it performs better when sufficient training data are available. Moreover, in [12] Shimpi et al (2026) have presented Temporal Convolutional Networks (TCN), Genetic Algorithm (GA) for engine fault diagnosis and Remaining Useful Life (RUL) prediction. TCN-GA captures short- and long-term patterns in sequential engine sensor data. Nonetheless, GA requires repeated evaluations of candidate feature subsets. To overcome these limitations, this paper proposes an HHO-Mamba-Transformer is used for AEFD.

2.1 Problem statement

Existing ML and DL techniques suffer from handling nonlinear patterns and high model complexity. To overcome these outcomes, this paper proposes an HHO-Mamba-Transformer structure for intelligent AEFD.

2.2 Research Contribution

This paper proposes an HHO-Mamba-Transformer structure for intelligent AEFD. It improves fault-diagnosis accuracy whereas efficiently handling complex engine operating data. HHO used to optimize the important parameters of the Mamba-Transformer

architecture. This improves convergence, learning efficiency, and diagnostic performance.

3. Proposed Methodology

For accurate AEFD, a raw data is fed to data pre-processing based on handling missing values, handling invalid values and data visualization is used to improve data quality then consistency. The pre-processed data is forwarded to feature engineering it transform the cleaned engine measurements into informative representations. Then, the dataset is distributed into training as well as testing subsets. Subsequently, the trained data is fed to propose HHO- Mamba-Transformer for further diagnosis. The Mamba is employed to efficiently learn long-range temporal dependences within the aircraft engine operating sequences. The Transformer uses self-attention mechanism to identify important global relationships and interactions among the extracted features. The HHO algorithm is utilized to optimize important constraints of the Mamba-Transformer to improve the convergence. Figure 1 displays the proposed block diagram for AEFD.

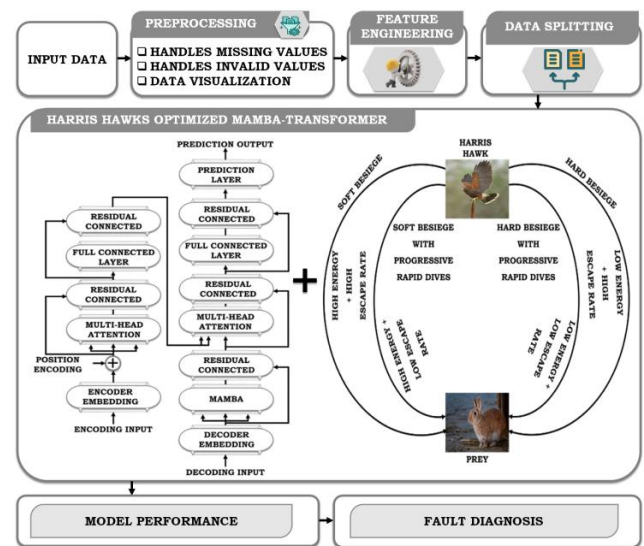


Figure 1: Block diagram for proposed work
(THE DIAGRAM NOT LOOKS CLEAR)

3.1 Data Preprocessing

The raw NASA C-MAPSS-1 turbofan engine degradation dataset are first processed to improve their quality and consistency using handling missing values, handling invalid values and data visualization. Handling missing values identifies the missing sensor measurements from the raw input data. Handling invalid values finds the abnormal, inconsistent in the dataset. In data visualization graphical analysis is implemented to understand the distribution, variation, trends, and relationships among the engine parameters. This identifies unusual patterns and potential data-quality issues. Next, the processed data is fed to feature engineering.

3.2 Feature Engineering

For AEFD feature engineering is used to transform the cleaned engine measurements into informative representations. The relevant features are extracted from the operating parameters to improve the model ability to distinguish among normal then faulty engine conditions. The featured data is fed to proposed HHO-Mamba-Transformer technique for further diagnosis.

3.3 Harris Hawks Optimized Mamba-Transformer

The Mamba is proposed to efficiently learn long-range temporal dependences within the aircraft engine operating sequences. It captures changes and interactions occurring over time, allowing the model to acquire temporal patterns related through different engine conditions. Figure 2 structure of Mamba-Transformer.

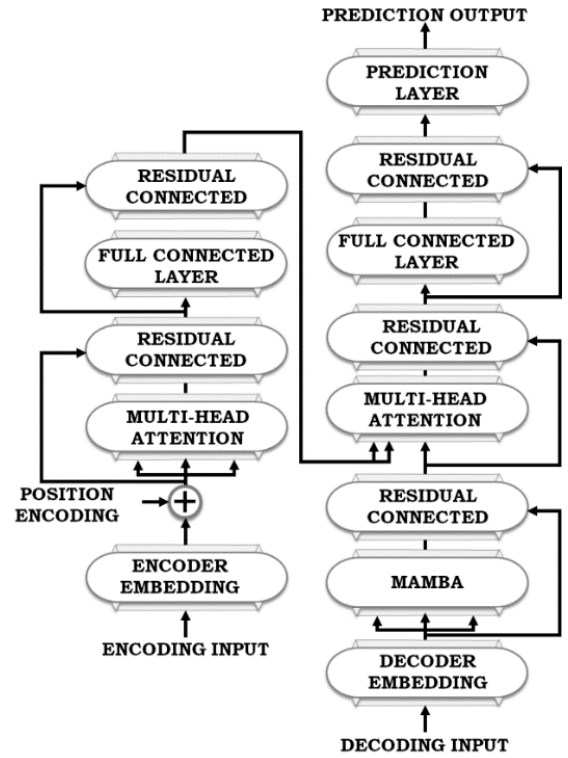


Figure 2: Structure of Mamba-Transformer

The learned feature representations are subsequently passed through fully connected layers to diagnosis the engine fault. The hidden state is efficient by the equation

$$h_t = Ah_{t-1} + Bx_t \quad (1)$$

Where, h_t indicates hidden state at time t , A specifies state transition matrix, B signifies input projection matrix, x_t represent input vector. The Mamba network selectively updates its internal state by

$$h_t = f(h_{t-1}, x_t, \theta) \quad (2)$$

Where, $f(\cdot)$ signifies the selective state-space function, θ denotes the learnable network parameters. The predicted AEFD is expressed as

$$\hat{y} = Wh_t + b \quad (3)$$

Where $\hat{y}$ specifies the diagnosis of engine fault, W denotes output weight matrix, b represent bias vector. The lightweight architecture of Mamba significantly reduces computational complexity whereas maintaining high prediction accuracy. Mamba is subsequently fed to the Transformer module for AEFD.

Transformer

The temporal information is captured by Mamba; the Transformer module captures global relationships and interactions among the extracted features. The Transformer uses self-attention mechanism to identify important global relationships and interactions among the extracted features in engine. In a transformer, self-attention is computed using dot-product attention

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (4)$$

Here, Q denoted as query matrix, K indicated as key matrix, V represented as value matrix and d_k signified as dimension of the key vectors. The attention weights are computed separately for each sub-vector group. The transformer-based attention identifies network by dynamically prioritizing the network state for diagnosis. The Mamba-Transformer parameters are fed to HHO algorithm.

Harris Hawks Optimization

The HHO algorithm is to optimize important parameters of the Mamba-Transformer model. To avoid getting trapped in a local optimum, random values are generated using logarithmic and exponential functions, the algorithm search unknown areas of the search space more effectively and reach new candidate solutions.

$$E = 2E_o(1 - \frac{t}{T}) \quad (5)$$

$$E_o = 2r_1 - 1 \quad (6)$$

Here, E signifies the energy of the escaping prey, E_o indicates its initial energy. A random value ranging from $[-1 \text{ to } 1]$ is used to present variation in the energy level, t indicates the current repetition, T signifies the maximum amount of repetitions, r_1 denoted as randomly generated value among $(0,1)$.

$$X_m(t) = \frac{1}{N} \sum_{t=1}^N X_t(t) \quad (7)$$

$$X(t+1) = \begin{cases} X_m(t) * 0.5 - ((X_{rand}(t) + r_1 * X(t)) + (X_{rand}(t) + r_1 * X(t))) & q \geq 0.5 \\ (X_{rabbit}(t) - X_m(t)) - r_3(LB + r_4(UB - LB)) & q < 0.5 \end{cases} \quad (8)$$

$$r_1 = 1 - \log(1 + e^{ub}) \quad (9)$$

$$X(t+1) = 0.01 * E * X_{rabbit}(t) - 0.1 * |J_1 * X_{rabbit}(t) - X_m(t)| \quad (10)$$

$$J_1 = (2 * rand - 1) \quad (11)$$

$$G_1 = i * (1 - \frac{t}{T}) \quad (12)$$

$$Z = X_{rabbit}(t) - rand * E |G_1 * JX_{rabbit}(t) - X_m(t)| - 1.5 * \frac{G_2}{Levy(dim)} \quad (13)$$

Here, $X(t+1)$ designates the location of the i^{th} hawk in the next repetition, $X_{rabbit}(t)$ signifies the current location of the rabbit. $X(t)$ specifies the present location of the hawk. r_3 are randomly produced values in the range $(0,1)$ and are updated during every repetition. The LB then UB represents the lower as well as upper bounds of the search space, correspondingly. $X_{rand}(t)$ signifies the location of a casually designated hawk, whereas $X_m(t)$ signifies the average location of the hawk populace. Figure 3 shows the flowchart for HHO.

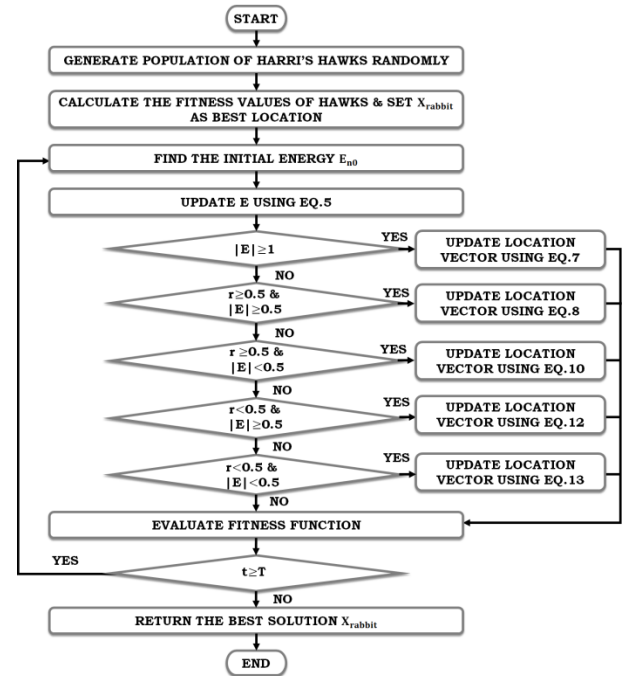


Figure 3: Flowchart for HHO

HHO searches for suitable parameter configurations that improve the learning process and the model reach an effective solution with better convergence and diagnostic performance. Therefore, this paper employs the HHO-Mamba-

Transformer method to reduce the number of relevant attributes in aircraft engine operating data and improve the efficiency of the diagnostic process.

4. Experimental Result and Discussion

For AEFD the proposed HHO-Mamba-Transformer method is implemented in Python Software using NASA C-MAPSS-1 turbofan engine degradation dataset. FD004 is designated with train trajectories of 248 and test trajectories of 249 as the experimental dataset because it combines six operating conditions with two degradation modes. Training dataset shape is about (61249, 28) and testing dataset shape (41214, 28).

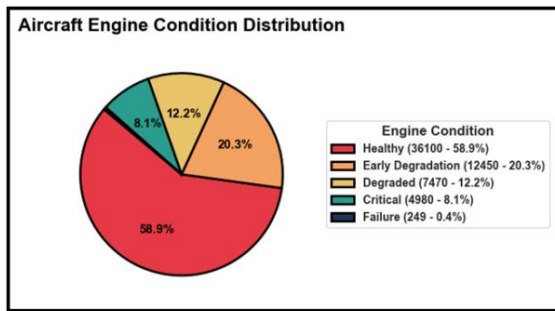


Figure 4: Aircraft engine condition distribution

Figure 4 shows the aircraft engine condition distribution for training class distribution 0 as critical with 4980 (8.13%), 1 as degraded with 7470 (12.20%), 2 as early degradation with 12450 (20.33%), 3 as failure with 249 (0.41%) and 4 as healthy with 36100 (58.94%) for AEFD.

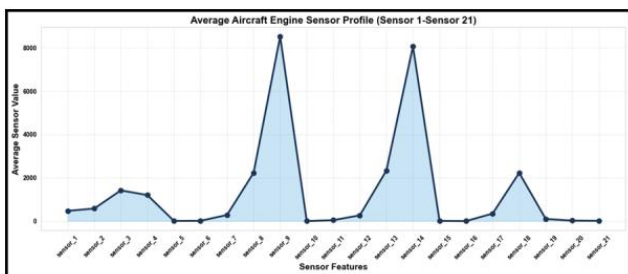


Figure 5: Average aircraft engine sensor profile

Figure 5 displays average aircraft engine sensor profile (sensor 1-sensor 21). It showing average sensor values across 21 distinct feature channels,

with distinct peaks at sensor 9 and sensor 14 (reaching over 8,000 units).

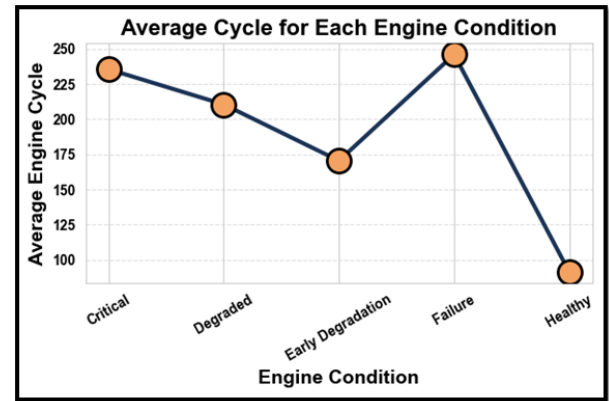


Figure 6: Average cycle for each engine condition

Figure 6 shows the average cycle for each engine condition. The failure engine contains 245 cycles which is highest compared to other engine conditions, critical engine contains 235 cycles, degraded engine contains 210 cycles, early degradation engine contains 170 cycles, healthy engine contains 90 cycles which is lowest compared to other engines, indicating the average engine condition.

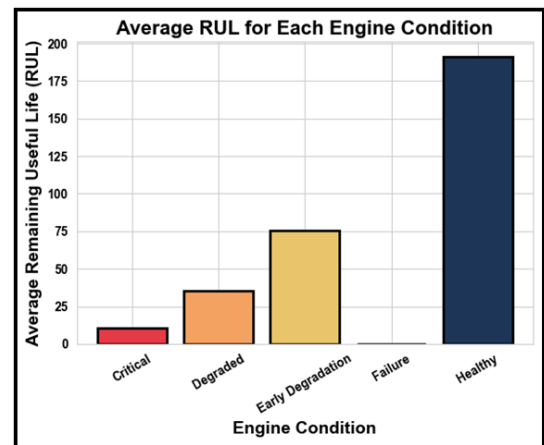


Figure 7: Average RUL for each engine conditions

Figure 7 shows average RUL for each engine conditions. The healthy engines have the highest average RUL of 190, whereas RUL decreases gradually through early degradation of 75, degraded of 35, and critical of 10 conditions. The failure condition is nearly zero RUL, representing

that the engine reached the end of its useful operating life.

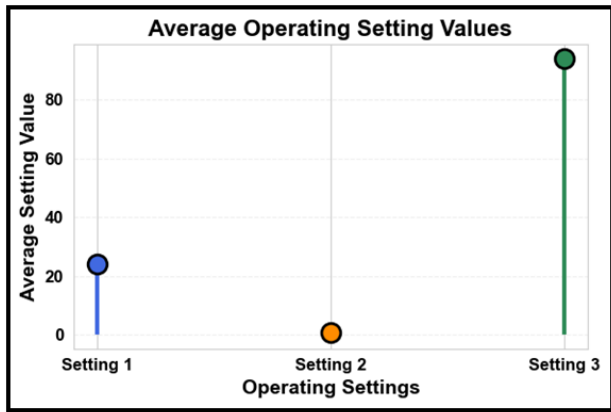


Figure 8: Average operating setting values

Figure 8 displays average operating setting values. The operating setting 3 have the maximum average value of 93, tracked by setting 1 of 24. The operating setting 2 remains close to zero, indicating minimal influence compared with the other settings.

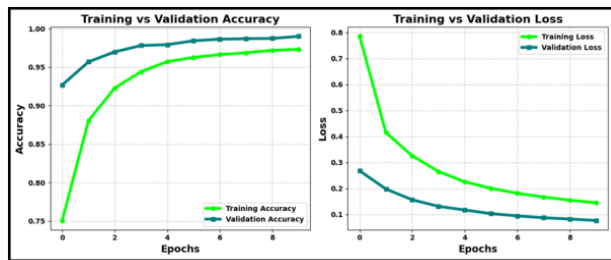


Figure 9: Training vs validation accuracy and loss

Figure 9 shows training vs validation accuracy then loss. The training accuracy starts at 75% and rises to around 97%, whereas validation accuracy starts higher at 92.5% and increases smoothly to nearly 99%. Training loss drops sharply from 0.78 down to 0.15, and validation loss decreases from 0.27 to below 0.08, indicating the HHO-Mamba-Transformer model acquires effectively and generalizes well to unseen data.

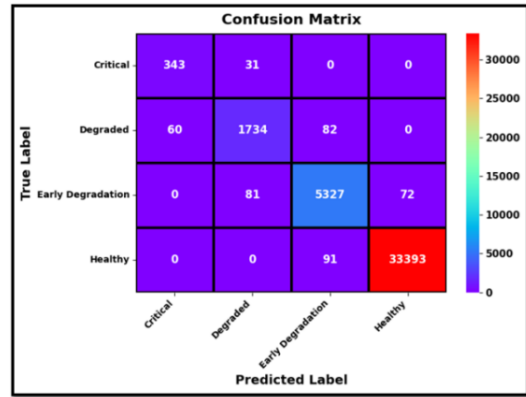


Figure 10: Confusion matrix for HHO-Mamba-Transformer model

Figure 10 shows the confusion matrix for HHO-Mamba-Transformer model. It displays strong classification performance, with 33,393 healthy, 5,327 early degradation, 1,734 degraded, and 343 critical samples correctly classified. Most misclassifications occur between neighboring engine conditions, such as early degradation as degraded (81 cases) and degraded as critical (60 cases), indicating gradual transitions between conditions.

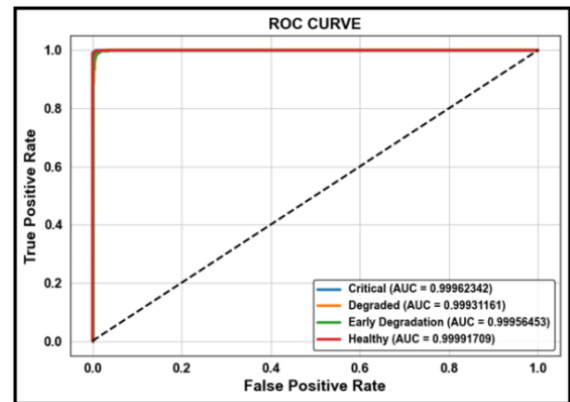


Figure 11: ROC curves using HHO-Mamba-Transformer model

Figure 11 displays the ROC curves using HHO-Mamba-Transformer model, with AUC values above 0.9993 for all engine conditions, indicating excellent class perception for AEFD.

4.1 Comparison with the proposed technique

In the evaluation with proposed technique the proposed HHO-Mamba-Transformer method is compared with the existing techniques as presented in table 1.

Table 1: Comparison with the proposed technique

Study	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Hu et al [5]	87.50	86.22	88.71	87.43
Abdulsahib et al [6]	97.8	97.8	97.8	97.8
Proposed Work	98.9	99	98.9	98.9

Hu et al [5] have the accuracy of 87.50%, precision of 86.22%, recall of 88.71 %, F1-score of 87.43%, Abdulsahib et al [6] have the accuracy, precision, recall, F1-score of 97.8%, then the higher value with accuracy, recall, F1-score of 98.9%, precision of 99%, using proposed HHO-Mamba-Transformer model for AEFD.

5. Conclusion

HHO-Mamba-Transformer is proposed for intelligent AEFD. The missing values are handled and visualized in the pre-processing stage, normal and different engine conditions are featured in feature engineering stage. Proposed Mamba-Transformer module learns important global relationships and interactions among the extracted features. The HHO algorithm optimizes the key parameters of the Mamba-Transformer model, improving the learning process and diagnostic effectiveness. The proposed framework is evaluated using the NASA C-MAPSS-1 turbofan engine degradation dataset then implemented using Python. The experimental results demonstrated that the HHO-Mamba-Transformer achieved an accuracy of 98.9%, recall of 98.9%, then F1-score of 98.9%, whereas obtaining a precision of 99%. It indicate that the proposed framework effectively identify aircraft engine faults and distinguish different degradation conditions with high diagnostic reliability, for supporting predictive maintenance and improving aircraft engine operational safety. Future work focuses on explainable artificial intelligence techniques incorporated to provide greater perception into the sensor features and operating

conditions that contribute to specific fault predictions.

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