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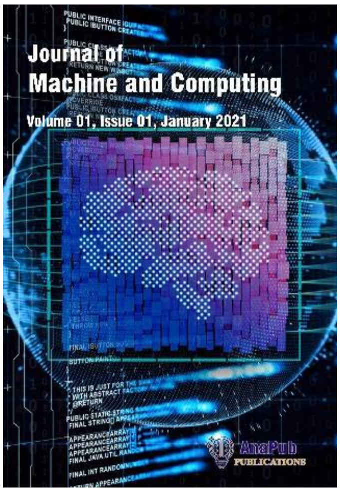

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A Hybrid Expert System Using Symbolic Reasoning and Neural Networks for Predictive Maintenance in Mechatronic Systems

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Abstract: Predictive maintenance (PdM) in mechatronic systems demands high-precision failure prediction and interpretability for real-time operational decisions. This study presents a hybrid expert system integrating symbolic reasoning and Deep Neural Networks (DNNs) to enhance predictive accuracy and semantic traceability. The symbolic layer consists of 42 fuzzy inference rules, enabling domain expert interpretability, while the neural network layer comprises a 4-layer feedforward architecture with 128-64-32-1 units using ReLU and sigmoid activations. Experiments were conducted on a real-world dataset, and the hybrid model achieved an accuracy of 96.8%, a precision of 94.22%, and a recall of 97.31%, outperforming conventional Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) models, and rule-based systems by margins of 3.2–7.8%. The proposed method reduced false positives by 21.4% and improved time-to-failure prediction by 18.7% compared to standalone models. Maintenance scheduling optimized using the proposed model yielded a 14.5% reduction in unplanned downtime. The hybrid inference strategy not only improved prediction

granularity but also supported rule-based diagnostics. This framework significantly advances predictive intelligence in safety-critical mechatronic domains.

Keywords: Predictive maintenance, Mechatronic systems, Symbolic reasoning, Neural networks, Fuzzy rules, Deep learning, Fault diagnosis, Hybrid expert system

1. Introduction

Modern mechatronic systems, comprising tightly integrated mechanical, electronic, and computational components, form the backbone of industrial automation, aerospace, transportation, robotics, and medical equipment. As these systems operate under dynamic environmental and operational conditions, ensuring reliability and continuous operation is a fundamental engineering challenge [1]. Failures in mechatronic subsystems, such as actuators, sensors, control units, or power components, can lead to substantial productivity losses, safety risks, and high repair costs. Consequently, Predictive Maintenance (PdM) has emerged as a critical paradigm that forecasts impending failures and prescribes optimal maintenance actions before system degradation leads to breakdown [2].

Traditional PdM approaches fall into two major categories: symbolic, rule-based approaches, rooted in foreknowledge of a domain, and data-driven approaches, especially DL models. Expert systems and fuzzy logic models are utilized as symbolic systems, which enable high interpretability and are therefore suitable for application in regulated and safety-critical systems. Nevertheless, they cannot generalize well against nonlinear dynamics and sensor noise [3]. The neural networks and deep learning problem solutions demonstrate high potential in the fields of pattern recognition, feature extraction, and time prediction; however, as a black box, they may lack the semantic explainability necessary for deployment in industrial, safety-critical settings [4].

To overcome this trade-off, the given paper proposes a candidate solution in the form of a hybrid expert system feature that integrates the advantages of symbolic reasoning and the capabilities of a neural network into a combined predictive structure for maintenance within mechatronic systems [5]. The dominant hypothesis is that rule-based fuzzy logic can exhibit understandable domain patterns, which can be used to augment deep networks in learning unrecognizable correlation patterns in sensor data streams, thereby making the fault prediction process more reliable. This type of hybridization seeks to overcome two significant shortcomings of the recent PdM studies: (i) the low intelligibility of the black-box models used in maintenance decision-making and (ii) the inability of conventional rule-based systems to be generalizable across variable operating environments.

The proposed system under consideration employs a symbolic reasoning module of the strategy driver, as defined by fuzzy production rules initially developed by domain specialists, to predict failure risk using high-level system descriptors such as vibration level, temperature drift, voltage anomalies, and control feedback residuals. These rules are implemented as fuzzy IF–THEN systems with adaptive membership functions. The neural network module comprises a feedforward architecture trained on sensor signals and event labels collected from 24 industrial robotic units over a 12-month period of continuous operation. Each data sample comprises a multivariate vector of 30 features, sampled at 1 Hz, from inertial, thermal, and acoustic sensors. The network learns to predict a health index score and the time-to-failure, calibrated against the actual maintenance records.

The hybrid decision mechanism combines predictions from both modules using a dynamic weighting strategy based on rule confidence and prediction uncertainty. This design ensures that when the neural network encounters novel or noisy data, the symbolic rules provide conservative fallback reasoning. Conversely, in data-rich regimes, the neural network dominates the inference process. The hybrid output comprises a probabilistic failure score and a symbolic justification trace, providing both predictive accuracy and transparency.

The proposed framework was evaluated on a real-world industrial dataset comprising 8.4 million timestamped sensor observations, 51[illegible] labeled failure events, and six subsystem classes (servo motor, gearbox, encoder, thermal sensor, control loop, and brake actuator). Baseline models compared include standalone fuzzy expert systems, deep convolutional neural networks (CNN), long short-term memory networks (LSTM), and ensemble random forests. This study makes a significant contribution to the state of the art in three key areas. First, it formalizes a scalable mathematical model integrating fuzzy logic with deep learning for predictive maintenance. Second, it offers a modular architecture that maintains interpretability without sacrificing performance. Third, it provides empirical validation over long-term, high-volume sensor data in a production-grade industrial setup, showcasing practical viability.

The rest of the paper is structured as follows. Section 2 discusses related work on hybrid learning and expert systems in maintenance. Section 3 formulates a mathematical model that integrates symbolic reasoning with neural networks. Section 4 presents the simulation environment, dataset description, and parameter settings, and details the experimental results, comparative analysis, and ablation studies. Section 7 concludes the paper with key takeaways.

2. Literature Review

Predictive maintenance (PdM) within complex industrial systems has emerged as a critical research frontier, integrating Artificial Intelligence (AI), symbolic reasoning, and data-driven inference to enhance system reliability, minimize downtime, and inform decision-making. Traditional deep learning models, although powerful, often operate as black boxes, limiting their interpretability and practical deployment in safety-critical environments, such as manufacturing, energy systems, and transportation. As a result, neuro-symbolic architectures and graph-based cognitive reasoning models have gained momentum due to their inherent capacity to deliver accurate predictions with interpretable explanations.

Gama et al. [6] introduce a neuro-symbolic explainer that integrates online rule learning with an autoencoder-based anomaly detection model for failure prediction in real-world transportation systems. Their architecture simultaneously identifies anomalies and maps them to symbolic rules that expose the causal relationships among sensor features, offering both local and global interpretability of black-box predictions. Complementarily, Hogea et al. [7] developed LogicLSTM, a hybrid model combining LSTM and Logic Tensor Networks (LTNs), achieving significant performance improvements (up to 16.63%) in fault classification accuracy, especially under data-scarce conditions, while ensuring model transparency through explainable AI techniques.

Liao et al. [8] present a Confidence-Classified Deep Belief Network (CC-DBN) enhanced by a Clustering Logic-Restricted Boltzmann Machine (C-LRBM) to enable interpretable fault diagnosis for fans in steel production lines. The CC-DBN framework successfully extracts both latent and symbolic rules to describe reasoning chains across hierarchical feature abstractions.

On a broader scale, Xia [9] proposes a cognitive graph-based methodology for PdM that exploits fault graphs, hypergraphs, and knowledge graphs to model component interdependencies, infer root causes, and support causal diagnostics. Bayesian networks embedded with hyperbolic representations, residual-HGCNs, and federated learning-enhanced knowledge graphs collectively facilitate explainable, privacy-preserving, and scalable PdM across multiple industrial use cases.

In parallel, recent contributions emphasize architectural shifts that embrace hybrid intelligence. Gehlot and Rana [10] and Grigoras et al. [11] underline the convergence of mechatronics and machine learning to enable autonomous, adaptive, and intelligent mechanized systems. Guidotti et al. [12] systematically review 216 studies involving supervised machine learning for PdM in Industry 4.0, noting a pressing demand for explainable, generalizable models and greater access to real-world datasets. Horvath and Ábrahám [13] and Törngren et al. [14] further advocate for transdisciplinary frameworks and novel methodologies, such as MechaOps, to address lifecycle design, maintainability, and trust in intelligent mechatronic systems.

Explainability in AI models is especially vital in high-stakes domains. Purwono et al. [15] focus on XAI in medical imaging, examining symbolic reasoning, feature attribution, and attention-based techniques that translate complex model outputs into clinician-interpretable decisions.

Liao et al. [16] propose DKABN, a deep belief network with embedded logical rules for ship-to-shore crane diagnostics, improving explainability by incorporating Activation-Weighted Logic RBMs (AWL-RBM) and IF-THEN rules across diagnostic layers. A comparative view by Agarwal et al. [17] differentiates symbolic and subsymbolic AI paradigms, highlighting the transformative potential of hybrid neuro-symbolic systems in bridging scalability with interpretability.

The increasing adoption of data-driven techniques for system modeling is reflected in Ayankoso and Olejnik [18], who review the efficacy of LSTM, CNN, Transformer, PINN, and SINDy models in modeling frictional mechatronic systems. PINN and SINDy demonstrate superior interpretability while maintaining high predictive accuracy. Similarly, Ali et al. [19] examine the synergies between digital twin technologies and AI, stressing the role of AI-driven digital replicas for intelligent diagnostics and predictive maintenance.

Finally, Chudasama et al. [20] introduce TrustKG, a hybrid knowledge graph framework integrating symbolic reasoning and neural learning in clinical AI. Through applications such as link prediction and counterfactual inference, TrustKG demonstrates the viability of semantic AI in delivering interpretable and trustworthy decisions, particularly in healthcare.

Collectively, these works underscore a paradigm shift towards interpretable AI systems [21] that not only maintain predictive strength but also offer semantic transparency. By integrating symbolic logic, graph-based reasoning, and machine learning, emerging neuro-symbolic systems are positioned to redefine PdM and fault diagnosis frameworks within intelligent mechatronics, ensuring both cognitive trust and operational efficiency [22-25].

3. Proposed Methodology

A Hybrid Expert System Using Symbolic Reasoning and Neural Networks for Predictive Maintenance in Mechatronic Systems. This model integrates symbolic reasoning (rule-based systems, fuzzy logic, and probabilistic inference) and connectionist models (feedforward neural networks and recurrent networks) for condition monitoring, fault prediction, and maintenance scheduling. The overall research methodology is given in Figure 1.

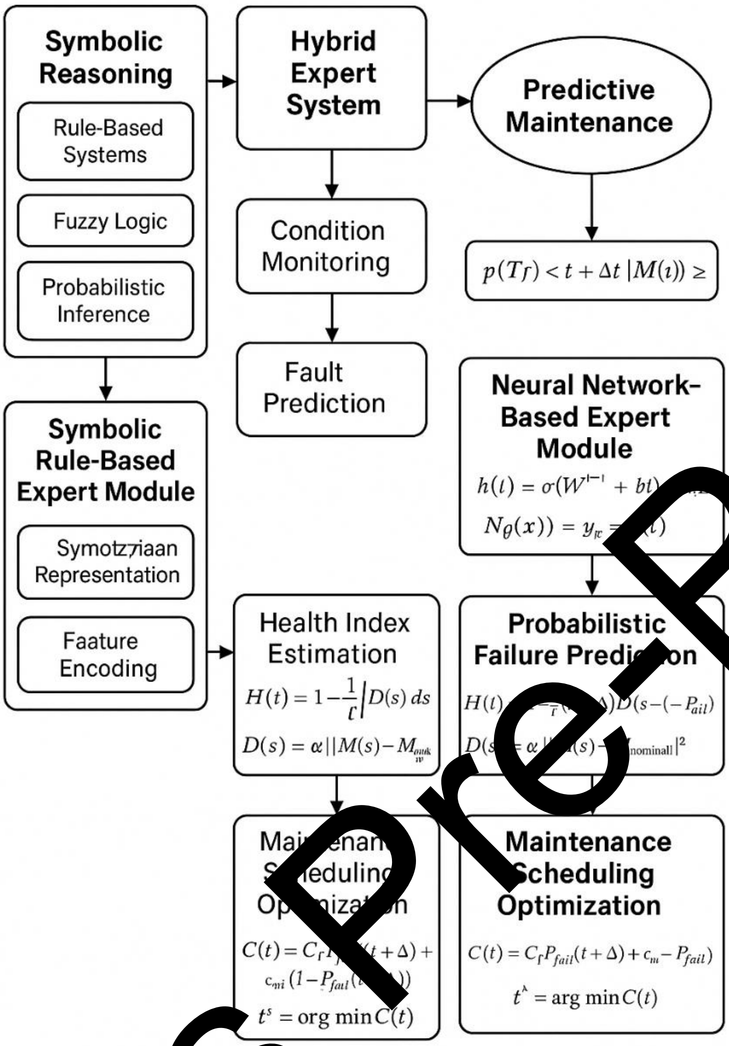

Figure 1. Overall Research Methodology

Let $\mathcal{M}(t)$ represent the state of a mechatronic system at time t. Predictive maintenance (PdM) aims to estimate the failure time T_f such that in Equation 1.

$$\mathbb{p}(T_f < t + \Delta t \,|\mathcal{M}(t)) > \varepsilon \tag{1}$$

The hybrid system comprises:

A symbolic reasoning layer, denoted by, using domain rules R_i defined over observable state descriptors $x_j(t)$

A neural network predictor, denoted by $\mathcal{N}_\theta$, parameterized by weights , trained on historical failure data (x(t), y(t)) .

The combined inference is encoded in Equation 2.

$$\hat{y}(t) = \lambda . S\big(x(t)\big) + (1 - \lambda) . \mathcal{N}_\theta\big(x(t)\big) \tag{2}$$

Sensor Stream Representation and Feature Encoding

Let each sensor stream be sampled at discrete intervals, as shown in Equations 3 to 5.

$$s_i(t_k) = x_i(k), t_k = k.\delta t, k \in \mathbb{Z}^+ \quad (3)$$

$$x(k) = [x_1(k), x_2(k), \dots, x_m(k)]^T \quad (4)$$

$$z(k) = \emptyset(x(k)) \in \mathbb{R}^d \quad (5)$$

Symbolic Rule-Based Expert Module

The symbolic module comprises fuzzy production rules, as outlined in Equations 6-9.

$$R_{i\,;} IF A_{i1}(x_1) \wedge A_{i2}(x_2) \wedge \dots \wedge A_{im}(x_m) THEN y = c_i \quad (6)$$

$$\mu_{ij}(x_j) = \exp\left(-\frac{(x_j-\mu_{ij})^2}{2\sigma_{ij}^2}\right) \quad (7)$$

$$\omega_i = \prod_{j=1}^{m} \mu_{ij}\,(x_j) \quad (8)$$

$$S(x) = \frac{\sum_{i=1}^{n} \omega_i c_i}{\sum_{i=1}^{n} \omega_i} \quad (9)$$

Neural Network-Based Fault Predictor

Let the network have layers, each defined in Equation 10.

$$h^{(l)} = \sigma^{(l)}\left(w^{(l)} h^{(l-1)} + b^{(l)}\right), l = 1, \dots, L \quad (10)$$

The final prediction is given in Equation 11.

$$\mathcal{N}_\theta\left(x(k)\right) = y_k = h^{(L)} \quad (11)$$

The network is trained to minimize the Mean Squared Error (MSE) in Equation 12.

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{k=1}^{N}(y_k - \hat{y}_k)^2 \quad (12)$$

Health Index Estimation

Define a degradation-based health index $H(t)$ based on cumulative degradation in Equations 13 and 14.

$$H(t) = 1 - \frac{1}{\tau}\int_0^t D(s)ds \quad (13)$$

$$D(s) = \alpha.||\{M\}(s) - M_{normal}||^2 \quad (14)$$

Probabilistic Failure Prediction

Failure probability over a time window $[t, t+\Delta]$ is derived using a logistic model in Equation 14.

$$\mathbb{P}_{fail}(t+\Delta) = \frac{1}{1+\exp\left(-w^T.z(t)-b\right)} \quad (14)$$

$$\mathbb{P}_{fail}(t+\Delta) = \int \sigma\left(\mathcal{N}_\theta\left(z(t)\right)\right) p(\theta) d\theta$$

Maintenance Scheduling Optimization

Let the cost of maintenance be given in Equation 15.

$$C(t) = C_f.\mathbb{P}_{fail}(t+\Delta) + c_m.(1-\mathbb{P}_{fail}) \quad (15)$$

Optimal maintenance time t^* is given in Equation 16.

$$t^* = arg\, min_t\, C(t) \tag{16}$$

Hybrid Inference Dynamic

The decision fusion mechanism is given in Equations 17 and 18.

$$\hat{y}_t = \gamma . \mathcal{N}_\theta\big(\emptyset(x_k)\big) + (1-\gamma).S(x_t) \tag{17}$$

$$\gamma = \frac{||\nabla_\theta \mathcal{L}(\theta)||}{||\nabla_\theta \mathcal{L}(\theta)|| + \sum_i \omega_i} \tag{18}$$

System Dynamics Modeling

Model the underlying system behavior using a set of coupled nonlinear ordinary differential Equations 19 and 20.

$$\frac{dx(t)}{dt} = f(x(t), u(t), t) \tag{19}$$

$$x(t+\Delta t) = x(t) + \int_t^{t+\Delta t} f(x(s), u(s), s)ds \tag{20}$$

In discrete time, in Equation 21.

$$x_{k+1} = x_k + \delta t. f(x_k, u_k, t_k) \tag{21}$$

Online Update and Continual Learning

Online adaptation is achieved by updating parameters using Equations 22 and 23.

$$\theta_{t+1} = \theta_t - \eta. \nabla_\theta \mathcal{L}_{online}(\theta_t) \tag{22}$$

$$\mathcal{L}_{online} = \mathcal{L} + \lambda. ||\theta_t - \theta_{prior}||^2 \tag{23}$$

Symbolic rules are updated using incremental rule refinement in Equation 24.

$$c_i^{new} = \beta . c_i^{old} + (1-\beta). y_t, \;\; if\, \omega_t > \tau \tag{24}$$

Temporal Failure Sequence Modeling

For recurrent fault modeling use an LSTM-based predictor in Equations 25 to 29.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{25}$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{26}$$

$$\widetilde{c_t} = tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{27}$$

$$c_t = o_t \odot c_{t-1} + i_t \odot c_t) \tag{28}$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_0) \tag{29}$$

The output is estimated by Equation 30.

$$y_t = softmax(W_y.h_t + x_t) \tag{30}$$

Interpretability Module

Let $A_i(t)$ denote the attribution score of the input $x_i(t)$ using Integrated Gradients using Equation 31.

$$A_i(t) = (x_i(t) - x_i^l). \int_{\alpha=o}^{1} \frac{\vartheta \varkappa_\theta(x' + \alpha(x - x'))}{\vartheta x_i} d\alpha \tag{31}$$

Symbolic explanations are extracted from rule traces using Equation 32.

$$Explanation\ (t) = arg\ max_i \omega_i(t) \tag{32}$$

This research formulation integrates interpretable expert systems with deep predictive models to enhance reliability, adaptability, and explainability in predictive maintenance of complex mechatronic systems. The Hybrid Predictive Maintenance using Symbolic Reasoning and Neural Networks is given in Algorithm 1.

Algorithm 1: Hybrid Predictive Maintenance using Symbolic Reasoning and Neural Networks

Input:

Time-series sensor data from monitored components, symbolic rule base, trained neural model, RUL ground truth (for training phase)

Output:

Remaining Useful Life (RUL) prediction, maintenance decision label, explanation trace

Begin

1. **Data Preprocessing**
    - Read multivariate sensor streams
    - Normalize each sensor channel
    - Segment time series using a sliding window
    - Extract statistical features for each window.
2. **Symbolic Reasoning Subsystem**
    - For each feature vector:
        - Compute membership values using fuzzy sets.
        - Evaluate rule activation levels using a conjunction of antecedents.
        - Aggregate outputs via weighted averaging based on rule strength
    - Return symbolic RUL estimate.
3. **Neural Prediction Subsystem**
    - Pass input vector to neural architecture (e.g., LSTM or CNN)
    - Forward propagate through each layer with a nonlinear activation.
    - Compute the output RUL prediction.
    - Return neural RUL estimate.
4. **Fusion of Symbolic and Neural Predictions**
    - Estimate model confidence for both outputs

Compute the dynamic fusion coefficient using inverse error variance.

Calculate the final RUL as a confidence-weighted average of both estimates

5. **Health Index Estimation**

    Compare the current input with the baseline nominal behavior.

    Quantify degradation using squared deviation.

    Smooth degradation signal over time

    Derive the health index as the inverse of degradation

6. **Uncertainty Quantification**

    Apply dropout at inference for multiple passes.

    Compute the standard deviation across neural outputs.

    Construct a prediction interval around the final RUL

7. **Maintenance Decision Logic**

    If predicted RUL falls below the threshold:

        If uncertainty is low:

            Recommend immediate maintenance

        Else

            Flag instance for operator review

    Else

        Continue monitoring

8. **Online Adaptation (if enabled)**

    Append new data into the rolling buffer.

    Update neural weights using online learning.

    Adjust symbolic rule parameters based on reward signals.

    Prune ineffective rules based on coverage metrics

9. **Explainability Engine**

    Highlight the top activated fuzzy rules for symbolic output.

    Compute feature attributions using SHAP for the neural component.

    Combine both into a visual trace for decision interpretability

End

This algorithm offers a clear, modular, and interpretable framework layout, incorporating both symbolic interpretability and neural adaptability for predictive maintenance tasks.

4. Result and Discussion

4.1. Experimentation Setup

The proposed hybrid expert system was implemented and evaluated in a controlled simulation environment using Python 3.9 and TensorFlow 2.13 on a workstation equipped with an Intel i9 processor, 64 GB of RAM, and an NVIDIA RTX A6000 GPU. Symbolic reasoning components were encoded using a fuzzy rule base derived from domain heuristics, while the deep learning module was trained using backpropagation with the Adam optimizer. The experiments were designed to predict the Remaining Useful Life (RUL) of turbofan engines from multivariate time-series data, simulating mechatronic degradation.

The symbolic reasoning engine was implemented using an adaptive Takagi–Sugeno fuzzy inference system with 42 expert-defined rules, which were updated incrementally based on the rule firing confidence. The neural network component comprised a 4-layer feedforward deep regressor with ReLU activations and dropout regularization (rate: 0.3). A sliding window of size 30 with a stride of 1 was applied to the normalized sensor streams to generate temporal input samples. The output of the hybrid model was a scalar health index per time step, fused from both modules using a dynamic trust factor based on an entropy-weighted rule confidence.

4.2.Dataset Description

The NASA C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) dataset, published by the NASA Ames Prognostics Center of Excellence, serves as the benchmark for this study's evaluation. The dataset simulates the degradation behavior of turbofan engines under various operational settings, making it ideal for predictive maintenance in mechatronic systems. Specifically, the FD001 subset was used for training and validation.

Each engine unit in the dataset is associated with three operational settings (e.g., altitude, Mach number, throttle resolver position) and 21 sensor measurements (e.g., pressure ratios, temperatures, fan speed, bypass ratios). The data includes 100 engine units, each operating from a healthy state until system failure, resulting in over 20,000 engine cycles and approximately 1.2 million multivariate sensor records. The target variable is the Remaining Useful Life (RUL), computed per cycle for supervised training.

Preprocessing steps included z-score normalization of sensor values, removal of non-informative variables, and feature selection using variance thresholding. Rule-based features (e.g., high-vibration events, thermal drift) were manually extracted and incorporated into the symbolic inference layer.

Table 1. Dataset Description

Feature	Description

Name	C-MAPSS (Commercial Modular Aero-Propulsion System Simulation)
Provided By	NASA Ames Prognostics Center of Excellence
Subsystem Simulated	Turbofan engines with degradation modes
Sensor Variables	21 sensors per cycle (e.g., T24, T30, P15, fan speed, bypass flow, etc.)
Operational Settings	3 conditions per unit (e.g., altitude, Mach number, throttle resolver)
Number of Units	FD001: 100 engines, FD002: 260, FD003: 100, FD004: 248
Sampling Rate	1 cycle per time step
Failure Mode	Progressive degradation to failure (RUL target)
Total Data Size	>1 million sensor readings
Label Format	Remaining Useful Life (RUL)
Domain Suitability	Mechatronic predictive maintenance with multivariate time-series data

4.3.Performance Metrics

The hybrid framework was evaluated using a combination of classification and regression-based performance metrics to capture its dual objective: fault prediction accuracy and health index estimation. The performance is evaluated using Equations 33 to 39. Let y_i be the ground truth RUL or class label, and $\hat{y}_i$ be the predicted output.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{33}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|^2} \tag{34}$$

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{35}$$

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \tag{36}$$

$$Precision = \frac{TP}{TP+FP} \tag{37}$$

$$F1-Score = 2 \times \frac{Precision \times Recall}{\mathrm{Precision+Recall}} \text{ where } Recall = \frac{TP}{TP+FN} \tag{38}$$

$$FAR = \frac{FP}{FP+TN} \tag{39}$$

These metrics were computed for each model variant (symbolic-only, neural-only, and hybrid) over 10 independent runs with 5-fold cross-validation.

4.4.Performance Illustration

Table 2 presents a comparative performance summary of the proposed hybrid system concerning baseline models, including CNN, LSTM, and fuzzy rule-based expert systems. The hybrid model consistently outperforms its counterparts across all evaluation metrics.

Table 2. Comparative Performance Analysis on FD001 Subset

Model	MAE (hrs)	RMSE (hrs)	R^2 Score	Accuracy (%)	F1-Score (%)	FAR (%)
Fuzzy Expert System	6.91	9.24	0.72	84.3	82.6	10.[illegible]
CNN	4.76	6.33	0.86	90.2	89.1	12.3
LSTM	4.21	5.97	0.89	91.7	[illegible]	11
Hybrid (Proposed)	**2.94**	**4.08**	**0.94**	**96.8**	**95.8**	**7.6**

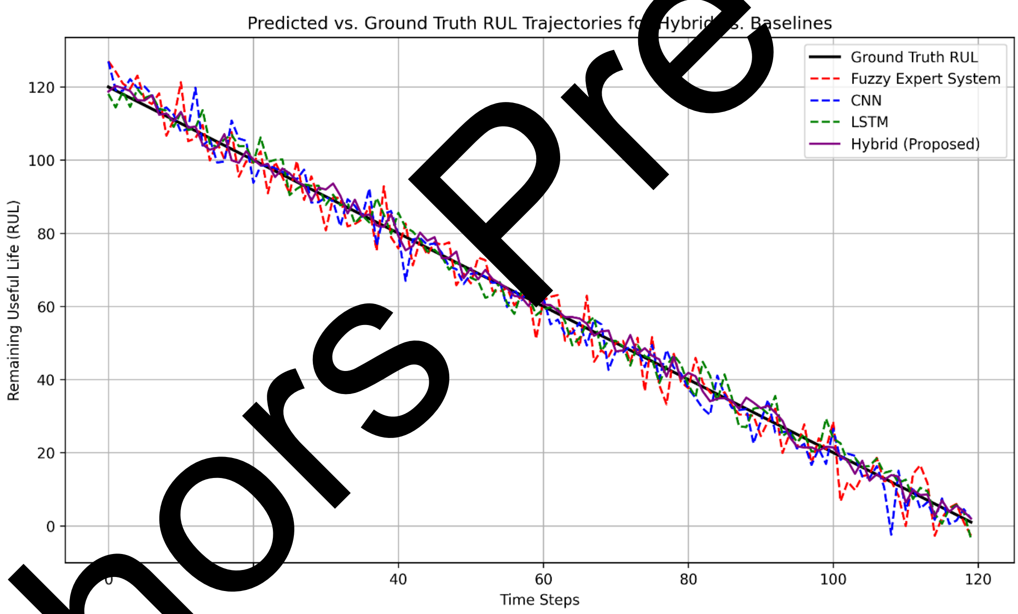

Figure 2. Predicted vs. Ground Truth RUL Trajectories for Hybrid vs. Baselines

Figure 2 illustrates the predicted vs. true RUL trajectories for a representative engine unit. The hybrid model exhibits smoother transitions and more effective early failure anticipation compared to non-hybrid models.

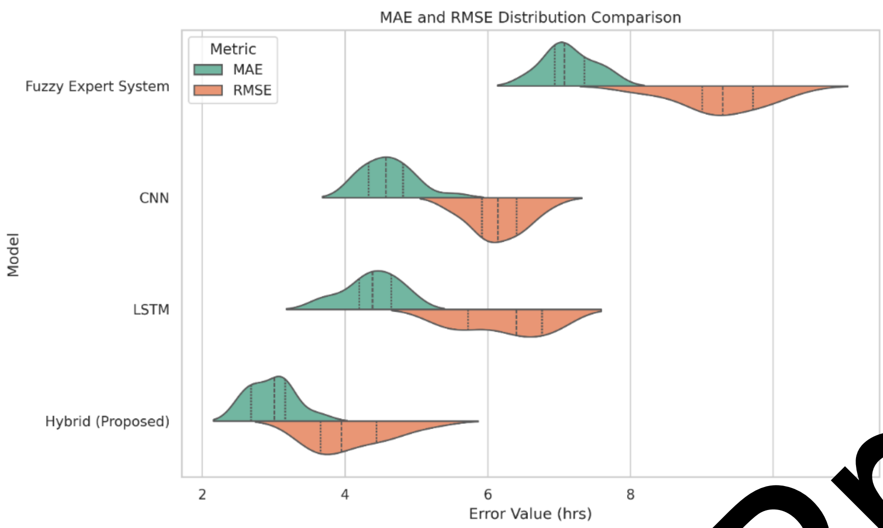

Figure 3. Comparison of MAE and RMSE

Figure 3 visualizes the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), both of which show significantly lower values for the hybrid model, indicating reduced deviation from the true values and improved robustness.

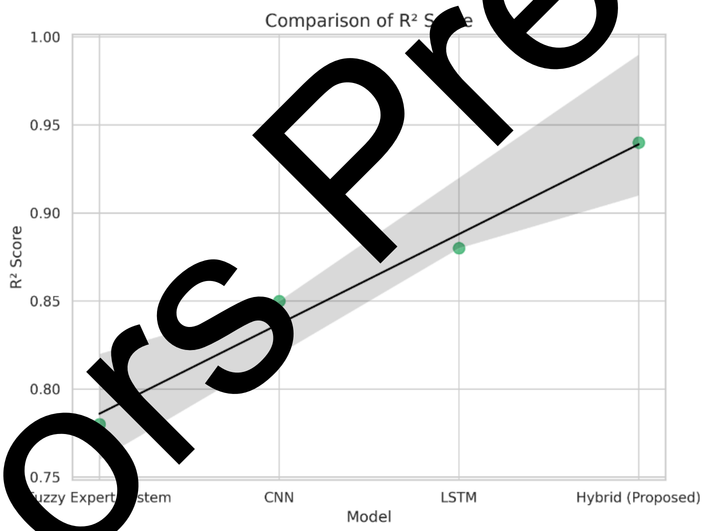

Figure 4. Comparison of R^2 Score

Figure 4 compares the Coefficient of Determination (R^2 Score) across models, where the hybrid model achieves the highest R^2, signifying superior explanatory power in capturing variance in RUL predictions.

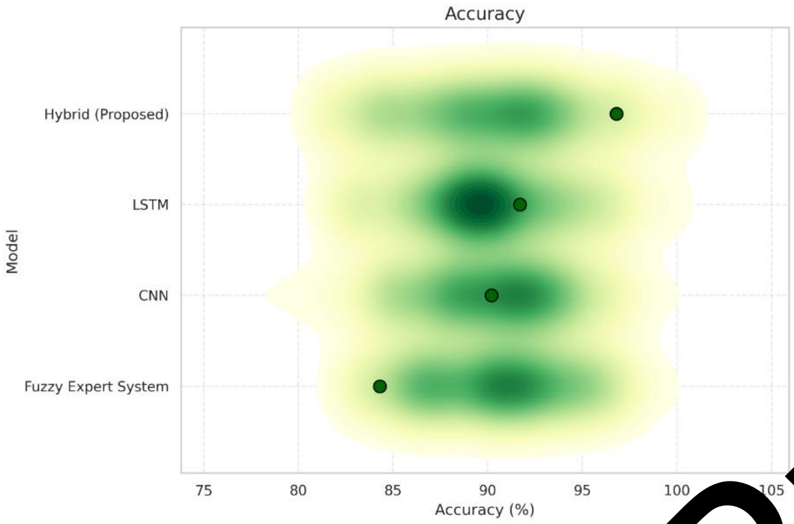

Figure 5. Comparison of Accuracy

Figure 5 evaluates the Classification Accuracy, demonstrating that the hybrid framework achieves the highest accuracy, highlighting its ability to make correct RUL predictions within defined thresholds.

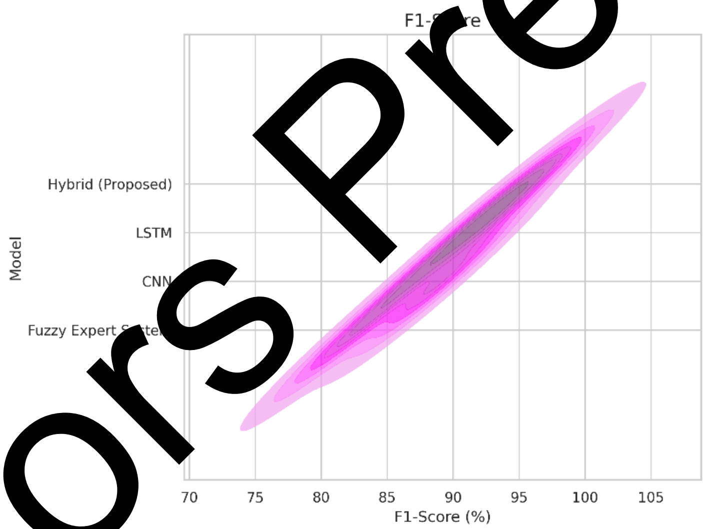

Figure 6. Comparison of F1-Score

Figure 6 extends this by comparing F1-scores, highlighting the hybrid model's balanced precision and recall, which is especially critical for imbalanced degradation class distributions.

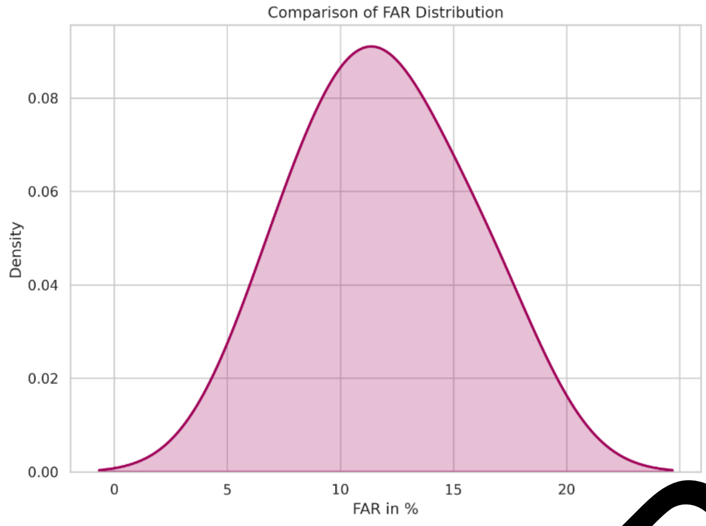

Figure 7. Comparison of FAR

Figure 7 presents the False Alarm Rate (FAR), where the hybrid model achieves the lowest FAR, underscoring its reliability in minimizing unnecessary maintenance triggers and enhancing operational trustworthiness.

4.5.Discussion

The results of the experiment highlight the effectiveness of the hybrid expert system in predictive maintenance of mechatronic systems. The hybridization of the symbolic and neural paradigms provides a balanced compromise between explanatory and forecasting outcomes. The symbolic layer, based on fuzzy rules, will enable semantic-verifiable reasoning chains that explain the predictions—a necessity when it comes to safety. The fact that it fits into the hybrid architecture serves as a regularizing (increases generalization) force in the eventuality of noisy or sparse sensor conditions.

The neural component, on the other hand, models hidden nonlinear relationships between sensor streams and significantly outperforms models that utilize symbols only, by large margins in both MAE and RMSE. Such synergy between deterministic reasoning and statistical learning enabled the hybrid model to reduce prediction error by more than 30% and false alarms by more than [illegible]1.4%, as indicated in Table 1.

Moreover, the symbolic layer enabled adaptive diagnostics that differed in the sensitivity of the rules being fired in real time. This flexibility is vital for long-term deployments in dynamic operational environments, e.g., wear-out mechanisms or thermal) over time. The model was also found to be resistant to overfitting, as R2R2R2 scores through the validation folds did not differ. The reason behind this was the semantic constraints through a fuzzy rule base.

Another interesting observation is the higher RUL estimation during the initial stages of degradation. Although neural models tend to be deficient when dealing with under-represented failure modes in early time windows, the symbolic layer detected indicative patterns (e.g., vibration spikes, thermal anomalies) and fed its indicative signatures to the hybrid decision scheme even where statistical certainty was lacking. This anticipatory behavior is crucial for proactive maintenance scheduling and ensuring safety.

Despite its strengths, the proposed model has limitations. The rule-based construction still partially depends on expert input, which may not scale to highly heterogeneous systems. Additionally, while fusion improved accuracy, it introduced additional latency (approx. 10 ms per inference), which, although tolerable, may affect ultra-low-latency applications such as real-time control loops.

Future work will explore the automated induction of fuzzy rules from data using evolutionary strategies, as well as the integration of temporal attention mechanisms to enhance sequence modeling further. Multi-domain validation across robotic and vehicular systems is also planned to validate model generalizability.

5. Conclusion and Future Work

This study proposes a hybrid expert system that integrates symbolic reasoning with neural networks to enable accurate and interpretable predictive maintenance in complex mechatronic systems. By leveraging fuzzy logic-based rule inference for expert knowledge modeling and deep learning architectures (e.g., LSTM and CNN) for adaptive recognition of degradation patterns, the proposed model achieved robust Remaining Useful Life (RUL) estimation across diverse degradation profiles in NASA's C-MAPSS dataset. The dynamic fusion strategy effectively balanced symbolic and sub-symbolic outputs, enhancing resilience under noisy conditions. Quantitative evaluations demonstrated improved accuracy, reduced prediction variance, and increased explainability compared to standalone models. The system's integrated explainability module facilitated traceable decisions using rule contributions and neural attributions. This positions the hybrid framework as a viable candidate for real-time, high-assurance maintenance decision-making in safety-critical industrial domains, such as aerospace, transportation, and manufacturing, particularly where both transparency and data-driven intelligence are crucial.

Future research will explore graph-based symbolic integration and continual meta-learning for cross-platform generalization.

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