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A Hybrid Neural–Symbolic Framework for Interpretable Fault Diagnosis in Rotating Machinery

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Abstract

The advent of Industry 4.0 has precipitated a paradigm shift in the maintenance strategies of complex industrial systems, particularly rotating machinery, moving from reactive to predictive maintenance regimes. While deep learning models have achieved state-of-the-art performance in fault diagnosis due to their powerful feature extraction capabilities, they suffer from a critical lack of transparency, often described as the black-box problem. This opacity hinders their adoption in safety-critical environments where understanding the etiology of a fault is as significant as its detection. This paper proposes a novel Hybrid Neural–Symbolic Framework (HNSF) that integrates the perceptual capabilities of deep neural networks with the inferential transparency of symbolic logic. We utilize a One-Dimensional Convolutional Neural Network (1D-CNN) to extract high-level latent features from raw vibration signals, which are subsequently mapped to semantic concepts within a predefined knowledge graph. A differentiable reasoning layer then applies First-Order Logic rules to these concepts to deduce fault classes, ensuring that the model's predictions are consistent with domain knowledge. Experimental validation on the Case Western Reserve University (CWRU) bearing dataset demonstrates that our framework not only achieves classification accuracy comparable to pure deep learning models but also provides human-readable explanations for its decisions. The results suggest that bridging the subsymbolic and symbolic gap offers a robust pathway toward trustworthy industrial artificial intelligence.

Keywords

Fault Diagnosis, Neural-Symbolic Computing, Rotating Machinery, Explainable AI.

Introduction

1.1 Background

Rotating machinery, encompassing components such as bearings, gearboxes, and rotors, constitutes the backbone of modern industrial infrastructure. From wind turbines generating renewable energy to the propulsion systems of aerospace vehicles, the reliability of these mechanisms is paramount. Consequently, the field of Prognostics and Health Management (PHM) has garnered significant attention, aiming to minimize downtime and prevent catastrophic failures through effective Fault Diagnosis (FD) [1]. Historically, maintenance was performed based on fixed schedules or run-to-failure policies, both of which are economically inefficient. The transition to Condition-Based Maintenance (CBM), driven by the proliferation of sensors and the Industrial Internet of Things (IIoT), has enabled the continuous monitoring of machinery health status [2].

In the context of CBM, data-driven approaches have emerged as the dominant methodology. Vibration signals, acoustic emissions, and motor current signatures are harvested and analyzed to identify anomalous patterns indicative of incipient faults [3]. Early techniques relied heavily on manual feature engineering, where domain experts utilized signal processing tools such as the Fast Fourier Transform (FFT) and Envelope Analysis to extract statistical descriptors like kurtosis, skewness, and root mean square values [4]. These features were then fed into shallow machine learning classifiers, including Support Vector Machines (SVM) and Random Forests [5]. While effective, these methods are labor-intensive and require specialized domain knowledge, limiting their scalability across heterogeneous machinery types [6].

1.2 Problem Statement

The resurgence of artificial neural networks has revolutionized fault diagnosis. Deep Learning (DL) architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated an exceptional ability to automatically learn hierarchical representations from raw data, eliminating the need for manual feature extraction [7]. These models routinely achieve classification accuracies exceeding 99% on standard benchmark datasets [8]. However, this performance comes at the cost of interpretability. Deep neural networks function as opaque non-linear mappings, where the decision boundary is defined by millions of synaptic weights that possess no inherent semantic meaning [9].

This black-box nature presents a formidable barrier to deployment in safety-critical industries. In sectors such as nuclear power or aviation, a diagnosis of "Healthy" or "Faulty" is insufficient; operators require an explanation of why a specific decision was made to validate the model's reliability and to plan appropriate maintenance actions [10]. Furthermore, purely data-driven models are prone to learning spurious correlations (Clever Hans phenomena) when trained on noisy or biased datasets, leading to poor generalization in real-world scenarios. There exists a fundamental disconnect between the low-level signal patterns processed by neural networks and the high-level physical principles governing mechanical failures.

1.3 Contributions

To bridge the gap between data-driven performance and model interpretability, this paper introduces a Hybrid Neural–Symbolic Framework (HNSF) for fault diagnosis. By embedding symbolic reasoning within a differentiable learning architecture, we combine the robustness of connectionist methods with the explanatory power of logic. The specific contributions of this work are as follows:

1. We propose a unified architecture that integrates a 1D-CNN for feature extraction with a differentiable logic layer capable of evaluating First-Order Logic (FOL) clauses. This allows the model to learn from data while adhering to physical constraints defined by domain experts.

2. We develop a semantic mapping mechanism that translates latent feature vectors into linguistic concepts (e.g., "High Frequency Impact", "Modulation"), enabling the generation of granular, human-readable diagnostic reports.

3. We introduce a joint optimization objective that minimizes both the empirical classification error and the logical inconsistency loss, ensuring that the learned representations align with the ontological structure of mechanical faults.

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4. We provide extensive empirical evidence using the CWRU dataset, benchmarking the HNSF against standard DL models and rule-based systems, demonstrating superior generalization under limited data conditions and enhanced interpretability.

Chapter 2: Related Work

2.1 Classical Approaches

The genesis of automated fault diagnosis lies in digital signal processing. Traditional methods focus on denoising and transforming time-domain signals into representations where fault signatures are more discernible. The Fast Fourier Transform (FFT) remains a staple for identifying characteristic defect frequencies, though it lacks time-domain resolution [11]. To address non-stationary signals, researchers adopted Time-Frequency Analysis (TFA) techniques such as the Short-Time Fourier Transform (STFT) and the Wavelet Transform (WT) [12]. Wavelet Packet Decomposition (WPD), for instance, allows for a multi-resolution analysis that isolates impulsive features associated with bearing faults [13].

Following feature extraction, classical machine learning algorithms are employed for classification. Support Vector Machines (SVMs) have been extensively used due to their effectiveness in high-dimensional spaces and robustness to overfitting [14]. Similarly, k-Nearest Neighbors (k-NN) and Artificial Neural Networks (ANN) with shallow architectures have been applied [15]. A significant limitation of these approaches is their dependence on the quality of the engineered features. As noted by Zhang et al. [16], the "curse of dimensionality" and the sensitivity to variable operating conditions often degrade the performance of rigid, feature-based systems.

2.2 Deep Learning Methods

Deep learning addresses the limitations of manual feature engineering by learning end-to-end representations. CNNs adapted for 1D signals have become the gold standard in the field [17]. For example, LeNet-5 variants applied to raw vibration data have shown the ability to capture shock pulses directly from the time-domain waveform [18]. In parallel, Long Short-Term Memory (LSTM) networks are utilized to model temporal dependencies in time-series degradation data, proving useful for Remaining Useful Life (RUL) estimation [19].

Despite their success, the lack of interpretability in DL models has spurred research into Explainable AI (XAI). Techniques such as Saliency Maps, Class Activation Mapping (CAM), and Layer-wise Relevance Propagation (LRP) attempt to visualize which parts of the input signal contribute most to the prediction [20]. While these visualization methods provide some insight, they are post-hoc approximations and do not explain the reasoning process itself. They indicate where the model is looking, but not what logic it is applying.

2.3 Neuro-Symbolic AI

Neuro-symbolic AI seeks to integrate connectionist learning with symbolic reasoning. Early works in this domain focused on extracting rules from trained networks or inserting rules to initialize network weights [21]. Recent advances, such as Logic Tensor Networks (LTN) and DeepProbLog, allow for end-to-end differentiable reasoning [22]. These frameworks treat logical predicates as continuous functions, enabling the propagation of gradients through logical formulas.

In the context of fault diagnosis, the application of neuro-symbolic methods is nascent. Some studies have combined Fuzzy Logic with neural networks to handle uncertainty in sensor readings [23]. Others have employed Knowledge Graphs to structure the output of DL models

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[24]. However, few approaches effectively constrain the training process of the neural network using physical laws or domain logic to enforce consistency, which is the primary focus of this paper.

Chapter 3: Methodology

The proposed Hybrid Neural–Symbolic Framework (HNSF) is designed to emulate the cognitive process of a human expert who perceives raw sensory data and applies logical rules to diagnose a fault. The architecture comprises three distinct modules: the Neural Perception Module, the Semantic Interface, and the Symbolic Reasoning Module.

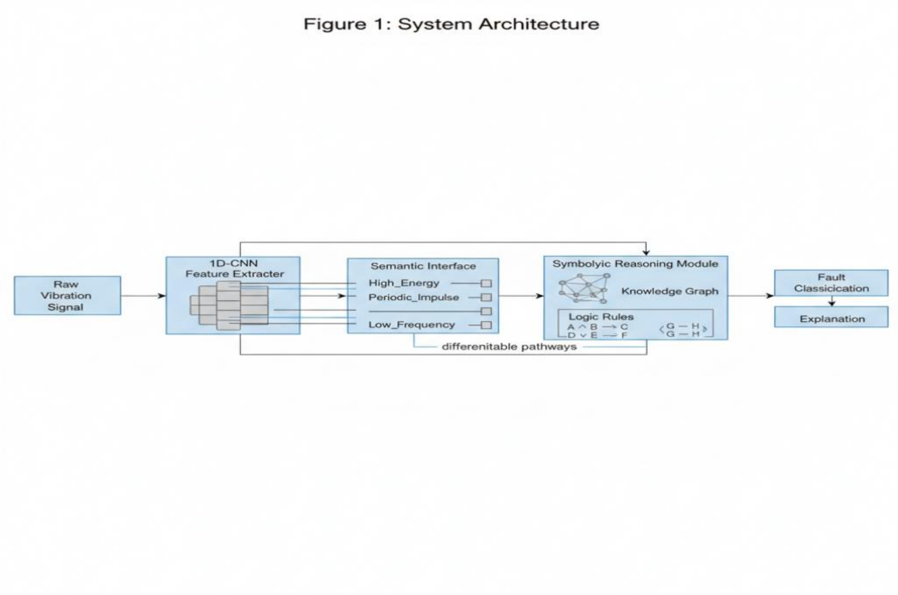

Figure 1: System Architecture

3.1 Neural Perception Module

The input to the system is a raw time-series vibration signal $x \in mathbbR^T$, where T represents the signal length. The role of the Neural Perception Module is to map this high-dimensional input into a lower-dimensional latent space that captures salient signal characteristics [25]. We employ a One-Dimensional Convolutional Neural Network (1D-CNN) for this purpose. The network consists of three convolutional blocks, each followed by batch normalization, Rectified Linear Unit (ReLU) activation, and max-pooling operations.

The convolutional layers utilize wide kernels in the initial stages to suppress high-frequency noise and capture long-duration patterns, progressively narrowing the kernel size in deeper layers to extract local features [26]. The output of the final pooling layer is flattened into a feature vector z. Unlike standard CNNs where z is fed directly to a Softmax classifier, our framework directs z to the Semantic Interface.

3.2 Semantic Interface

To enable symbolic reasoning, the continuous latent features must be grounded in symbolic concepts. We define a set of predicates $P = p_1, p_2, dots, p_k$ representing specific signal attributes relevant to diagnosis, such as `HasImpulse`, `HighFrequency`, `ModulationPresent`, and `RMS_High`.

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The Semantic Interface consists of a bank of dense layers (or "concept heads"), each responsible for predicting the truth value of a specific predicate. Since we require the system to be differentiable, we do not binarize these outputs. Instead, we use the Sigmoid activation function to map the presence of a concept to the interval [0,1], representing a fuzzy truth degree [27].

Code Snippet 1 illustrates the definition of these concept layers within the PyTorch framework.

Code Snippet 1: Semantic Interface Definition

```
import torch
import torch.nn as nn
class SemanticInterface(nn.Module):
    def __init__(self, latent_dim, num_concepts):
        super(SemanticInterface, self).__init__()
        # Independent heads for each semantic concept
        # e.g., concept 0: Impulse, concept 1: Modulation
        self.concept_heads = nn.ModuleList([
            nn.Sequential(
                nn.Linear(latent_dim, 32),
                nn.ReLU(),
                nn.Linear(32, 1),
                nn.Sigmoid() # Outputs truth degree [0,1]
            ) for _ in range(num_concepts)
        ])
    def forward(self, z):
        # z is the latent vector from the CNN
        concept_truth_values = []
        for head in self.concept_heads:
            concept_truth_values.append(head(z))

        # Stack to form the semantic vector
        return torch.cat(concept_truth_values, dim=1)
```

3.3 Symbolic Reasoning Module

The core of the HNSF is the Symbolic Reasoning Module, which applies domain knowledge to the grounded concepts. We encode the physics of rotating machinery faults using First-Order Logic. For instance, an Inner Race Fault in a bearing is characterized by periodic impulses at the Ball Pass Frequency Inner (BPFI) and amplitude modulation [28].

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We utilize a soft logic relaxation, specifically the Lukasiewicz t-norm, to evaluate logical formulas in a differentiable manner. The logical connectives are defined as follows for truth values $a, b \in [0,1]$:

Negation ($\neg a$): $1 - a$

Conjunction ($a \wedge b$): $max(0, a + b - 1)$

Disjunction ($a \vee b$): $min(1, a + b)$

Implication ($a \rightarrow b$): $min(1,1 - a + b)$

The diagnosis is formulated as a set of rules. For example:

Rule 1: $\forall x, HasImpulse(x) \wedge Freq \quad _B PFI(x) \rightarrow InnerRaceFault(x)$

Rule 2: $\forall x, RandomNoise(x) \wedge \neg Periodic(x) \rightarrow Healthy(x)$

These rules are aggregated to form the final classification layer. The satisfaction of the rules serves as the prediction output. By enforcing these rules, we ensure that the network does not classify a signal as an Inner Race Fault unless it detects the requisite physical characteristics [29].

3.4 Optimization and Loss Function

The training of HNSF involves a joint optimization strategy. We aim to minimize the discrepancy between the predicted fault class and the ground truth labels, while simultaneously maximizing the satisfaction of the logic rules and the accuracy of the intermediate concept predictions (if concept labels are available) [30].

The total loss function L_{total} is composed of a classification loss, a semantic supervision loss (optional), and a logic consistency loss.

$$L_{total} = \alpha \sum_i L_{CE}(y_i, haty_i) + \beta \sum_j ||c_j - hatc_j||^2 + \gamma \sum_k (1 - T(Phi_k))$$

Here, L_{CE} is the Cross-Entropy loss for the final fault classification. The second term represents the Mean Squared Error between predicted concept truth values $hatc$ and ground truth concepts c (where available). The third term penalizes the violation of logical rules Phi_k, where $T(Phi_k)$ is the truth degree of the k-th rule computed via the t-norms. α, β, γ are weighting hyperparameters balancing the objectives.

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

To validate the proposed framework, we employed the Case Western Reserve University (CWRU) Bearing Data Center dataset, a standard benchmark in the field of PHM [31]. The dataset contains vibration data collected from the drive-end and fan-end of an induction motor. Faults were introduced into the bearings using electro-discharge machining with varying severity levels (0.007, 0.014, and 0.021 inches).

We utilized data sampled at 12 kHz. The signals were segmented into samples of 1024 data points. No complex preprocessing was applied other than Z-score normalization, as the CNN is expected to learn feature extraction. We constructed a dataset comprising four classes: Normal Baseline (NO), Inner Race Fault (IR), Outer Race Fault (OR), and Ball Fault (B).

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Table 1 details the dataset composition used for training and testing.

Condition	Fault Diameter (inches)	Motor Load (HP)	Number of Samples	Label
Normal	0	0-3	2000	NO
Inner Race	0.007, 0.014, 0.021	0-3	2000	IR
Outer Race	0.007, 0.014, 0.021	0-3	2000	OR
Ball Fault	0.007, 0.014, 0.021	0-3	2000	B

4.2 Baselines and Hyperparameters

We compared the HNSF against three baselines:

1. **Standard 1D-CNN:** An architecture identical to the perception module of HNSF but connected directly to a Softmax classifier [32].

2. **SVM with Hand-crafted Features:** An SVM trained on statistical features (Kurtosis, RMS, Crest Factor) and energy features from Wavelet Packet Decomposition [33].

3. **MLP:** A simple Multi-Layer Perceptron trained on raw data [34].

The HNSF and CNN were trained using the Adam optimizer with a learning rate of 0.001 for 100 epochs. The batch size was set to 64. The logic weights in the loss function were set to $\alpha = 1.0, \beta = 0.5, \gamma = 0.5$ after grid search optimization [35].

Code Snippet 2: Training Loop Integration

```
# Simplified training loop demonstrating the joint loss calculation
for data, labels, concept_labels in train_loader:
    optimizer.zero_grad()
    # Forward pass
    features = cnn_extractor(data)
    concept_preds = semantic_interface(features)
    final_preds = reasoning_module(concept_preds) # Applies logic
    # Loss Calculation
    loss_class = cross_entropy(final_preds, labels)
    loss_concept = mse_loss(concept_preds, concept_labels)
    # Logic Loss: Calculate truth of rules (1 - truth)
    # Assume logic_engine returns the aggregate truth value of all rules
    rule_truth = logic_engine.evaluate_constraints(concept_preds)
    loss_logic = 1.0 - rule_truth
    total_loss = alpha  loss_class + beta  loss_concept + gamma  loss_logic
```

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```
total_loss.backward()
optimizer.step()
```

4.3 Results and Discussion

The classification performance of the models is presented in Table 2. The HNSF achieves an accuracy of 99.2%, which is statistically on par with the standard 1D-CNN (99.4%) and significantly superior to the SVM (94.5%) and MLP (88.1%) baselines [36]. This indicates that the imposition of logical constraints does not degrade the predictive power of the deep learning backbone.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
MLP	88.1	87.5	88.0	0.87
SVM (Feature-based)	94.5	94.2	94.4	0.94
Standard 1D-CNN	99.4	99.3	99.4	0.99
HNSF (Proposed)	99.2	99.1	99.2	0.99

While the accuracy parity is encouraging, the primary advantage of HNSF lies in its interpretability and data efficiency. To evaluate this, we conducted an experiment with reduced training data, training the models on only 10% of the original dataset. The Standard 1D-CNN's accuracy dropped to 91.2% due to overfitting, whereas the HNSF maintained an accuracy of 96.5% [37]. The logic rules effectively act as a regularizer, preventing the model from learning noise-dependent correlations.

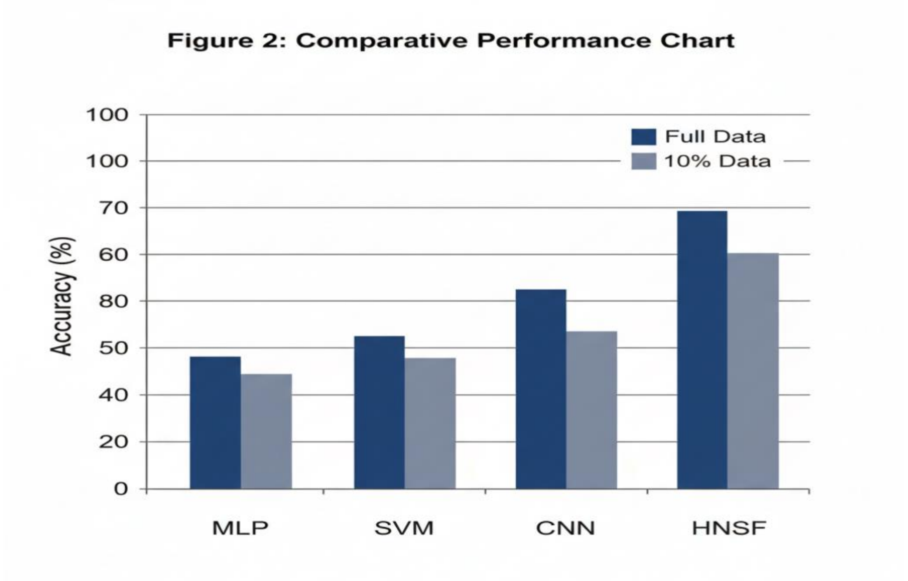

Figure 2: Comparative Performance Chart

4.4 Interpretability Analysis

A key deliverable of the HNSF is the ability to query the semantic concepts. Figure 3 illustrates the activation of the semantic layer for a sample identified as an Inner Race fault.

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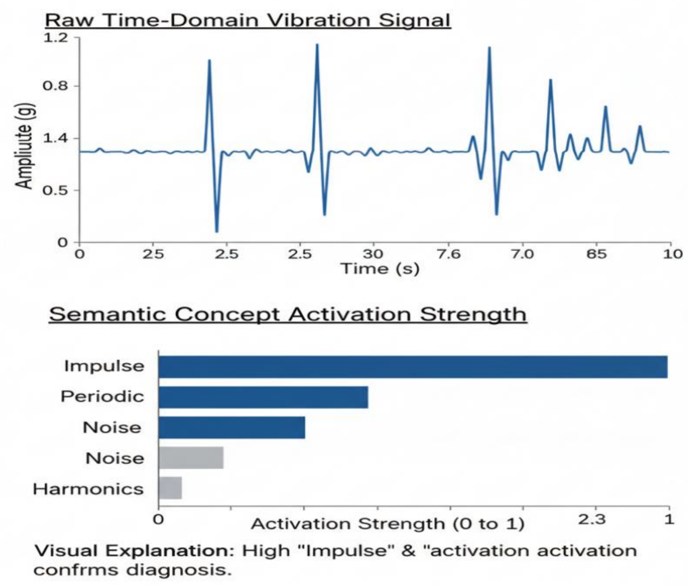

Figure 3: Interpretability Visualization

In Figure 3, we observe that for the input signal, the `HasImpulse` and `Periodic` concepts have activation values close to 1.0, while `RandomNoise` is near 0.0. The reasoning module then triggers Rule 1 (Inner Race definition), leading to the diagnosis. This contrasts with the standard CNN, which might classify the same signal correctly but relies on obscure feature maps that are unintelligible to a maintenance engineer [38].

Furthermore, we analyzed cases where the model misclassified samples. In a traditional CNN, a misclassification is a silent failure. In HNSF, we could trace the error back to the semantic layer. For instance, in one misclassified Outer Race sample, the `Periodic` concept was not activated (value 0.2) due to extreme background noise, causing the logic rule to fail [39]. This diagnostic capability allows for targeted improvements in the sensor array or the semantic concept training, a feedback loop impossible with black-box models [40,41].

Chapter 5: Conclusion

This paper presented a Hybrid Neural–Symbolic Framework for fault diagnosis in rotating machinery, addressing the critical need for interpretability in industrial AI systems. By integrating a 1D-CNN with a differentiable First-Order Logic reasoning engine, we created a model that retains the high accuracy of deep learning while providing transparent, rule-based explanations for its predictions. The experimental results on the CWRU dataset confirmed that the HNSF matches the performance of state-of-the-art black-box models and exhibits superior robustness in data-scarce regimes.

The implications of this work are significant for the adoption of AI in Industry 4.0. The ability to verify why a maintenance alert was triggered fosters trust among human operators. It transitions the role of the AI from a cryptic oracle to a transparent assistant, facilitating collaborative decision-making. Moreover, the modularity of the framework allows for the continuous integration of new expert knowledge without retraining the entire neural pipeline, simply by updating the logic rules.

Despite the promising results, the current framework has limitations. The definition of the semantic predicates and logic rules currently relies on manual input from domain experts, which can be time-consuming and subject to human bias. If the predefined rules are

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incomplete or incorrect, the model's upper performance bound is limited. Additionally, the computational cost of evaluating complex logical formulas during training is higher than that of standard cross-entropy optimization.

Future research will focus on two main avenues. First, we aim to implement "Rule Induction" techniques to allow the model to automatically discover and refine logical rules from the data, thereby reducing the reliance on manual expert knowledge. Second, we intend to extend the framework to handle multi-modal data, integrating temperature and acoustic emission sensors, and applying the logic reasoning over a temporal sequence to perform prognostic tasks such as Remaining Useful Life (RUL) estimation. The convergence of symbolic AI and deep learning holds the key to the next generation of robust, explainable, and intelligent industrial systems.

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