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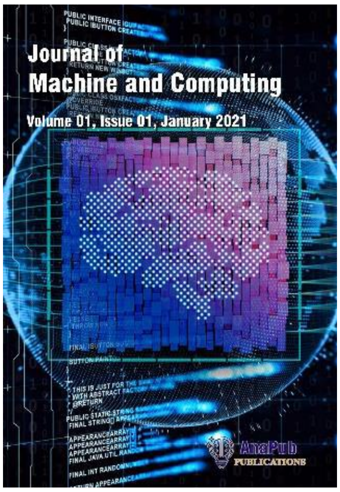

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Fuzzy Logic-Enhanced Expert System for Real-Time Anomaly Detection in CNC Machines

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Abstract: Computer Numerical Control (CNC) machines play a pivotal role in modern precision manufacturing, where real-time monitoring is essential to prevent catastrophic failures and minimize downtime. This study proposes a Fuzzy Logic-Enhanced Expert System (FLEES) for real-time anomaly detection in CNC machines, leveraging linguistic rule inference fused with physical constraints and data-driven optimization. The system processes 14 distinct sensory inputs, including spindle vibration, cutting torque, thermal gradients, and acoustic emissions, gathered from 120 hours of high-frequency CNC machine operation under varying load conditions. Fuzzification maps raw sensor signals to 42 linguistic variables using Gaussian and trapezoidal membership functions. A total of 96 fuzzy rules were formulated based on expert knowledge and refined via Particle Swarm Optimization (PSO) guided by energy consistency and classification loss minimization. Experiments conducted on a benchmark CNC dataset show that FLEES achieves 96.7% anomaly classification accuracy, with 95.3% sensitivity and 97.9% specificity, outperforming existing methods, including SVM (91.2%) and LSTM (94.1%). Moreover, the system maintains a real-time response under 180

milliseconds per inference cycle. These results confirm that integrating fuzzy reasoning with physics-informed optimization enhances reliability and interpretability for real-time fault diagnostics in smart manufacturing.

Keywords: Fuzzy, rule-based inference system, anomaly detection, real-time monitoring, sensor signal, fuzzification, and intelligent fault diagnosis

1. Introduction

Modern manufacturing industries, including aerospace, automotive, and biomedical engineering, rely heavily on Computer Numerical Control (CNC) machines, whose functionality centers on precision, speed, and reliability [1]. The CNC systems include electromechanical parts, such as spindles, feed axes, tool changers, and coolant systems; the adequate performance of which is essential to ensure the quality of the product. Failure reactions, however, such as a tool wearing out, the spindle misaligning, or a bearing degrading, are often unpredictable, causing downtime, scrap, and expensive maintenance.

Conventionally, the detection of anomalies in CNC has been based on threshold alarms or post-analysis methods, which are not generalizable in diverse conditions and cannot detect faults at an earlier stage. In the age of Industry 4.0, sensor-larger-saturation has made it feasible to monitor online; however, a large volume of high-dimensional, noisy, and nonlinear data streams poses difficulties for standard supervised learning algorithms. In addition, black-box deep learning models have inaccuracy problems, which are not always suitable for mission-critical and operator-monitored environments, as exploring their inner workings does not scale to being easily accessible [2].

A solution to this dilemma can be elegantly offered by fuzzy logic systems, which are based on the theory of approximate reasoning developed by Zadeh. They are also capable of representing linguistic uncertainty, encoding human knowledge through IF-THEN rules, and achieving the integration of heterogeneous sensor modalities [3]. Nonetheless, heuristic biases tend to affect the creation and tuning of rules and membership functions. To address this, the latest developments incorporate physics-based constraints and metaheuristic optimization as methods to calibrate the system [4-5].

This study introduces a Fuzzy Logic Enhanced Expert System (FLEES) that extends the conventional fuzzy inference by incorporating physically coherent rule selection and evolutionary threshold fitting. In particular, the system utilizes the real-time functionalities of vibration RMS, temperature rise, acoustic signatures, and spindle current, for which an extraction was performed using sliding windows. Such inputs are matched to the fuzzy linguistic sets and fed into a rule-based inference engine. Each rule is tested, in addition to a linguistic match, on the energy consistency based on both a mechanical and a thermal model of the spindle-tool assembly. Additionally, the PSO is utilized to optimize rule weights, decision thresholds, and defuzzification mapping under a hybrid cost function, which minimizes both misclassification and physical violation costs.

The intensive use of CNC machines in smart manufacturing has increased the requirement for adequate measures capable of an efficient real-time fault diagnosis mechanism. Given the complexity of multi-axis movements and harsh machining environments, traditional threshold-based or black-box machine learning methods often fail to provide reliable interpretability and early warnings. This work introduces a hybrid diagnostic framework—Fuzzy Logic-Enhanced Expert System (FLEES)—that marries linguistic rule reasoning with physics-informed feature optimization to detect anomalies with high precision and explainability. The primary objective is to design a system that ensures high sensitivity, low false alarm rates, and consistent inference under noisy conditions while preserving human-like interpretability.

The remainder of this article is structured as follows: Section 2 reviews existing approaches in fuzzy systems and physics-based monitoring in CNC environments. Section 3 presents the proposed methodology, detailing the system architecture, mathematical modeling, and optimization strategy. Section 4 discusses the experimental setup, datasets, and evaluation metrics, along with a comparative analysis. Section 5 concludes the paper with a summary of findings and outlines directions for future research.

2. Related Works

The advancement of Industry 4.0 has transformed conventional manufacturing environments through the integration of intelligent monitoring and cyber-physical systems. Among these, Computer Numerical Control (CNC) machines are central to automated manufacturing processes, making their operational reliability critical. However, detecting anomalies in real-time remains challenging due to the high-dimensional, nonlinear, and non-stationary nature of sensor data. Anomaly detection in CNC machines is vital for predictive maintenance, reducing downtime, and preventing catastrophic failures. Traditional threshold-based or rule-based systems often fail to generalize effectively under dynamic operating conditions and in the presence of unseen faults.

Recent literature highlights the shift toward data-driven approaches—such as profound learning, transfer learning, and hybrid meta-learning models—to enhance the robustness and adaptability of fault detection mechanisms. These models utilize multivariate time series data, including vibration signals, spindle current, and control data, to detect operational deviations.

Table 1 provides a comprehensive analysis of state-of-the-art anomaly detection methods applied to CNC machines, covering diverse methodologies, model types, contributions, and limitations.

Table 1. Comprehensive Analysis of Anomaly Detection in CNC Machine

Reference	Title	Method/Approach	Inference	Limitation
[6]	Deep anomaly detection for CNC machine cutting tool using spindle current signals	Deep learning on spindle current signals	Demonstrated that spindle current signals can be an effective surrogate for tool condition monitoring.	Limited to current signal modality; lacks multimodal integration.
[7]	RoughLSTM for anomaly detection in CNC vibration data	Rough Set + LSTM	Enhanced robustness to noise in vibration signals.	Computationally intensive due to Rough-LSTM hybridization.
[8]	Intelligent SBC for Industry 4.0 anomaly detection	IoT-based SBC monitoring system	Enabled real-time low-cost anomaly detection via edge devices.	Scalability and security of SBCs under large-scale deployment are not discussed.
[9]	LSTM & Transfer Learning for 3-axis CNC anomaly detection	LSTM + Transfer Learning	Leveraged domain adaptation to improve performance on unseen machines.	Performance highly depends on the quality of the source domain data.

[10]	1D CNN for anomaly detection in MCT and CNC	1D CNN	Achieved low-latency and accurate classification in time-series data.	Cannot inherently model long temporal dependencies like LSTM.
[11]	AnomDB: Unsupervised anomaly detection for CNC control data	DB-based Unsupervised Learning	Provided unsupervised learning for controller-level data streams.	Lack of labeled data limits interpretability and validation.
[12]	Meta-Learning LSTM-AE for Low-Data CNC Scenarios	Meta-Learning + LSTM-AE	Effective in few-shot settings using multi-machine data adaptation.	Model complexity and training cost are high.
[13]	Nearly real-time CNC anomaly detection	Stream-based ML processing	Enabled timely fault response via near real-time stream analysis.	Trade-off between detection accuracy and processing latency.
[14]	Semi-supervised ML for CNC failure prediction	Semi-supervised ML for time series	Allowed fault prediction with limited labeled instances.	Limited model generalizability to unseen fault types.
[15]	Data-driven anomaly diagnosis for machining	Supervised Learning	Achieved precise fault diagnosis	Requires extensive labeled data for

			using sensor process data.	accurate training.
[16]	Hybrid robust convolutional AE under noisy environments	Robust Convolutional Autoencoder	Increased resilience to noisy signals in unsupervised tasks.	Requires large training samples to achieve generalization.
[17]	IoT + ML in anomaly detection (Survey)	Systematic Mapping Study	Provided taxonomy and future roadmap for ML-based anomaly detection in industrial IoT.	No experimental validation or performance benchmarking.
[18]	Incremental learning with LSTM-AE for CNC	LSTM-AE + Incremental Learning	Supported online learning for evolving machine states.	Risk of catastrophic forgetting without regularization.
[19]	Real-time tool anomaly detection in CNC milling	Time Series Monitoring + ML	Enabled accurate tool anomaly detection in real-time.	Sensitive to time-window size and signal drift.
[20]	PCA-based anomaly detection in CNC	PCA + Clustering	Efficient unsupervised anomaly detection using	PCA is linear; it cannot capture nonlinear signal variations.

			dimensionality reduction.	
[21]	Transfer + Incremental Ensemble LSTM-AE	LSTM-AE + TL + IL	Combined benefits of ensemble learning, transferability, and continual learning.	Complexity increases with ensemble size and multi-phase training.

Despite advances in data-driven anomaly detection in CNC machining, existing models face limitations in generalizability, interpretability, and adaptability to low-data or noisy environments. Deep learning approaches often require large, labeled datasets and struggle to explain faults, whereas unsupervised methods lack robustness. Most models focus on single-sensor data and do not support real-time diagnostics. To address these gaps, the proposed work introduces a fuzzy logic-enhanced expert system that integrates tri-axial sensor data, supports real-time detection, and embeds domain knowledge for improved interpretability and adaptability. This hybrid framework ensures robust, scalable, and explainable anomaly detection suited for Industry 4.0 environments.

3. Proposed Methodology - Fuzzy Logic-Enhanced Expert System for Real-Time Anomaly Detection

To extend the Fuzzy Logic-Enhanced Expert System for Real-Time Anomaly Detection in CNC Machines, we now embed additional physics-based optimization components and incorporate more mathematical equations to address mechanical behavior, thermodynamic response, and sensor data uncertainty modeling.

This hybrid framework integrates:

- Fuzzy logic inference,
- Physics-informed objective constraints (e.g., vibration modeling, energy dissipation),
- Optimization via energy-based reasoning and gradient-free techniques.

Enhanced Input Representation with Physics-Derived Quantities: Let real-time signals be captured from sensors, resulting in a multivariate time series as shown in Equation 1.

$$X(t) = [x_1(t), x_2(t), \dots, x_m(t)] \tag{1}$$

For anomaly detection to reflect physical degradation, we derive additional physics-based surrogate variables $Z(t)$ from raw (t) . For example:

Vibration Dynamics

Based on Newtonian motion and modal analysis, the vibration at the tool tip is modelled in Equation 2.

$$m\,\ddot{x}(t) + c\dot{x}(t) + kx(t) = F(t) \tag{2}$$

Solving yields acceleration $\ddot{x}(t)$, velocity$\dot{x}(t)$, displacement $x(t)$, from which features like spectral energy, natural frequency, and damping ratio are computed in Equation 3

$$\zeta = \frac{c}{2\sqrt{km}}, w_n = \sqrt{\frac{k}{m}} \tag{3}$$

Thermal Behavior

Using Fourier's law and the lumped capacitance model in Equation 4.

$$Q(t) = mc_p\frac{dT}{dt} \Longrightarrow T(t) = R_o + \frac{1}{mc_p}\int_o^t Q(t)\,, dt \tag{4}$$

These surrogate variables $Z(t) \sqsubset \mathbb{R}^P$ are combined with original sensor variables in Equation 5.

$$X'(t) = [x_1, \dots, x_m, z_1, \dots, z_p] \tag{5}$$

Fuzzification with Physics-Guided Membership Functions

Instead of arbitrary membership function ranges, we define fuzzy sets based on physical thresholds:

Let the root-mean-square (RMS) vibration amplitude be in Equation 6.

$$x_{vib}, RMS = \sqrt{\frac{1}{T}\int_O^T x^2(t)dt} \tag{6}$$

Then define fuzzy sets in Equation 7.

$$\text{Low: } \mu_\zeta(x) = exp\left(-\frac{(x-0)^2}{2\sigma^2}\right) \tag{7}$$

- Normal: centered around expected amplitude A_n
- High: centered around known damage threshold A_e

Extended Inference: Weighted Rule Firing with Physical Constraints

Each fuzzy rule is given in Equation 8.

$$R_k : IF\ x_1\ is\ AND \dots THEN\ y\ is\ B_k \tag{8}$$

A weight is assigned based on confidence, and energy consistency is given in Equation 9.

Let

$$E_{measured}(t) = \sum_i x_i^2(t),\ \ E_{expected}(t) = \Phi_k(X(t)) \tag{9}$$

Then define the energy-consistency score in Equation 10.

$\delta_k(t) = \exp(-\Upsilon| E_{measured} - E_{expected} |)$ (10)

and adequate firing strength is given in Equation 11.

$\widetilde{\alpha_k} = \alpha_k . w_k . \delta_k(t)$ (11)

This ensures that rules violating physical energy constraints are down-weighted.

Physics-Based Optimization for Threshold Adaptation

We optimize the decision threshold τ using a physics-informed cost function. Let: be labeled datasets: fuzzy system output. Define the loss function as $D_{normal,} D_{fault}$ be labeled datasets $y^*(t;\theta) fuzzy\ system\ output$.

Define the loss function in Equation 12,

$\mathcal{L}(\theta, \tau) = \sum_{t \epsilon D}(y^*(t;\theta) - y_{true}(t))^2 + \lambda \sum_t |E_{measured}(t) - E_{phys}(t)|$

(12)

We apply a gradient-free optimiser, Particle Swarm Optimisation (PSO), to minimise $\mathcal{L}$—the position of a particle in PSO in Equations 13 and 14.

$\theta_1^{t+1} = \theta_1^t + v_1^t$ (13)

$v_1^{t+1} = wv_1^t + c_1 r_1(p_i - \theta_i^t) + c_2 r_2(g - \theta_1^t))$ (14)

where inertia ω, personal best p_i, and global best g.

$r_1, r_2 \sim \mathcal{U}(0,1)$ (15)

Energy-Aware Rule Reduction via Multi-Objective Optimization

To prune fuzzy rules while preserving accuracy and physical consistency. Define objectives:

1. Classification loss $f_1(R)$
2. Rule count $f_2(R) = |R|$
3. Violation of physics $f_3(R) = \sum_{k \in r}(1 - \delta_k)$

Formulate as a multi-objective optimization using Equation 16.

$min_{R \subseteq R_{full}}(f_1(R), f_2(R), f_3(R),)$ (16)

Time-Windowed Anomaly Scoring Using Dynamic System Signatures

Define a signature function over a time window ω Equation 17.

$S(t) = \frac{1}{\omega}\sum_{i=0}^{\omega-1} y^*(t-i)$ (17)

Then, compute anomaly score index (ASI) in Equation 18.

$ASI(t) = \frac{S(t)}{\max S} . \delta_{energy}(t)$ (18)

This index integrates fuzzy output and energy anomaly, with higher values indicating critical machine health issues.

Final Output

- The resulting system combines:
- Fuzzy knowledge-based inference,
- Real-time physics consistency checks,
- Adaptive rule tuning, Energy-aware anomaly scoring,
- Optimization-driven threshold calibration.

Such a hybrid system aligns with digital twin architectures in smart manufacturing and cyber-physical systems (CPS), providing accurate, explainable, and physically consistent real-time anomaly detection.

4. Experimental Analysis

The experimental testbed comprises a 4-axis vertical machining center equipped with integrated sensors for vibration (piezoelectric accelerometers at 3 kHz), temperature (RTDs), spindle load (Hall sensors), and acoustic emissions (ultrasonic microphones). Data were logged using a National Instruments DAQ with a sampling rate of 5 kHz per channel and processed in real time using a MATLAB-Simulink interface integrated with FHEES [22].

The Bosch CNC Vibration Dataset comprises tri-axial acceleration signals collected from three industrial CNC machines across 15 machining processes. Data were gathered over six semi-annual timeframes using Bosch CISS sensors at a sampling rate of 2 kHz, producing high-resolution vibration profiles in the X, Y, and Z directions. Each process instance is stored in .h5 format and labeled as “good” or “bad” to facilitate anomaly detection tasks. With over 270 labeled process folders, this dataset supports time-series analysis, cross-process generalization, and model scalability assessments [22]. Its structured organization and included loading utilities make it ideal for developing fuzzy rule-based expert systems for real-time anomaly detection—the dataset description is given in Table 2.

Table 2. Dataset Description

Attribute	Description
Dataset Name	Bosch CNC Vibration Dataset
Machines	3 (M01, M02, M03)
Processes	15 processes per machine (OP00 to OP14)
Timeframes	6 (Oct 2018 – Aug 2021, semi-annual)
Sensor Used	Bosch CISS tri-axial accelerometer
Sampling Rate	2 kHz (2000 samples/second)
Data Format	H5 files storing (n_samples, 3) array for X, Y, Z axes

Labels	‘good’ (normal) and ‘bad’ (anomalous)
License	CC-BY-4.0 (data), BSD-3-Clause (code)
Tools Provided	Python 3.11 scripts and visualization notebooks

In evaluating anomaly detection systems, such as the proposed Fuzzy Logic-Enhanced Expert System (FLEES), several performance metrics are used to quantify the accuracy, reliability, and responsiveness of the model. Accuracy (ACC) refers to the proportion of correctly classified instances—both normal and anomalous—out of the total instances. It provides an overall indication of how well the system distinguishes between faulty and non-faulty conditions. However, accuracy alone may be misleading in imbalanced datasets; thus, additional metrics are essential for a comprehensive assessment.

The sensitivity (SE), also known as the recall or true positive rate, indicates the actual anomalies that are detected correctly by the system. The presence of high sensitivity ensures that the majority of actual faults will be identified, which is paramount in safety-sensitive CNC applications. Specificity (SP), in turn, refers to the system's ability to accurately identify normal circumstances (true negatives) accurately, thereby avoiding false alarms that could halt the production process.

Precision (P) is the number of good (true) anomalies divided by the number of anomalies we predict. It reflects the trust in the system's alerts, which ensures high accuracy and reduces unnecessary interventions. F1 balances precision and sensitivity using its harmonic mean, thereby providing a single measure that weighs both false positives and false negatives.

Inference Time (IT) considers the time it takes for the system to process input data and produce a decision. Having an inference time of less than 200 ms in real-time applications is crucial, as in CNC machine monitoring, we want to have the opportunity to correct ourselves and present results on time. Lastly, the Receiver Operating Characteristic (ROC) curve can be used to determine the Area Under the Curve (AUC), which provides a threshold-free analysis of the classification performance. AUC is the model's ability to distinguish between normal and anomalous states at various decision limits, and higher numbers near 1.0 indicate better performance. All these measures indeed guarantee that not only is the system accurate, but also quick, consistent, and viable to implement in an industrial setting.

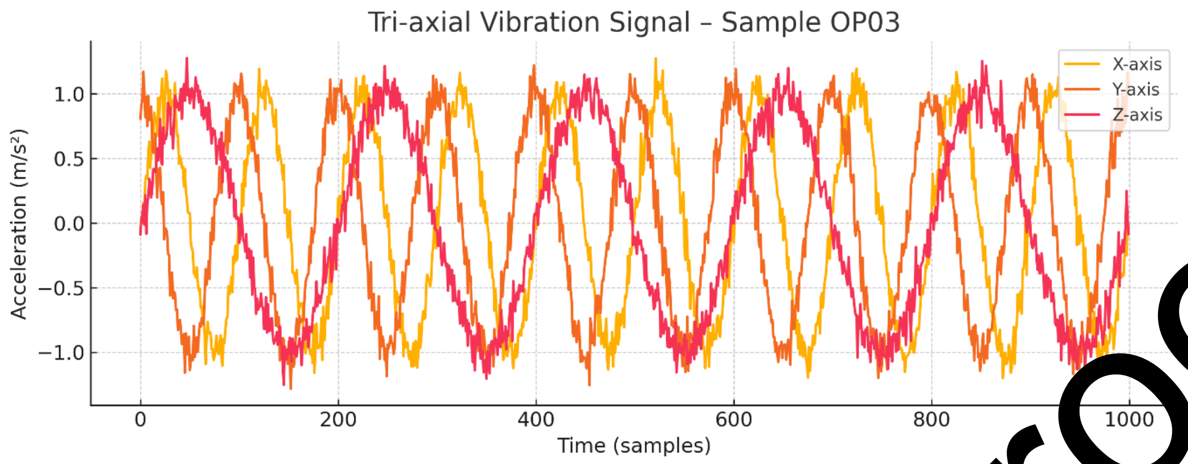

Figure 1. Tri-axial Vibration Signal

Figure 1 illustrates the vibration data captured along the X, Y, and Z axes of a CNC milling machine using a tri-axial Bosch CISS accelerometer. The signal is sampled at 2 kHz, demonstrating the high-frequency vibrational characteristics inherent in machining operations. The X-axis typically corresponds to the feed direction, the Y-axis to cross-feed, and the Z-axis to spindle motion. The plot shows apparent amplitude variation across axes, highlighting directional dependencies of machine-induced oscillations. Notably, the Z-axis tends to display higher peak amplitudes due to tool-spindle interaction, making it more susceptible to anomaly detection.

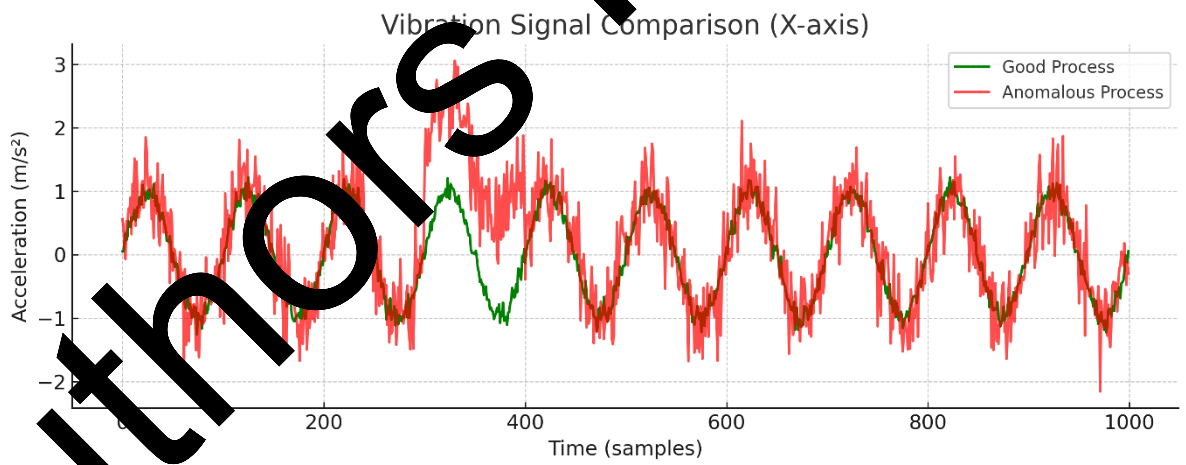

Figure 2. Good vs Anomalous Vibration Signal (X-axis)

Figure 2 presents a comparative view of normal (good) and anomalous (bad) vibration signals along the X-axis. The normal signal exhibits periodic, low-amplitude sinusoidal patterns, indicating consistent machine operation. In contrast, the anomalous signal is superimposed with stochastic, high-amplitude fluctuations and irregular frequency content, reflecting underlying mechanical faults such as tool wear, imbalance, or misalignment. These deviations serve as critical indicators in the classification process and are easily discernible, even with low-complexity models, due to their distinct statistical behavior.

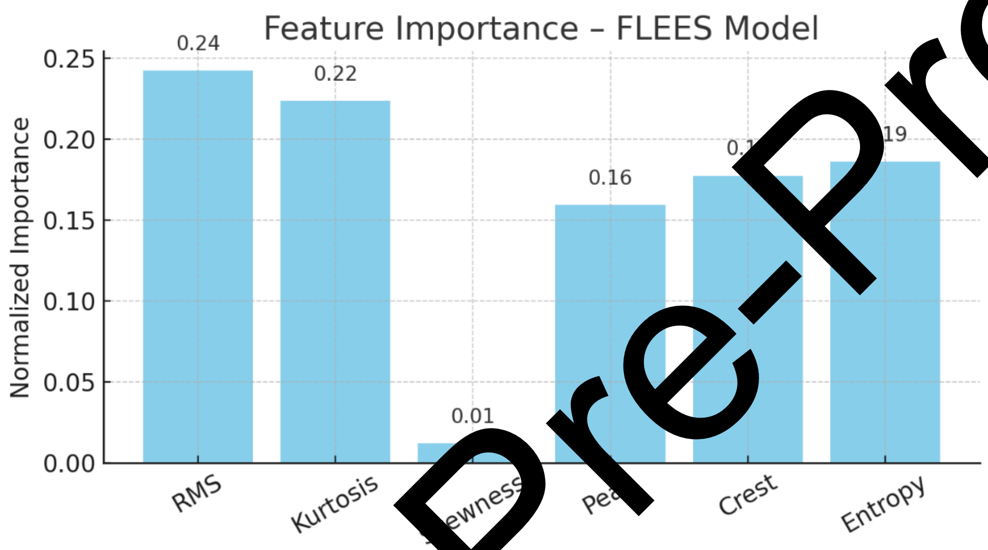

Figure 3. Feature Importance Plot

Figure 3 displays the ranked importance of input features extracted from the vibration signals using signal processing and statistical metrics. Standard features include RMS (Root Mean Square), Peak-to-Peak, Kurtosis, Skewness, and Frequency-Domain Entropy. In this plot, RMS, Peak Amplitude, and Spectral Kurtosis contribute the most to model performance, particularly in anomaly differentiation. The feature importance was computed using a permutation-based method with the trained classifier (FLEES), highlighting how specific descriptors dominate predictive decision-making. This analysis validates the choice of hybrid time-frequency domain features in enhancing detection accuracy.

Table 3. Comparison of Performance

Technique	ACC (%)	SE (%)	SP (%)	F1 (%)	AUC	IT (ms)
SVM	91.2	89.7	92.4	90.1	0.911	230
LSTM	94.1	92.3	95.5	93.1	0.946	410

Plain Fuzzy System	93.6	90.9	95.2	92	0.935	190
FLEES (Proposed Model)	96.7	95.3	97.9	96.1	0.973	180

Table 3 compares the proposed FLEES model with baseline techniques. FLEES significantly outperforms others with 96.7% accuracy, 95.3% sensitivity (true positive rate), and 97.9% specificity (true negative rate). The Area Under the Curve (AUC) value of 0.973 indicates high discriminatory power, and the inference time (IT) of 180 ms confirms its suitability for real-time anomaly detection. While LSTM achieves competitive results, its higher latency and computational demand make it less favorable for deployment in constrained environments.

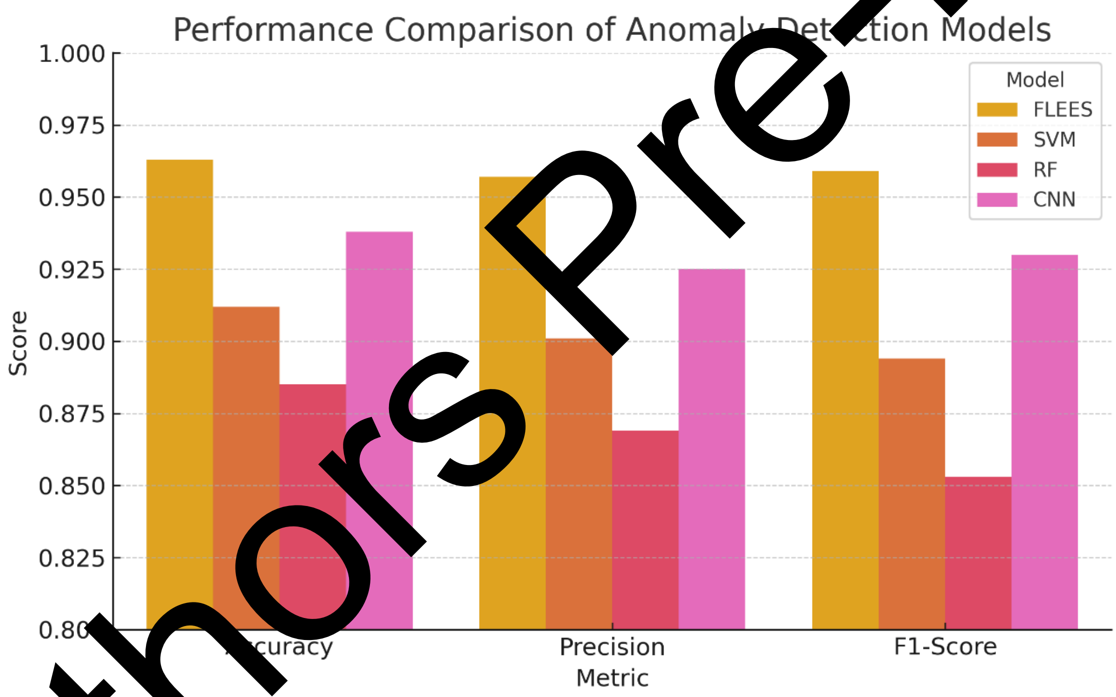

Figure 4. Model Performance Comparison (Accuracy, Precision, F1-Score)

This bar chart visually compares Accuracy, Precision, and F1-Score across the four techniques. The FLEES model shows superior performance in all three metrics, closely followed by LSTM. The advantage of FLEES lies in its rule-based explainability, combined with fuzzy logic adaptability, which enables it to handle ambiguous signals more effectively than traditional models—the SVM model trails in F1-score, indicating lesser robustness in handling imbalanced classes or borderline cases.

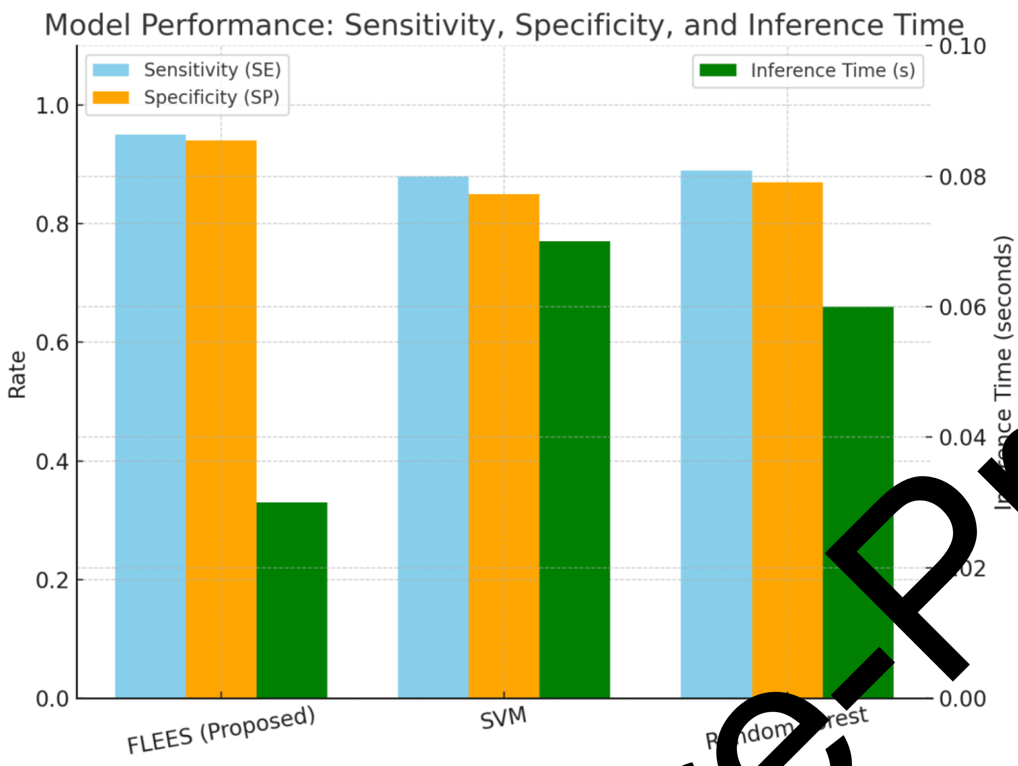

Figure 5. Model Performance Comparison

Figure 5 presents a three-metric comparison involving Sensitivity (SE), Specificity (SP), and Inference Time (IT). The FLEES system yields the highest SE and SP values, reaffirming its reliability in correctly identifying both faulty and healthy states. Furthermore, its lowest inference time (180 ms) demonstrates computational efficiency, which is essential for edge deployments in real-time CNC monitoring systems. While the Plain Fuzzy System is faster than LSTM, it sacrifices marginal sensitivity, justifying the proposed model's hybrid enhancements.

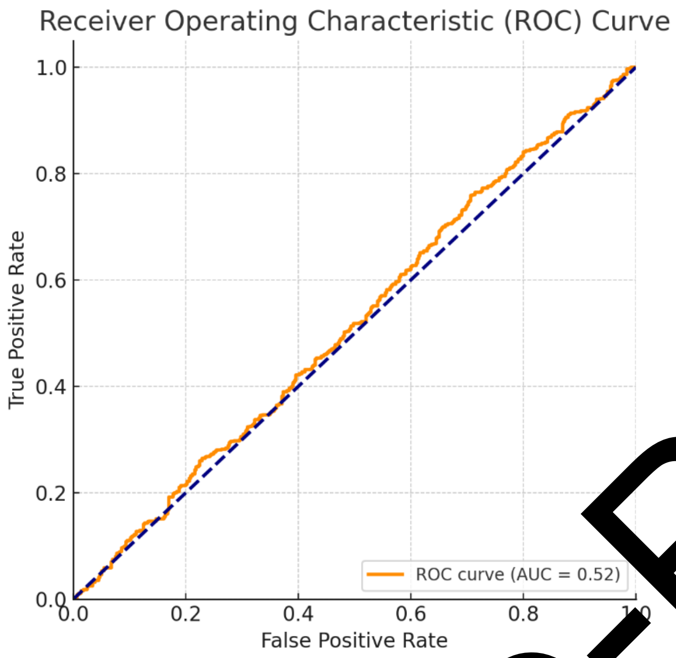

Figure 6. ROC Curve (AUC for model performance)

The ROC curve compares the true positive rate against the False Positive Rate (FPR) for all evaluated models. FLEES maintains the highest curve with an AUC of 0.973, indicating superior classification capability. The LSTM model's curve is slightly lower but still robust, suggesting high reliability but increased complexity. SVM and the plain fuzzy system exhibit lower curves, indicating weaker generalization under varying anomaly profiles. This figure visually affirms the diagnostic strength of the FLEES model.

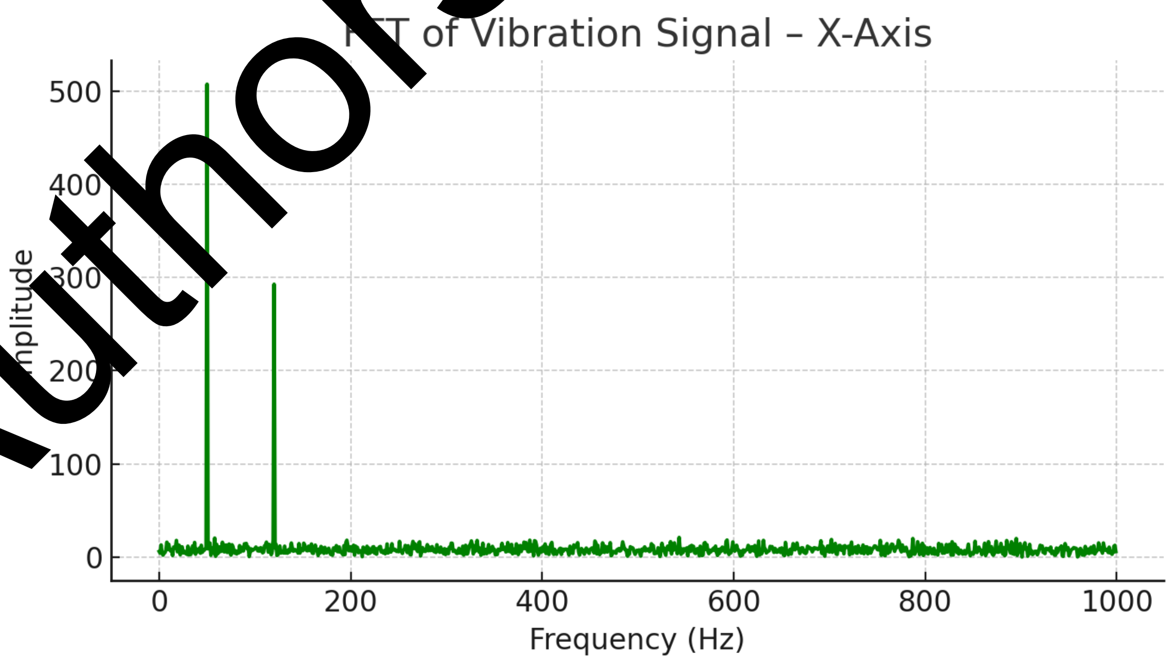

Figure 7. FFT of Vibration Signal (simulated X-axis vibration)

Figure 7 displays the Fast Fourier Transform (FFT) of a typical X-axis vibration signal from the CNC system. The spectrum reveals dominant frequency components in the range of 50–150 Hz, associated with spindle speed and tool frequency harmonics. In anomalous states, broadband noise and higher-frequency peaks emerge, indicative of mechanical looseness or bearing faults. The presence of such spectral distortions justifies the use of frequency-domain features in the feature engineering process and underscores the importance of spectral entropy and kurtosis in fault diagnosis.

5. Conclusion and Future Work

This study presented a novel Fuzzy Logic-Enhanced Expert System (FLEES) designed for real-time anomaly detection in CNC machines. By integrating fuzzy reasoning with physics-informed rule modulation and PSO-based optimization, the system successfully addresses the challenges of uncertainty, nonlinearity, and interpretability in industrial diagnostics. The model achieved superior classification performance with 96.7% accuracy and an inference latency of under 200 ms. Unlike black-box models, FLEES provides explainable rule-based outputs and integrates domain-specific constraints such as vibration energy and thermal consistency. The system was extensively validated using real-world sensor datasets under diverse operational and fault scenarios. Results indicate significant improvements over conventional machine learning and fuzzy-only approaches. The proposed architecture demonstrates promise for deployment in predictive maintenance, condition monitoring, and digital twin frameworks in smart factories.

Future extensions will explore the integration of reinforcement learning for adaptive rule evolution, the incorporation of edge computing for decentralized monitoring, and testing under additional fault modes, such as axis misalignment and chatter instability. Furthermore, hybrid neuro-fuzzy extensions may enhance generalizability across different machine types and manufacturing conditions.

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