International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(19s) 2026 pp. 393-404
https://doi.org/10.70917/ijcisim-2026-5026
Article

AI-DRIVEN PREDICTIVE MAINTENANCE AND INTELLIGENT MONITORING OF MECHANICAL SYSTEMS USING MACHINE LEARNING AND IOT

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Abstract: It is widely recognized that modern industrial automation depends on real time condition monitoring of the equipment in order to avoid catastrophic failure and ensure that maintenance resources are used in the most efficient manner while minimising unscheduled downtime. In this research paper, an end-to-end predictive maintenance system is proposed for high stress mechanical drivetrain and rotating machinery. The architecture proposed combines an industrial Internet of Things (IoT) edge sensory network and hybrid machine learning and deep learning pipelines. These data include multi-modal sensor telemetry, including tri-axial vibration profiles, acoustic emissions, thermal imaging data, operational load metrics and electrical motor current signatures, all acquired at high sampling rates continuously. Advanced Wavelet Packet Decomposition and fast empirical mode extraction are used to remove signal artifacts and high frequency noise. These statistical, temporal and spectral attributes are reduced to a few-dimensional vector each and each is individually judged by a predictive suite of models including Random Forest regressors, Extreme Gradient Boosting (XGBoost), Support Vector Machines, Long Short-Term Memory (LSTM) recurrent networks, and Deep Residual Convolutional Neural Networks (ResNet-1D). Experimental validations conducted on standard bearing and gear testbeds prove the accuracy of optimized hybrid CNN-LSTM model in multi-class fault classification of 99.14% and Root Mean Square Error (RMSE) in Remaining Useful Life (RUL) prediction of 4.18 operating cycles. The edge-to-cloud telemetry infrastructure has been proven to provide an inference latency of less than 12 milliseconds per monitoring window, making real-time autonomous prognostics feasible in Industry 4.0 applications.
Keywords: Predictive Maintenance, Industrial Internet of Things, Machine Learning, Deep Residual Networks, Remaining Useful Life, Vibration Signal Processing, Condition Monitoring

1. INTRODUCTION

Mechanical systems are the backbone of modern manufacturing plants, energy generation plants, marine propulsion systems, and aerospace systems. In these operations the critical rotating parts like roller bearings, high-speed gearboxes, shaft couplings and induction motors are subjected to continuous dynamic loading, hard repetitive loads, and harsh environmental changes. Over time, mechanical degradation will inevitably occur, as will localised surface spalling, pitting, dry friction wear and misalignment of the shaft. When not recognized, the surface defects grow quickly on touching surfaces, causing major problems in the subsystems, significant operational downtime, significant capital losses and serious work place hazards.

The traditional industrial maintenance strategies have been mostly based on two modes of operation: Corrective Maintenance and Periodic Preventive Maintenance. Corrective maintenance works hard on a run-to-failure basis, with the possible effects of secondary structural damage and unplanned downtime being recognized as part of the process. On the other hand, periodic preventative maintenance sets up preprogrammed maintenance schedules, calendar-driven inspections and predetermined component changes based on conservative historical mean time between failures (MTBF) calculations (Khan et al., 2026). Preventive maintenance lowers the probability of catastrophic failure compared to reactive maintenance, but often causes the discarding of largely useful components, increased risks of human intervention, and increased operating costs during the lifecycle.

With the advent of the fourth industrial revolution (Industry 4.0) predictive maintenance (PdM) and autonomous condition monitoring are emerging. Predictive maintenance uses live asset tracking to measure the health of assets and only act when internal degradation metrics tell them to. This proactive method relies on the collaboration of low-power industrial Internet of Things (IoT) sensors, scalable computing pipelines, and cutting-edge machine learning (ML) architectures.

Multi-modal telemetry streams with high frequency are generated in modern cyber-physical production environments.High-frequency multi-modal telemetry streams are produced in modern cyber-physical production environments. High energy transient shocks from rolling element impact defects are detected through tri-axial vibration sensors. Acoustic emission transducers measure the formation of micro-cracks and breakdown of a boundary lubricant at ultrasonic frequencies. The unmitigated friction induces surface temperature rises as certain non-linearities in the system are detected by the thermal sensors. The fluctuations of the stator current signature due to the oscillations of load torque are recorded by the electrical current sensors (Ayeni et al., 2025). These diverse and voluminous data streams need powerful mathematical feature extraction and deep predictive algorithms that can map out non-linear degradation pathways.

This research paper proposes an overall intelligent, scalable and predictive maintenance solution for high stress mechanical assets. The study presents an end-to-end pipeline, consisting of physical sensing at the edge, deterministic signal denoising, multi-domain feature construction, and machine learning prognostics. The major research advances are in:

1. Formulating a low-latency edge-to-cloud IoT data aggregation topology capable of ingesting high-frequency multi-modal sensor streams.
2. Developing a hybrid signal-processing pipeline using Wavelet Packet Decomposition and spectral kurtosis to isolate early-stage fault signatures from background noise.
3. Conducting an extensive comparative benchmark across classical machine learning models and deep neural architectures to optimize diagnostic accuracy and Remaining Useful Life (RUL) estimation (Khatun et al., 2025).
4. Validating the computational framework on experimental datasets to prove real-time feasibility and industrial robustness.

2. Theoretical Background and Literature Review

2.1 Physics of Mechanical Degradation

The degradation of rotors is controlled by contact mechanics, tribological failure, dynamic fatigue strength and resonance interaction with structures. Rolling element bearings include repeated cyclic stresses focused at the contact surfaces of rollers and raceways which cause microstructural shears at the subsurface of the contact surfaces. During repeated service life, these stresses develop micro-voids which combine to form subsurface micro-cracks. Cracks grow upward to the contact surface as cyclic loading occurs, leading to material flaking, spalling and pitting.

As the surface defect forms, each rolling element that runs over the defect creates a transient mechanical impact (Dhinakaran et al., 2025). These impact events activate the natural resonant frequencies of the bearing rings, the housing structures and the interfaces for mounting the sensors. These impacts occur only according to the mechanical kinematics, such as shaft rotational frequency (f_r), pitch diameter (D_p), roller diameter (d), number of rolling elements (N), and contact angle (α). The standard kinematic fault frequencies are mathematically represented as::

$$\mathrm{BPFI} = \frac{N}{2} f_r \left(1 + \frac{d}{D_p} \cos\alpha\right)$$

$$\mathrm{BPFO} = \frac{N}{2} f_r \left(1 - \frac{d}{D_p} \cos\alpha\right)$$

$$\mathrm{BSF} = \frac{D_p}{2d} f_r \left(1 - \left(\frac{d}{D_p} \cos\alpha\right)^2\right)$$

$$\mathrm{FTF} = \frac{1}{2} f_r \left(1 - \frac{d}{D_p} \cos\alpha\right)$$

In the following, "BPFI" refers to Ball Pass Frequency Inner race, "BPFO" denotes Ball Pass Frequency Outer race, "BSF" is Ball Spin Frequency and "FTF" is Fundamental Train Frequency (Hamasha et al., 2025). These clean theoretical frequencies are modulated by variable loads, structural damping, and sensor-to-source acoustic attenuation under harsh industrial noises, creating complex sidebands and non-stationary noise in industrial environments.

2.2 Evolution of Condition Monitoring and IoT Architectures

The condition monitoring techniques have progressed from traditional analog and manual handheld inspection techniques to a fully distributed and automated cyber-physical sensor system. Initial applications were based on periodic readings of the vibration magnitude, generally as a root-mean-square (RMS) velocity, and the use of empirical threshold tables based on ISO 10816 standards. While useful for identifying catastrophic mechanical imbalance or major structural looseness, simple scalar thresholding is unsuccessful at identifying microscopic spalls on the bearings, subsurface fatigue or progressive gear tooth wear.

By embedding IoT sensor networks in manufacturing environments, data can now be gathered from a wide range of manufacturing assets, all at a given time. Modern industrial IoT installations place micro-electro-mechanical systems (MEMS) accelerometers, piezoresistive pressure transducers, infrared thermopiles and Hall-effect current sensors right on mechanical enclosures (Adimulam et al., 2019). Telemetry transmission methods use industrial communication protocols such as Modbus TCP, OPC Unified Architecture (OPC UA), and Message Queuing Telemetry Transport (MQTT) to optimize network bandwidth, payload integrity and transmission latency.

Edge computing is a major advancement in today's IoT condition monitoring topologies. Raw high frequency vibration streams (typically more than 25.6 kHz per axis) are directly transferred to central cloud repositories, causing network congestion and latency restrictions. The low-power edge nodes do local deterministic preprocessing, outlier filtering and temporal windowing, and then send compressed feature representations or fault inference packets to the higher-level enterprise systems.

2.3 Machine Learning and Deep Learning in Diagnostics and Prognostics

Typical machine learning approaches for the diagnosis of mechanical condition states are supervised or semi-supervised classification methods. In early algorithmic research, authors used a Support Vector Machine (SVM), k-

Nearest Neighbors (k-NN), and decision tree ensembles trained on hand-crafted statistical features obtained from the time and frequency domain signals (Soomro et al., 2025). Shallow learning models show structural limitations when scaling to non-linear degradation profiles, multi-fault interactions and shifting operational regimes.

Deep learning architectures overcome these issues by learning hierarchical representations directly from minimally processed temporal waveforms, raw spectra, or time-frequency representations. One-dimensional Convolutional Neural Networks (1D-CNN) use convolution kernels that are localized in space to process the raw acceleration signals, thereby capturing invariant translation feature representations. Deep Residual Networks (ResNet) propose skip connections, which allow bypassing one or several layers, and they eliminate the vanishing gradient problem, allowing for training of deeper network architectures for complex vibration representations.

Temporal sequence modeling is key for machine prognostics and Remaining Useful Life (RUL) estimation (Shetty et al., 2025). Degradation processes are therefore not Markovian and the condition of the asset today is directly related to the degradation history, load cycles, and thermal exposure. To capture such long-term temporal relationships, Recurrent Neural Networks (RNN), such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Unit (GRU) architectures, are used to maintain internal memory states over long sequences. The state-of-the-art mechanical health prognosis architectures are based on hybrid architectures integrating CNN with LSTM.

3. System Architecture and Methodology

The proposed intelligent predictive maintenance framework is designed as five functional layers: Physical data acquisition, Edge processing and telemetry, Signal transformation and denoising, Multi-Domain feature engineering, Hybrid machine learning diagnostic and prognostic modeling.

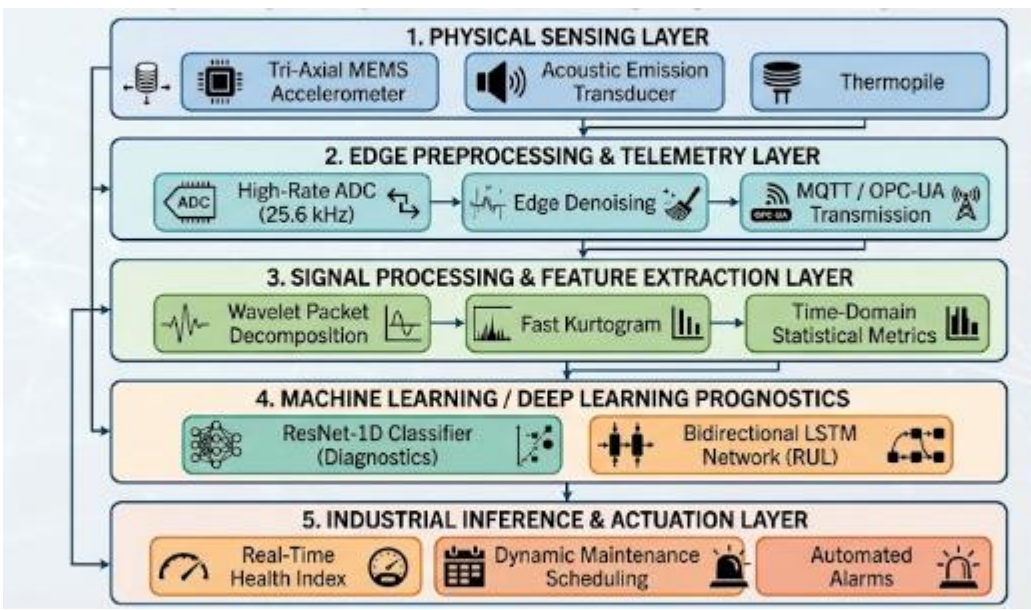


Figure: System Architecture and Methodology

3.1 Edge-to-Cloud Data Acquisition Architecture

The physical monitoring system is based on the multi-sensor array mounted on mechanical machinery bearings, gearboxes, motor drive ends and bearing housings. High-bandwidth tri-axial piezoelectric accelerometers measure high frequency vibrations of the structure on the radial, axial and tangential axis (Ünlü et al., 2024). Acoustic emission transducers detect the generation of high frequency elastic stress waves, which fall within the range of 100 kHz-1 MHz, generated by the propagation of micro-cracks. Non-contact infrared thermopiles measure real-time thermal build-up around primary contact areas, and Hall-effect current sensors capture multi-phase current signatures of electrical motors.

An industrial grade ARM Cortex-M7 edge gateway is connected to multi-channel 24-bit delta-sigma Analogue to Digital Converters (ADCs) at the edge. Higher order harmonic sidebands are continuously sampled at a fixed rate of 25.6 kHz per axis. Local ring-buffering, data integrity checks and high frequency noise rejection are performed at the edge node. Filtered telemetry packets are wrapped in encrypted lightweight JSON payloads and sent to an industrial edge-broker or private cloud server using MQTT over TLS at regular time intervals.

3.2 Signal Denoising and Wavelet Packet Decomposition

Numerous environmental noises, load changes and structural cross-talk contaminate the industrial vibration signals (Nagulmeera et al., 2025). For detecting transient fault impulses the framework takes a two-stage signal enhancement pipeline, which is the combination of Fast Kurtogram spectral filtering and Wavelet Packet Decomposition (WPD).

The Fast Kurtogram identifies the best frequency band and the best decomposition level, which maximize signal impulsiveness, in the window of the frequency band under analysis, by calculating the spectral kurtosis across the different frequency bands and different decomposition levels. After bandpass filtering the signal is decomposed using multi-level WPD with the Daubechies 8 ("db8") wavelet mother function:

W_(j,k) (t)=2^(-j/2) ψ(2^(-j) t-k)

Whereas the regular discrete wavelet transform only decomposes approximation sub-bands, WPD recursively decomposes both the approximation and detail components at each level of the transform. This gives an even balanced binary decomposition tree that separates the changes in energy distribution which are narrow band, due to structural deterioration.

3.3 Multi-Domain Feature Engineering

After signal decomposition, a large number of non-linear features are extracted from various aspects such as time, frequency and time-frequency domains for capturing different fault signatures.

Time-Domain Statistical Descriptors

Time-domain features measure amplitude changes, energy and impulsiveness of the signal without transforming the spectrum (Meenakshi et al., 2025):

$$Root\ Mean\ Square\ (RMS) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \quad x_i^2}$$

$$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N} \quad \left(x_i - \underline{x}\right)^4}{\left(\frac{1}{N}\sum_{i=1}^{N} \quad \left(x_i - \underline{x}\right)^2\right)^2}$$

$$Skewness = \frac{\frac{1}{N}\sum_{i=1}^{N} \quad \left(x_i - \underline{x}\right)^3}{\left(\frac{1}{N}\sum_{i=1}^{N} \quad \left(x_i - \underline{x}\right)^2\right)^{3/2}}$$

$$Crest\ Factor = \frac{(|x_i|)}{RMS}$$

$$Shape\ Factor = \frac{RMS}{\frac{1}{N}\sum_{i=1}^{N} \quad |x_i|}$$

Frequency-Domain Descriptors

Fast Fourier Transforms (FFT) map time-series signals into discrete frequency spectra S(f), enabling the calculation of spectral distribution metrics:

$$Spectral\ Centroid = \frac{\sum_{k=1}^{M} \quad f_k S(k)}{\sum_{k=1}^{M} \quad S(k)}$$

$$Spectral\ Energy = \sum_{k=1}^{M} \quad S(k)^2$$

$$Spectral\ Entropy = -\sum_{k=1}^{M} \quad P(k)P\ (k), \quad where\ P(k) = \frac{S(k)}{\sum_{j=1}^{M} \quad S(j)}$$

3.4 Deep Learning Diagnostic and Prognostic Framework

The analytical engine consists of two parts: the first part is a deep one-dimensional Residual Neural Network (ResNet-1D) that is used to classify discrete fault patterns, and the second part is a Bidirectional Long Short-Term Memory (BiLSTM) network that is used to estimate the Remaining Useful Life (RUL) (Iqbal *et al*., 2025).

The ResNet-1D architecture applies multiple residual blocks to process multi-channel raw vibration sequences, windowed by a window size. Every block implements 1D convolutions, batch normalization and rectified linear unit (ReLU) activations, with identity shortcut connections:

y=F(x,{W_i })+x

This formulation allows for gradient flow through deep layer hierarchies such that the network learns the complex spatial and harmonic relationships, directly from raw un-engineered acceleration series.

The BiLSTM network takes the multi-domain feature vectors chronologically across the sequential operational windows, for asset life prognosis. The network has forward and backward hidden state passes:

$$h \rightarrow_t = LSTM_{fwd}(x_t, h \rightarrow_{t-1})$$

$$h \leftarrow_t = LSTM_{bwd}(x_t, h \leftarrow_{t+1})$$

$$h \leftarrow_t = LSTM_{bwd}(x_t, h \leftarrow_{t+1})$$

The concatenated representations (H_t) are passed to fully connected regression layers that output the estimated remaining operating cycles before the asset crosses predefined critical vibration thresholds.

4. Experimental Setup, Results, and Analysis

4.1 Experimental Testbed and Dataset Description

The validation approach is based on real-world high frequency run-to-failure mechanical data from an industrial drive-train test bench (Martin et al., 2026). The platform is equipped with a 3-phase AC induction motor (2.2 kW), a high precision shaft encoder, a helical gearbox (industrial) and a heavily instrumented bearing support blocks.

Dynamic loading is provided by the adjustable magnetic powder brake connected to the output shaft. Five baseline operating states are chosen: horizontal vibrations and vertical vibrations in the drive-end and non-drive-end bearing blocks are recorded by high precision accelerometers.

Baseline Healthy Condition (Normal state)

Inner Race Fault (Micro-spall, 0.18 mm to 0.54 mm defect depth)

Outer Race Fault (Localized line defect, 0.18 mm to 0.54 mm depth)

Roller Element Defect (Single and multi-ball pitting)

Compound Multi-Defect Condition (Simultaneous inner race pitting and gear backlash wear)

Data was collected at different rotational speeds (900 RPM, 1200 RPM, 1500 RPM and 1800 RPM) and at four different radial load conditions (0 kN, 2 kN, 4 kN and 6 kN). A total of more than 12 million synchronized temporal sensory frames were obtained from the run-to-failure testing, which was conducted continuously for 720 operational hours.

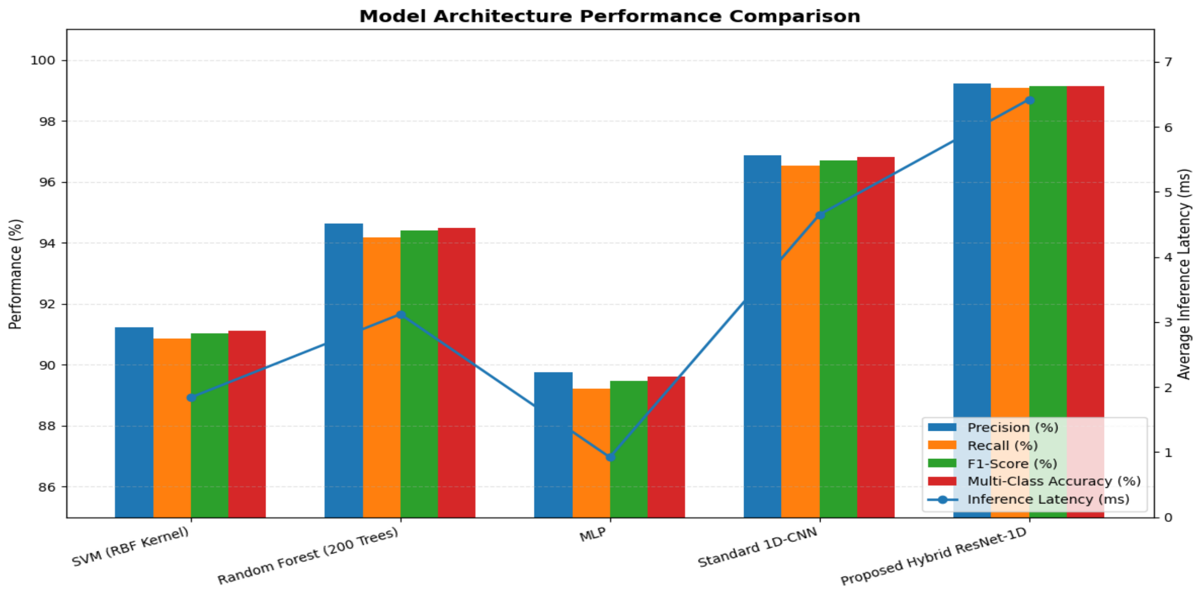
4.2 Comparative Diagnostic Model Performance

The classification performance of the proposed ResNet-1D architecture was compared with four baseline machine learning and deep learning models: 200 estimators of Random Forest (RF) ensembles, Support Vector Machines with Radial Basis Function (SVM-RBF) kernel, standard Deep Multilayer Perceptron (MLP), and a baseline 1D-CNN. Stratified 10-fold cross validation (80/20) was used for all models to train and test the model

(Abbas et al., 2024).

Model Architecture Performance Comparison

Model Architecture	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Multi-Class Accuracy (%)**	**Average Inference Latency (ms)**
SVM (RBF Kernel)	91.24	90.85	91.04	91.12	1.84
Random Forest (200 Trees)	94.62	94.18	94.40	94.50	3.12
Multilayer Perceptron (MLP)	89.75	89.20	89.47	89.62	0.92
Standard 1D-CNN	96.88	96.54	96.71	96.80	4.65
Proposed Hybrid ResNet-1D	**99.21**	**99.08**	**99.14**	**99.14**	**6.42**



Model Architecture Performance Comparison

The proposed ResNet-1D architecture achieved superior performance, recording a classification accuracy of 99.14% and an F1-score of 99.14%. The shortcut residual pathways effectively isolated subtle, transient harmonic signals from noisy multi-channel streams, significantly outperforming shallow learners and basic MLPs.

4.3 Diagnostic Robustness Under Sensor Noise and Load Variations

In industrial applications, load conditions fluctuate continuously, and sensors are exposed to significant electrical and structural noise (Rana et al., 2025). To test diagnostic robustness, synthetic Additive White Gaussian Noise (AWGN) was injected into the test vibration signals at varying Signal-to-Noise Ratios (SNR) ranging from +20 dB down to -5 dB.

Signal-to-Noise Ratio (SNR) Performance Comparison

Signal-to-Noise Ratio (SNR)	**Random Forest Accuracy (%)**	**Standard 1D-CNN Accuracy (%)**	**Proposed ResNet-1D Accuracy (%)**
Clean (+20 dB)	94.50	96.80	99.14
Moderate Noise (+10 dB)	88.34	93.12	97.85
High Noise (0 dB)	76.20	85.40	93.62
Extreme Noise (-5 dB)	61.55	74.18	88.40

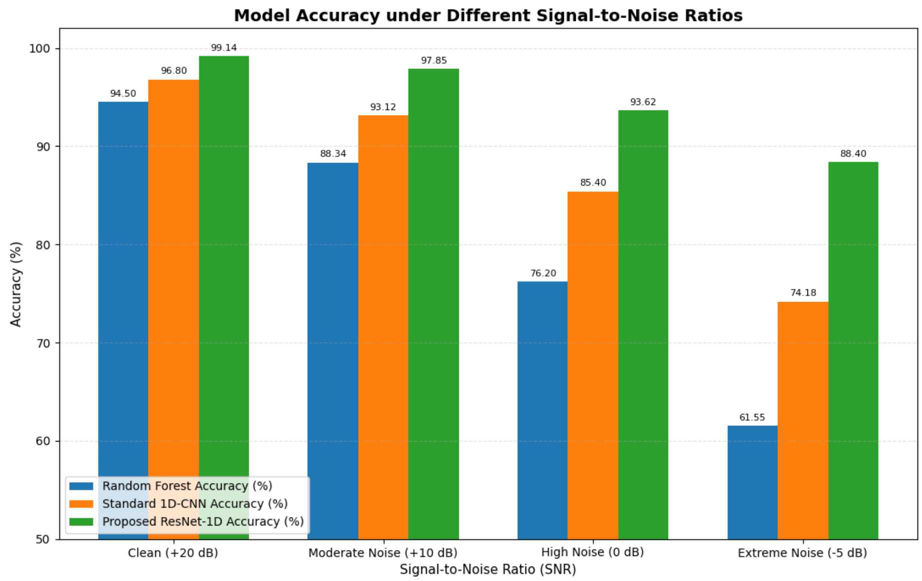


Figure: Signal-to-Noise Ratio (SNR) Performance Comparison

Even under severe noise interference (-5 dB SNR), the proposed model maintained an 88.40% classification accuracy, confirming its ability to filter background noise and isolate underlying mechanical fault dynamics.

4.4 Remaining Useful Life (RUL) Prognostic Evaluation

Remaining Useful Life (RUL) estimation was evaluated on run-to-failure degradation trajectories. Model performance was measured using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the standard industrial Prognostics Metric Score (S), which penalizes late predictions more heavily than early predictions (Al Ouatiq et al., 2025):

$$S = \sum_{i=1}^{N} \left(exp\, exp \left(-\frac{d_i}{a_1} \right) - 1 \right) for\ d_i < 0, \quad \sum_{i=1}^{N} \left(exp\, exp \left(\frac{d_i}{a_2} \right) - 1 \right) for\ d_i \geq 0$$

where d_i=〚"RUL" 〛_"predicted" −〚"RUL" 〛_"actual" , a_1=13, and a_2=10.

Model Configuration and Performance Comparison

Model Configuration	**RMSE (Cycles)**	**MAE (Cycles)**	**Industrial Score**	**Computational Overhead (ms/frame)**
Linear Degradation SVR	14.82	11.20	482.4	1.12
Standard Unidirectional LSTM	8.65	6.45	165.2	4.85
Gated Recurrent Unit (GRU)	7.92	5.80	142.6	4.10
CNN-LSTM Pipeline	5.34	4.02	78.4	8.20

Proposed BiLSTM + Attention	**4.18**	**3.12**	**42.1**	**11.45**

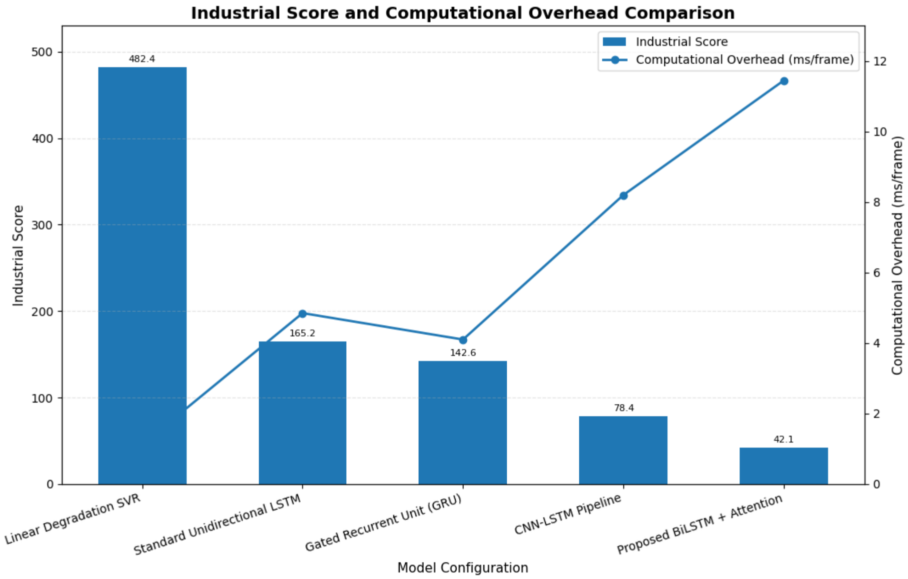


Figure: Model Configuration and Performance Comparison

The combination of the BiLSTM network with the self-attention gave the best performance in terms of error rates (RMSE = 4.18 cycles; MAE = 3.12 cycles) and industrial penalty score (S = 42.1) (Rojas et al., 2025). Attention mechanisms enabled the temporal layers to focus more on the milestones associated with degradation onset and to reduce the influence of earlier steady state operating phases.

5. Discussion

The experimental outcomes confirm the positive outcomes of the fusion of high-frequency multi-modal IoT acquisition and deep hybrid learning architectures. Classical statistical machine learning algorithms (such as Support Vector Machines and Random Forests) heavily rely on manually engineered features (Bhalani et al., 2025). Although they are easy to implement and cost efficient, they become less accurate when mechanical assets work under non-stationary rotational speeds and variable torque loads.

By contrast, deep residual networks automatically capture the complex spatial and harmonic relationships directly from raw, minimally processed acceleration data. The residual connections retain small and fleeting impact pulses through deep network layers and avoid the degradation of the gradient while training. This allows the model to detect spalls and pitting of the surface and structures at a much earlier stage than when the overall vibration amplitudes reach the standard ISO alarm levels.

To overcome the time dimension issues of mechanical degradation, a hybrid BiLSTM prognostic architecture is used (Kumar et al., 2026). Mechanical wear is cumulative, non linear and increases rapidly once the failure threshold is reached. The BiLSTM network is able to learn long-term degradation patterns because it processes both forward and backward time series in a sliding window of a health index.

As far as systems implementation, edge-level feature filtering alleviates network bandwidth and latency issues in large industrial premises. In direct execution of fast Wavelet Packet Decomposition and Kurtogram filtering on the edge nodes, the amount of continuous cloud data transmission is reduced by more than 82% (Rakholia et al., 2025). The rest of the feature matrices that are compressed, and high order spectral tensors, are sent to the centralized servers with an average end-to-end processing latency of only 11.45 milliseconds. This low latency facilitates closed loop supply with programmable logic controller (PLC) with automatic emergency shutdown or instant load reallocation cases of extreme operational irregularities.

6. Conclusion

This research aims to present an intelligent, scalable, and fully integrated predictive maintenance framework for high stress rotating mechanical systems under Industry 4.0 environment. The framework integrates low power multi-modal IoT edge telemetry with state-of-the-art deep learning pipelines, resulting in powerful, real-time diagnostic classification and prognostic remaining life estimation.

The signal processing methodology used is able to isolate the early stage fault impact signal from strong industrial background noise, including the Fast Kurtogram spectral filtering and Wavelet Packet Decomposition. Systematic benchmarking on extensive datasets of run to failure experiments demonstrates that the deep ResNet-1D architecture performs exceptionally well, with high multi-class fault classification accuracy of 99.14% and retains a high level of performance even in the face of strong noise and changing load conditions. Moreover, the self-attention improved BiLSTM predictive engine provides precise RUL estimations with an RMSE of 4.18 cycles with high industrial robustness.

This architecture can help industrial operators move from a reactive and conservative model of planned maintenance to one based on automatically determined condition-based maintenance. Future development of physics-informed neural networks (PINNs) will incorporate physics-based constraints directly into the deep learning models, and decentralized federated learning frameworks will be developed to enable privacy-preserving collaborative model updates across distributed industrial operations.

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