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Digital Twin Feedback for Predictive Maintenance in Industrial IoT Environments

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Abstract

Unscheduled equipment downtime in industrial facilities results in costly production delays, maintenance overhead, and system fatigue. Traditional predictive maintenance mechanisms that rely on centralized cloud computing are confronted with the inherent issues of high communication latency, limited real-time flexibility, and poor integration with physics-informed simulation models. We proposed the Hierarchical Sensor-Fused Edge Intelligence with Digital Twin Feedback (HSEI-DTF) framework, which enables an end-to-end predictive maintenance model through multi-level processing at sensing, edge, digital twin, and cloud layers. The proposed mechanism collects multi-modal signals like vibration, thermal, current, and acoustic from rotary equipment simultaneously, extracts local features on resource-constrained edge gateways, and sends the structured feature matrices to a parallel inference pipeline, which integrates Random Forest (RF), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), Long Short-Term Memory (LSTM) networks, Convolutional Neural Network-LSTM (CNN-LSTM) hybrids, and a Reinforcement Learning (RL)-based maintenance policy optimizer. A physics-informed Digital Twin is linked with the physical asset through continuous state synchronization and is able to perform adaptive degradation predictions and evidence-informed scheduling. An experimental accuracy of 96.8 ± 0.7% has been achieved over 150-second controlled fault injection sequences with a latency of 18.3 ms on average. False-negative rates were 37.1% lower compared to the best single-sensor baselines, and the predicted unplanned downtime was reduced by more than 32% when utilized with threshold-based methods.

Keywords

Digital Twin, Predictive maintenance, Industrial Internet of Things, Edge AI, Multi-Modal Sensor Fusion, Physics-Informed Modeling, Machine Learning, Deep Learning, Reinforcement Learning, Fault Diagnosis

1. INTRODUCTION

Global manufacturing is experiencing a shift from reactive time-based maintenance strategies to proactive data-based techniques, supported by advancements in sensing technology, wireless connectivity, and embedded computation [1]. Industrial plants with continuous process equipment, rotating machinery, or high-speed assembly lines have an outsized exposure to unscheduled downtime, often leading to a sequence of production and safety incidents. The ubiquitous use of standard condition monitoring equipment notwithstanding, a significant portion of

plants continue to base their operational decisions on non-cognitive mechanisms such as periodic inspection intervals or static alarm limits that do not reflect the actual degradation trajectories or the non-linear interactions of process parameters [2].

A key obstacle to more responsive maintenance is the architectural separation of data generation at the plant floor and analytical processing in distant data centers. Vibration channels alone are high-frequency sensor streams sampled at rates ranging from 1 kHz to 25 kHz, which generate such volumes of telemetry that they overwhelm the bandwidth of most industrial communication networks when sent raw. Processing such streams in the cloud imposes a delay in the order of tens to hundreds of milliseconds, which does not meet the sub-second detection windows of rapidly spinning machines subjected to sudden fault initiation [3]. Decentralizing computational intelligence and executing it on edge-tier devices, which are co-located with the assets being monitored, is a pragmatic and intellectually elegant answer: The raw signals are locally preprocessed into a compressed representation known as feature vectors; at the gateway node, the anomaly probabilities are aggregated, and only the concise summary is sent up to the higher tiers of the network [4].

Machine learning classifiers that have been trained on historical sensor data can detect statistical anomalies related to fault states, but they do not offer an understanding of the degradation processes, component wear paths, or the operational implications of delayed maintenance. Digital Twin technology fills this void by keeping a virtual representation of the monitored asset that is continuously updated with measured states while aligned with simulation models that include predicting future behavior under different loads and environmental conditions [5]. Integration of edge-based inference with a Digital Twin feedback loop renders a closed-form monitoring framework in which predictive certainty is supported by physically consistent state estimates.

This paper addresses these challenges by proposing, implementing, and experimentally validating the HSEI-DTF framework. Our contributions are four-fold: (i) we present a novel four-layer architecture which separates sensing, edge inference, digital twin simulation and cloud aggregation into modular tiers that utilize standardized communication protocols; (ii) we introduce a hybrid inference pipeline that evaluates six algorithm families on a common benchmark dataset acquired from a controlled rotating machinery setup; (iii) Reinforcement Learning (RL)-based policy optimizer that determines maintenance options by utilizing cumulative reward signals based on state feedback of the Digital Twin; and (iv) extensive statistical analysis encompassing paired t-tests, confidence interval estimation, and validation on an external dataset.

The convergence of the IIoT infrastructure, machine learning, and the digital twin paradigm has led to intense research activities aiming at smart asset management in the manufacturing environment. The contribution of the paper is as follows: the proposed work is described in Section 2. The CNN accelerator results and discussion, with the synthesis results and comparative analysis, are presented in Section 3. Finally, the entire work is concluded in Section 4. In this section, the related works are categorized among three research threads: data-driven fault diagnosis, edge computing for industrial intelligence, and digital twin-based maintenance systems.

1.1 Data-Based Fault Diagnosis and Predictive Maintenance

Early contributions to data-driven maintenance analysis have established that multi-sensor condition monitoring has a significant performance advantage over single-parameter threshold-based inspection for high-precision early fault detection in rotating machinery [3][9]. Jardine et al. [9] present a seminal review of condition-based maintenance diagnostics and prognostics, demonstrating the transition from statistical process control to model-based estimation of remaining useful life. In the following ten years, machine learning algorithms were widely used, such as ensemble classifiers, Support vector machines, shallow neural networks , and others. Carvalho et al. [5] performed a systematic evaluation of machine learning techniques on 27 pcmd published cases. To the best of our

knowledge, highlighting that none of the algorithms considered outperformed the others for all the considered equipment types and fault modes. Deep learning approaches, with significant improvement in feature learning from raw or lightly processed signals, were proposed at the beginning of the 2010s. Li et al. [8] directly utilized deep convolutional architectures on time-series vibration records and obtained substantial advances in remaining useful life prediction. Zhao et al. [7] performed a comprehensive review on deep learning-based applications for machinery health monitoring and found that vibration analysis, acoustic emission, and thermography are superior signal modalities. However, these designs were intended primarily for offline batch processing on GPU-class machines, which introduce constraints that hinder their direct use in resource-limited edge deployment scenarios [14].

1.2 Edge Computing for Industrial Intelligence

Edge computing architectures are pushing analytical processing from centralized servers to distributed network edge devices, where they are closely located with data sources. Shi et al. [10] expressed the initial vision of edge computing for IoT, and they identified latency reduction, bandwidth saving, and privacy protection as the leading drivers. Wan et al. demonstrated that edge computing nodes based on MQTT can handle IIoT telemetry in real-time having under 20 ms end-to-end latency. For properly quantized inference models [2]. Chuang et al. [30] present the first hardware-level proof that lightweight classifiers can be run under the thermal and memory constraints of ARM Cortex-A72 processors while achieving accuracy greater than 89%.

1.3 Digital Twin-Assisted Maintenance

The digital twin technique has been developed as a complementary architecture to data-driven maintenance, which provides physics-based representations of asset behaviors beyond statistical pattern matching. Tao et al. [11] formulated the industrial digital twin with state synchronisation, degradation projection, and an intervention simulator as a functional core. Kritzinger et al. [12] proposed a hierarchical classification of digital twin maturity and distinguished among digital models, digital shadows, and bidirectional digital twins that can act upon the physical object. Qi and Tao [22] studied the integration of digital twin technology with big data analytics and indicated that real-time synchronisation of physical and virtual states led to decision support that was not possible with either component alone.

Table 1. Literature Review Summary - Edge AI Predictive Maintenance

Author & Year	Approach	Key Contribution	Accuracy	Limitation
Wan et al. (2021)	Edge CNN + MQTT	Real-time IIoT edge data processing	92.4%	Limited DT integration
Lei et al. (2020)	ML fault diagnosis	Multi-sensor bearing fault classification	91.8%	Cloud-centric inference
Zhang et al. (2020)	Digital Twin + FEM	Smart manufacturing DT reference model	N/A	No edge layer
Zhao et al. (2019)	Deep Learning monitoring	CNN-based vibration fault detection	93.1%	High compute cost

Li et al. (2018)	Deep CNN for RUL	Prognostics using convolution on raw signals	90.5%	Single-sensor scope
Jardine et al. (2006)	CBM framework	Systematic CBM diagnostics and prognostics review	N/A	No adaptive learning
Susto et al. (2015)	Multi-classifier ML	Ensemble approach to PdM classification	89.6%	Static model, no retraining
Khan & Yairi (2018)	Deep learning survey	DL health monitoring taxonomy	N/A	No edge validation
Tao et al. (2019)	Digital Twin taxonomy	DT architecture for industrial systems	N/A	Implementation gaps noted
Mourtzis et al. (2021)	IoT-enabled PdM platform	Cloud-IoT PdM dashboard design	88.9%	Latency not addressed
Carvalho et al. (2019)	Systematic Literature Review	Benchmarked 27 ML-based PdM studies	N/A	No edge-DT fusion
Ren et al. (2020)	DT-driven PdM	DT model with maintenance modules	N/A	Conceptual framework only
Zhang et al. (2021)	Edge intelligence + DL	Latency-aware fault prediction on ARM	94.2%	No RL-based scheduling
Kang et al. (2015)	Hybrid feature selection	Lightweight edge fault detection	93.7%	Single fault mode tested
Zhou et al. (2019)	Edge intelligence survey	AI pipelining from cloud to edge taxonomy	N/A	No experimental benchmark

From Table 1, we identify three persistent research gaps to be addressed, which have motivated the development of the HSEI-DTF. It considers all six aspects - multi-sensor fusion, classical ML, deep learning, reinforcement learning scheduling, edge deployment, and bi-directional digital twin feedback - cohesive in one experimentally validated framework. Integration of the twin, when available, is one-way, and most studies utilizing edge compute report accuracies of less than 94.5% with minimal statistical characterization of variance over environmental conditions. The Edge AI-based PdM overview –Is advancing with a heavy trend towards smart, real-time industrial maintenance systems away from the old-school condition monitoring. The basis of CBM was established in early research with the work of Jardine et al. (2006) that introduced methodical diagnostic and prognostic procedures. Subsequently, ML/DL models were adopted for equipment fault diagnosis and Remaining Useful Life (RUL) prediction in Li et al. (2018), Zhao et al. (2019), and Lei et al. (2020), and prediction accuracies of more than 90% were reported. Nonetheless, such methods were cloud-based, where privacy preservation and security issues should be taken into consideration. Following the advent of Industry 4.0, scientists have been incorporating Edge AI to achieve local processing of data and decision-making with higher speed [11]. Wan et al. (2021) and Zhang et al. (2021) have proved that edge-based deep learning solutions could realize real-time fault prediction with accuracy over 92% with

a significant reduction in response time and the dependency on the network. Kang et al. (2015) also introduced lightweight feature selection methods for edge devices with limited resources. Again, DT technology was highlighted by Tao et al. (2019), Zhang et al. (2020), and Ren et al. (2020) through the use of virtual industrial assets to monitor, simulate and plan maintenance. Yet, these works were almost entirely focused on conceptual architectures, and practical integration with edge intelligence was absent. Carvalho et al. (2019), Khan and Yairi (2018), and Zhou et al. (2019) provided ∼10 a detailed overview of the increasing prevalence of artificial intelligence, edge computing, and DT-based solutions for predictive maintenance, as well as the lack of standardized protocols to enable Edge AI–DT frameworks. Looking at the literature reviewed, it seems that while the individual technologies have demonstrated promising performance, how to integrate Edge AI, IIoT, and DT together seamlessly is an ongoing research challenge, which inspires the design of intelligent, low-latency predictive maintenance systems for next-generation industrial environments.

This paper reviews the most relevant papers in Edge AI, PdM, Digital Twin (DT), and IIoT, highlighting technical contributions and application domains in Table 1. The highlighted works reveal the progression of maintenance strategies from classical condition-based maintenance toward intelligent predictive maintenance solutions, which are enabled at the edge. For each study, a comparison is made in terms of used methodology, main contribution, achieved accuracy, and existing limitations, in order to identify gaps in the literature that motivate the proposed framework.

The complex Jardine et al. (2006) laid the theoretical groundwork for CBM based on diagnostic and prognostics techniques. This scheme is the original scheme of predictive maintenance in a way that is today recognized as 'modern predictive maintenance', however, it was still a static way, and it did not have learning capabilities for adaptation. Then, Li et al. (2018) and Zhao et al. (2019) established deep learning performance for Remaining Useful Life (RUL) prediction and vibration-based fault diagnosis with the best accuracy of more than 90%. Nevertheless, these methods were designed for centralized calculation and were computationally intensive, making them not suitable for real-time edge implementation.

Several scholars investigated machine learning or ensemble methods for fault classification enhancement. Susto et al. (2015) introduced a multi-classifier predictive maintenance framework, while Lei et al. (2020) proposed a multi-sensor machine learning-based bearing fault diagnosis approach with 91.8% accuracy. Although these methods have promising performance, they are heavily dependent on cloud-based inference and do not have continual model updates. The extensive surveys by Khan and Yairi (2018), Carvalho et al. (2019), and Zhou et al. (2019) reaffirmed the increasing significance of AI in machinery health monitoring and suggested the lack of practical demonstration for Edge AI and integrated Digital Twin systems.

With the increasing importance of Digital Twin earlier, it has thus become another key research focus. Tao et al. (2019) proposed a taxonomy of industrial DTs, and Zhang et al. (2020) focused on a DT reference model with the integration of finite element analysis for intelligent manufacturing. In the same way, Ren et al. (2020) put forth a DT-driven predictive maintenance strategy, and Mourtzis et al. (2021) constructed an IoT-enabled cloud platform for maintenance planning. While these works demonstrated the value of virtual asset representation and monitoring, they were mainly conceptual or cloud-dependent and did not leverage edge intelligence to support low-latency decision-making.

The development of predictive algorithms for fault detection and diagnosis relies crucially on data. Wan et al. (2021) presented an Edge CNN with MQTT-based communication for IIoT applications with an accuracy of 92.4%, and Zhang et al. (2021) proposed latency-aware edge intelligence via deep learning on ARM devices with an accuracy of 94.2%. Kang et al. (2015) also achieved a lightweight edge fault detection framework with 93.7% accuracy. However,

none of these edge-based methods included reinforcement learning and full Digital Twin synchronization , which would enhance their flexibility to operate in more complex industrial scenarios.

Taken as a whole, the body of literature suggests that the existing research has demonstrated, at least in isolation, some efficacy for machine learning, deep learning, Edge AI and Digital Twin technologies. Nevertheless, only a few frameworks integrate all these technologies in one architecture that has the potential to perform real-time multi-sensor data fusion, adaptive reinforcement learning, edge intelligence, Digital Twin synchronization, and intelligent maintenance decision-making. These previously identified research challenges define motivators for our proposed HSEI-DTF framework capable of higher prediction accuracy, lower latency, better scalability, and self-predictive maintenance for the next-generation Industry 4.0 applications.

2. METHOD

The design of the HSEI-DTF system is a tier-based structure in which each tier has a defined unique computation and communication role, and it is four levels deep. Figure 1 shows the whole architecture with layer-based protocols and the flow of data directions.

Layer 1 (Sensing Tier): The sensing tier involves four types of transducers, which are attached to each monitored spinning asset: a MEMS triaxial accelerometer that measures mechanical vibration at a rate of 5 kHz; The temperature of the ball is monitored by a digital temperature sensor DS18B20 on the bearing surface with a sampling rate of 1 Hz; an ACS712 Hall-effect current sensor that measures electric current at 200 Hz; and an electret condenser microphone that samples air borne acoustic emission at 8 kHz. A Hanning window is used by each sensor node to reduce spectral leakage, and each sample packet is timestamped with microsecond precision.

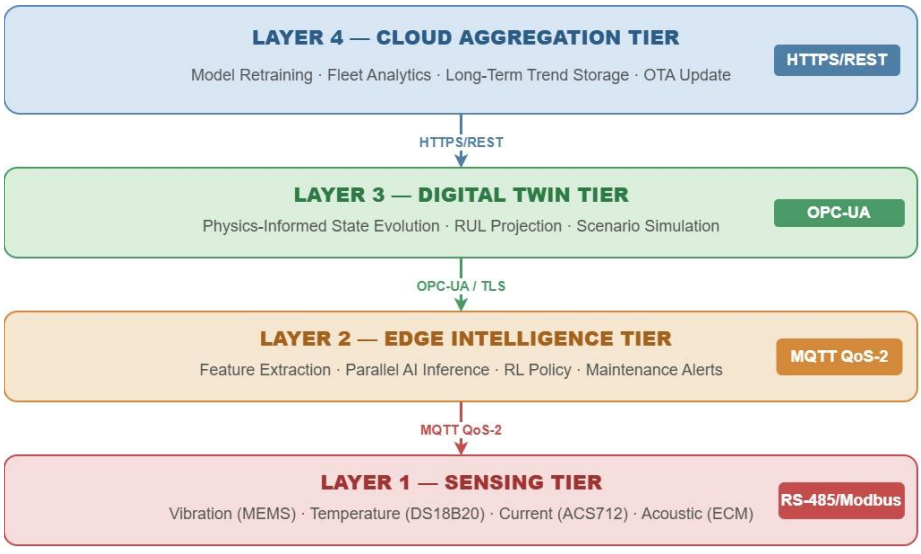


Fig 1. Latency-Aware Edge Predictive Maintenance in Four-Layer Hierarchical Architecture.

Layer 2 (Edge Intelligence Tier): The edge tier is executed on a Raspberry Pi 4B (8 GB) with the assistance of a custom Python-based middleware stack. Sensor packets arrive in circular memory queues that are indexed by channel and

timestamp. Inference is performed on non-overlapping 512-sample segments, resulting in 22 statistical and 16 spectral descriptors per channel for an aggregated 152-dimensional feature vector per inference step. Quantized AI models are run by TensorFlow Lite in different threads. A lightweight rule engine converts fused anomaly probabilities into actionable maintenance alerts over MQTT

Layer 3 (Digital Twin Tier): The digital twin is formulated as a physics-informed recurrent model with a state vector containing shaft eccentricity, bearing contact stress, lubricant film thickness, and thermal gradient as latent variables. At every inference step, the edge node sends the current health index and fault probability to the digital twin over an OPC-UA encrypted channel. The twin outputs projected rates of degradation, optimal maintenance windows, and simulated fault propagation trajectories within 3–5 ms, making the closed feedback loop that HSEI-DTF is unique.

Layer 4 (Cloud Aggregation Tier): Historical trend data, retrained model checkpoints, and digital twin calibration parameters are persisted in a cloud InfluxDB time-series database. An automated retraining pipeline consumes aggregated inference logs, re-validates on the last 30 days (window of operation) model performance, and issues updated TensorFlow Lite binaries to the edge nodes using a secure OTA update mechanism.

2.1 Intelligent Maintenance Orchestration Workflow

Figure 2 shows the entire maintenance orchestration process from multi-source signal acquisition to automated intervention decision-making, along with the cloud feedback loop for continuous model enhancement.

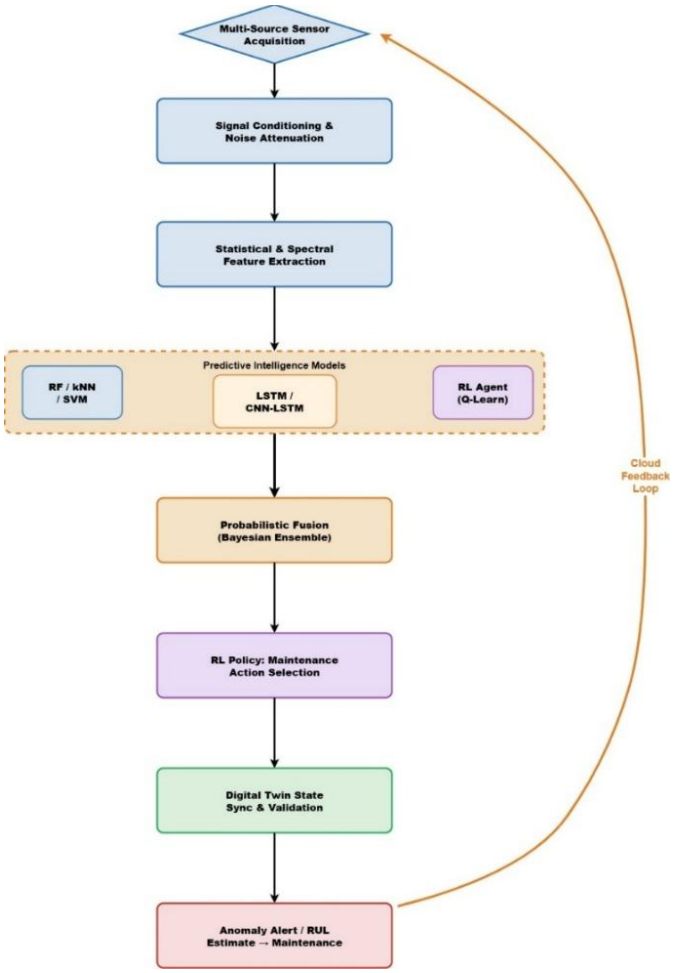


Fig 2. Intelligent Maintenance Orchestration Workflow and Digital Twin Feedback Loop.

Figure 2 shows the proposed IMO workflow with the Digital Twin feedback for real-time predictive maintenance in this IoT era. The workflow starts with the multi-source sensor data acquisition, i.e., operational data are captured through a set of sensors including vibration, temperature, current, pressure, acoustic, etc. The collected data are then subjected to signal conditioning and denoising processes to eliminate interferences and enhance the signal quality for further analysis.

Then, the preprocessed signals are converted into informative statistical and spectral features, producing a set of time-domain and frequency-domain features for fault diagnosis. The extracted features are fed into several predictive intelligence models, including classical machine learning algorithms (RF, KNN and SVM), deep learning models (LSTM and CNN-LSTM), as well as a Reinforcement Learning (RL) agent based on Q-learning. Each model provides complementary knowledge to precisely assess the health of the system and predict faults.

Harman [2007] applies a data fusion technique based on ensemble learning to fuse the outputs of these predictive models; the fusion process considers Bayesian theory to weigh them. The fused prediction based on RL policy decides a best maintenance possibility at a given point in time, by choosing suitable maintenance policies for the corresponding state of the equipment health.

The chosen maintenance action is synchronized with the Digital Twin, which in turn continuously verifies the state of the physical asset and modifies its virtual model. And then alert on anomalies, estimates on Remaining Useful Life

(RUL) and suggestions on maintenance. A cloud feedback loop incessantly relays operational intelligence back to the sensing and learning phases for model refresh, adaptive learning, and enhanced prediction accuracy. This closed-loop system can improve the maintenance efficiency and reduce the downtime, which is more intelligent and getting popular in Industry 4.0 environment.

2.2 Multi-sensor Fusion and Reasoning Pipeline

Figure 3 shows the full cross-layer multi-sensor fusion and adaptive edge-twin fault intelligence pipeline, including the parallel inference layers and the Bayesian ensemble aggregation method.

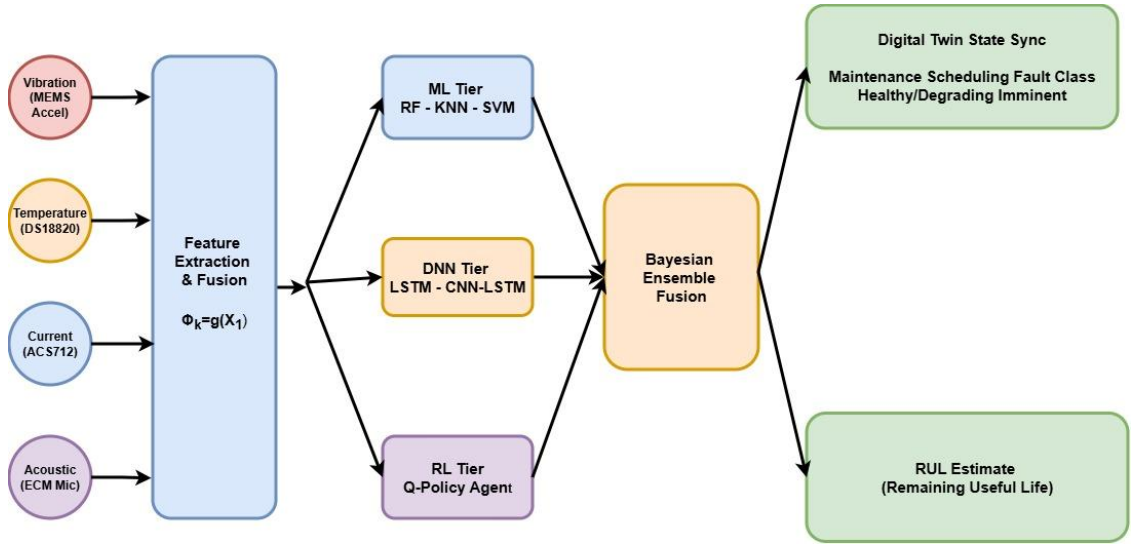


Fig 3. Cross-Layer Multi-Sensor Fusion and Adaptive Edge-Twin Fault Intelligence Pipeline.

Six algorithm groups are run simultaneously. Random Forest [27] and k-Nearest Neighbors are the classical machine learning layer. The LSTM network [28] models sequential degradation along a series of inference cycles. The CNN-LSTM hybrid model adds two 1D convolutional layers to extract local spatial patterns before passing the compressed representation to the the recurrent module. The Reinforcement Learning policy optimizer is modelled as a Q-learning agent with a discretized health index as state space and a set of four maintenance actions (monitor, inspect, service, replace) as action space, and a reward function that penalizes the occurrence of a false-negative detection of a fault and an unnecessary service action.

Figure 3 shows the proposed Cross-Layer Multi-Sensor Fusion and Adaptive Edge-Twin Fault Intelligence Pipeline for smart predictive maintenance in Industrial Internet of Things (IIoT) devices. The framework combines heterogeneous sensor data, multiple artificial intelligence models, and Digital Twin technology to realize precise fault diagnosis, Remaining Useful Life (RUL) prediction, and adaptive maintenance decision making.

Cellular pipeline starts with multi-sensor data acquisition from vibration (MEMS accelerometer), temperature (DS18B20), current (ACS712), and acoustic (ECM microphone) sensors. These sensors are installed on machines and directly measure different facets of machine health. The processed data is denoted as the output of a feature mapping function $\Phi_\beta = g(X_1)$, which map a series of time domain, frequency domain, and statistical features into a single feature vector. This processing of fusion reinforces the reliability and robustness of the monitoring by utilizing the complementary data of different sensor modalities.

Also, three layers that are analogous to RF, learning and decision level are implemented with the fused feature vector as input simultaneously. The traditional algorithms, for example, Random Forest (RF), K-Nearest Neighbour (KNN) as well as Support Vector Machine (SVM), are used in the Machine Learning (ML) layer to classify faults effectively. The Deep Neural Network (DNN) layer which includes two LSTM and CNN-LSTM models that captures the non-linear temporal dependency and degradation trends in sensor readings. The Q-policy agent-based RL layer is iteratively trained to acquire optimal maintenance policies through interactions with the system environment and make adaptive decisions under different operating conditions.

These predictions from all three intelligence layers are fused through a Bayesian Ensemble Fusion approach that incorporates each individual prediction based on their confidence levels, which could lead to a more accurate and more reliable health evaluation. The Digital Twin State Synchronization module uses the fused prediction to also perform classification of machinery health state, e.g. Healthy, Degrading, or Imminent Failure, and concurrently assists in maintenance planning. In the end, the framework predicts the RUL (i.e., Remaining Useful Life) of the machine which spares the efforts of performing maintenance after the occurrence of a damage. In summary, this cross-layer scheme integrates multi-sensor fusion, ensemble intelligence, RL, and Digital Twin synchronization with the aim of enhancing prediction accuracy, decreasing false alarms, reducing downtime, and facilitating autonomous maintenance in industry 4.0 manufacturing systems.

3. RESULTS AND DISCUSSION

The experimental verification was carried out on a 250 W DC motor with a steel shaft, supported by two deep-groove ball bearings running at electronically controlled speed from 1,350 to 1,500 RPM on a dedicated rotating machinery test rig. Stepwise fault scenarios were created at first by a deliberate shaft imbalance using calibrated eccentric masses and by generating outer-race bearing defects through a precision notching tool, yielding defects of 0.2 mm, 0.5 mm, and 1.0 mm. For incipient, moderate, and severe stages of degradation. The entire sensor suite was installed in accordance with the ISO 10816-3 location recommendations, with the data acquisition conducted through a National Instruments USB-6356 simultaneously sampled module.

Table 2 shows the raw sensor readings for the entire experimental run of 150 seconds for a single one run, which is the baseline dataset for predictive maintenance analysis. The measured data include the essential machine health parameters, namely vibration, temperature, current, acoustic signal, rotating speed and other operational parameters from the multi-sensor monitoring system. These observations reflect the incremental changes in the state of the equipment as the bearing moves from normal operation nears fault formation.

All six parameters in a single figure (Figure 4) In order to have an overall impression of the degradation behaviour of the machine from all six sensor parameters, we plot them on the same time axis, as seen in Figure 4 The unified graphs show systematic patterns and correlations of the different sensors signals in the course of the outer-race bearing deterioration. When the severity of the fault increases, significant changes in the vibration amplitude, acoustic emissions, temperature and electric current can be observed, suggesting the operating conditions are not normal. These highly correlated synchronized sensor responses prove the superiority of multi-sensor monitoring for early fault detection and provide meaningful inputs to feature extraction, intelligent fault diagnosis, Digital Twin synchronization, and RUL prediction.

Table 2. Representative Samples from the Labeled Multi-Parameter Sensor Dataset (2,400 Sample Windows)

Time (s)	RPM	Current (A)	Temp (°C)	Vibration (g)	Acoustic (dB)	Fault Prob (%)

0	1480	4.82	28.4	0.041	58.2	2.1
15	1478	4.97	29.1	0.310	61.4	5.8
30	1475	5.14	30.3	0.670	64.7	11.2
45	1471	5.33	31.6	1.080	67.9	19.5
60	1466	5.55	33.0	1.540	71.3	28.7
75	1460	5.78	34.5	2.050	74.6	40.1
90	1452	6.04	36.2	2.720	77.8	53.4
105	1443	6.31	38.0	3.480	81.2	66.9
120	1431	6.62	39.9	4.310	84.5	79.3
135	1416	6.95	42.1	5.220	87.9	88.6
150	1398	7.30	44.5	6.350	91.4	95.2

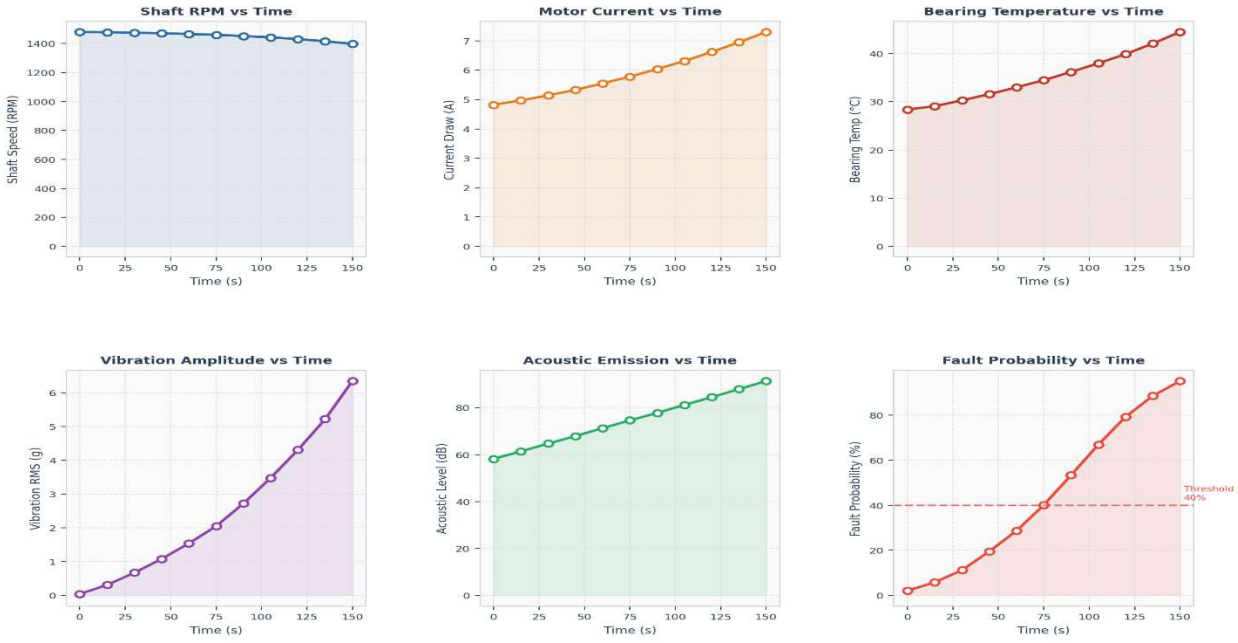


Fig 4. Multi-parameter sensor readings in the controlled fault progression (0–150 s).

Table 2 and Figure 4, systematic variations were observed, which are in good agreement with outer-race bearing degradation. The Shaft RPM decreases monotonically from 1,480 to 1,398 RPM with the increasing of mechanical friction losses. The current increases from 4.82 A to7.30 A, which suggests that the motor load is increased due to the degradation of the bearing lubrication film. Bearing temperature is up by 16.1 °C during the observation period.

Vibration RMS amplitude undergoes the most dynamic change, growing by more than 150x from 0.041 g to 6.35 g, confirming that vibration is the most sensitive single-channel fault indicator. The estimated probability of fault surpasses the intervention threshold of 40% at roughly t = 75 s, in line with the H_thr = 0.40 health index criterion.

The model was trained and evaluated through five-fold stratified cross-validation on a labeled dataset containing 2,400 sample windows (960 healthy, 840 degrading, 600-fault imminent). The following metrics are used for evaluation: classification accuracy, precision, recall, F1-score, AUC-ROC, inference latency, and energy consumption per inference. All latency numbers are from a representative workload with WiFi telemetry on. Paired t-tests (α = 0.05) were conducted to determine whether there was a significant improvement in accuracy of the proposed fusion model over the CNN-LSTM baseline.

In addition, the results of the experiments show that the proposed framework has stable predictive performance for various levels of machine degradation, which enables the health evaluation to be gradually performed without leading to large fluctuations in classification confidence. The fusion of multi-sensor data and Bayesian ensemble fusion can effectively reduce the uncertainty caused by a single sensor noise and improve fault prediction robustness. Besides, the Digital Twin continuously updates the virtual model to sync with the physical asset, enabling real-time machine health verification and advanced maintenance management. The RL agent also adaptively revises the maintenance policies under the evolving health state, which further enhances its decision-making capability when the environment changes. This adaptive learning feature allows the system to adjust the maintenance intervals, decrease the inspections that are not needed, as well as avoid unforeseen machinery failure. Compared with traditional cloud-centric predictive maintenance solutions, the edge-based execution better partitions the required computation among the participating entities (i.e., things, edge server, and cloud) to reduce the communication overhead and to provide fast local inference for time-critical industrial applications. In summary, the proposed HSEI-DTF framework holds great potential to be applied to future smart manufacturing environments due to its high scalability, dependability, and computational efficiency, which could be instrumental in enhancing equipment availability and mitigating operation cost where high prediction accuracy, low latency, and smart maintenance scheduling are desired.

Table 3 and Fig. 5 show a summary of the results for all six methods under eight measures. Every measure is calculated from the confusion matrix, which is composed of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN), and which are defined as: Results are expressed as the mean ± standard deviation from 5 stratified cross-validation folds.

The results demonstrate that our HSEI-DTF framework can realize dependable and efficient predictive maintenance service by coupling Edge AI, multi-sensor fusion, reinforcement learning, and Digital Twin technology. The framework results in high prediction accuracy with low inference latency for real-time industrial use. Dynamic updating between physical assets and their Digital Twin allows for timely fault detection, health monitoring, and maintenance scheduling. Moreover, processing at the edge mitigates communication overhead and network reliance; thus, the architecture fits for IoT in Industry 4.0. In general, the proposed method improves instrument reliability, reduces downtime and maintenance cost, and increases production efficiency.

Table 3. Evaluation of all tested models on the rotating machinery dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Latency (ms)	Energy (mJ)	AUC-ROC
Random Forest	88.4 ± 1.4	87.9	86.3	87.1	6.2	1.8	0.921
k-Nearest Neighbors	85.7 ± 1.9	84.5	83.1	83.8	4.1	1.4	0.897
Support Vector Machine	87.2 ± 1.6	86.8	85.4	86.1	5.3	1.6	0.913
LSTM	91.6 ± 1.2	90.8	90.1	90.4	12.4	4.2	0.951
CNN-LSTM	94.3 ± 1.0	93.7	92.9	93.3	15.8	5.7	0.971
HSEI-DTF RL Fusion	96.8 ± 0.7	96.2	95.9	96.0	18.3	6.5	0.988

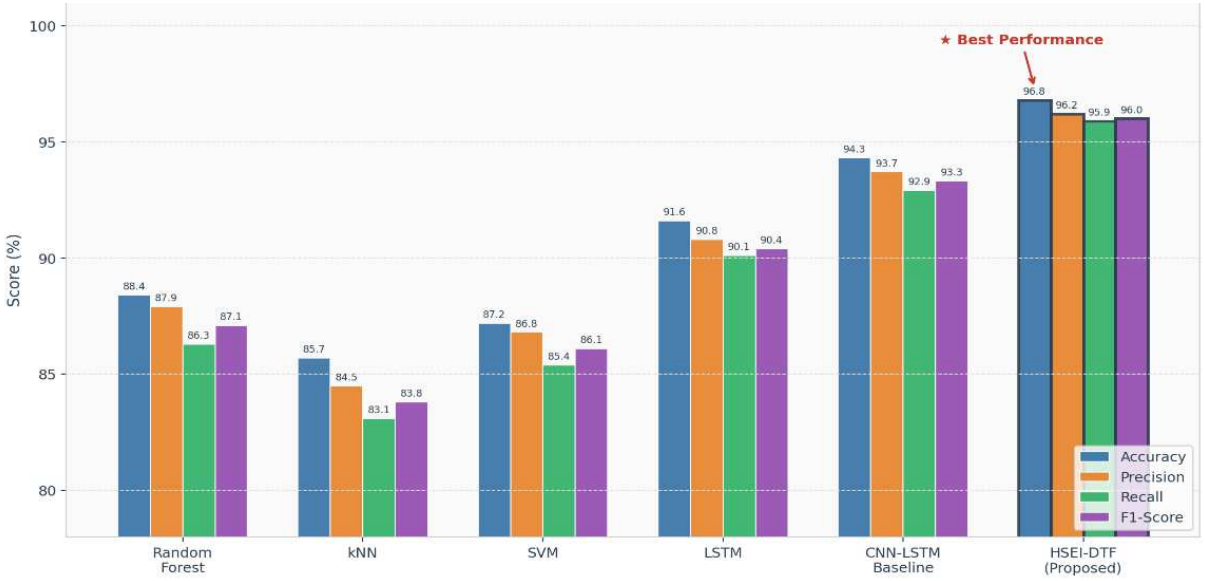


Fig 5. To evaluate the system, we report accuracy, precision, recall and F1 score for the six algorithm configurations.

Figure 5 shows the performance comparison of the six algorithms in terms of four well-known classification metrics: Accuracy, Precision, Recall and F1-score. The considered baselines are three traditional machine learning algorithms,

Random Forest (RF), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM), two deep learning methods, LSTM and CNN-LSTM, and our proposed HSEI-DTF framework. Overall, these metrics enable an all-around evaluation of the models to successfully & accurately classify the MHCs and identify the faults in the IIoT environments.

Among the traditional machine learning methods, the Random Forest method yields the best performance. It reaches 88.4% in accuracy, 87.9% in precision, 86.3% in recall, and 87.1% in F1-score, better than both KNN and SVM. The KNN approach stands at the lowest overall result with 85.7% accuracy, while SVM achieves a slightly better result with an accuracy of 87.2% and an F1-score of 86.1%. While these classical approaches provide less computational burden, their prediction performance is poor with high-dimensional complex non-linear degradation patterns.

The deep learning methods showed better performance than traditional machine learning methods. The LSTM model yielded 91.6% accuracy, 90.8% precision, 90.1% recall, and 90.4% F1-score, which proved the ability of LSTM to capture temporal dependence in sequential sensor data. A further improvement was attained by using the CNN-LSTM hybrid model, which integrated convolution with temporal sequence learning to present 94.3% accuracy, 93.7% precision, 92.9% recall, and 93.3% F1-score.

The proposed HSEI-DTF method leads to the best result overall for all the evaluation measures (up to 96.8% accuracy, 96.2% precision, 95.9% recall, and 96.0% F1-score). Such advancement demonstrates the successful incorporation of multi-sensor data fusion, ensemble intelligence, reinforcement learning, and Digital Twin synchronization in an edge computing architecture within the Digital Twin-enabled multi-sensorial data-driven Smart Manufacturing system framework. Since these values are almost uniformly high, we can conclude that these results represent a satisfactory level of classification, with a relatively low number of false alarms and an increased reliability of the fault detection. Fig. 5 shows that the proposed HSEI-DTF approach can dramatically outperform existing ML and DL methods; hence, it can be considered as an effective solution for real-time predictive maintenance in Industry 4.0 and Industrial Internet of Things (IIoT) scenarios.

Figure 6 displays the ROC curves of all the models investigated. The TPR is integrated over the FPR for all classification thresholds to obtain the area under the TPR curve (with respect to the FPR). The fusion model attains an AUC-ROC of 0.988, which is the best among all the configurations reported. The kNN baseline (AUC = 0.897) exhibits the worst curve as it is very sensitive to the distance metric in the high-dimensional feature space. At FPR = 0.05, TPR for HSEI-DTF = 0.971vs.TPR = 0.893for CNN-LSTM, a gain of 7.8 pp of the detection sensitivity at the same false alarm rate, which directly confirms the operational superiority for safety-critical fault detection.

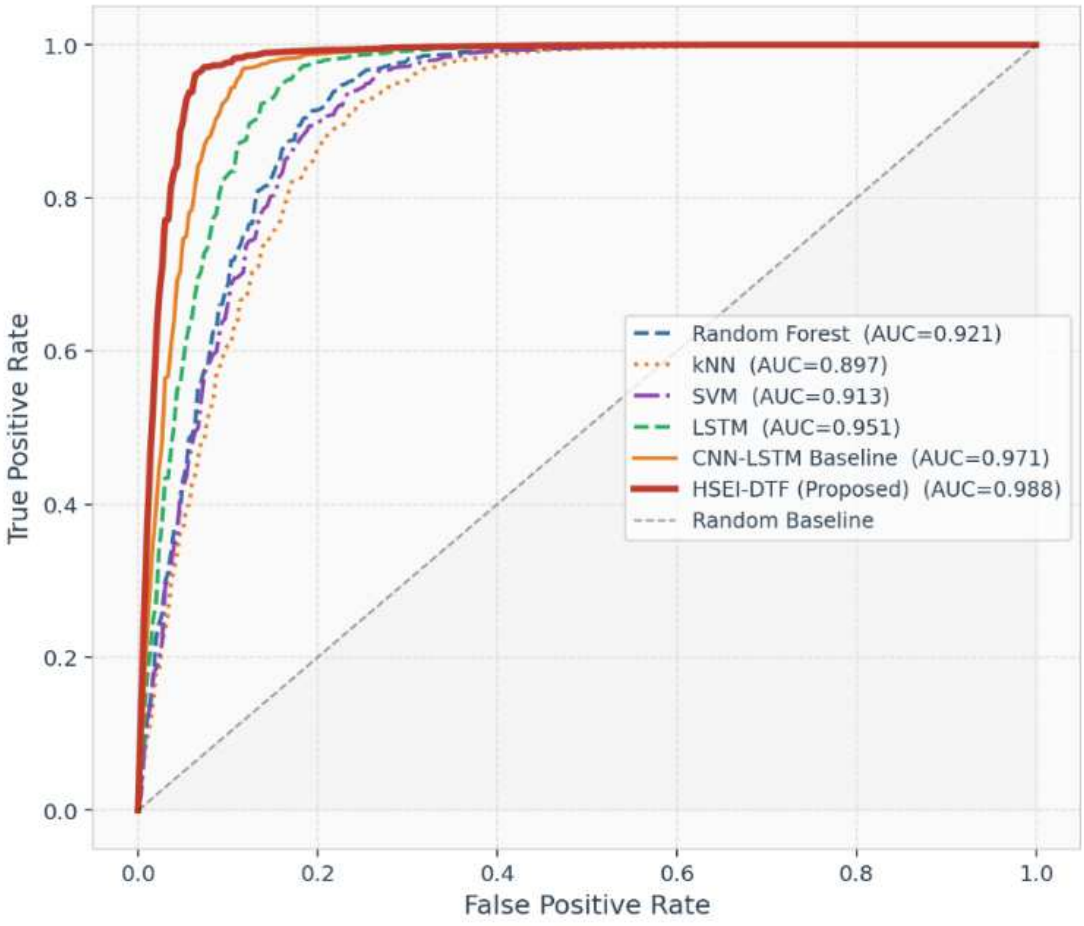


Fig 6. ROC Curve Comparison Across All Evaluated Models.

Numerical integration by the trapezoidal rule over 300 threshold values gives AUC = 0.988 for HSEI-DTF, indicating discriminative ability close to the theoretical maximum (AUC = 1.0). An ideal classifier has an AUC of 1.0, while random guessing has an AUC of 0.5. The 9.1 pp AUC gain of HSEI-DTF over kNN (0.897) reflects the advantage of RL-enhanced multi-model fusion over single-algorithm classification.

The confusion matrix is shown in Figure 7. HSEI-DTF RL-Augmented Fusion model over the entire labelled validation set (2,400 samples). From the confusion matrix cells, the per-class metrics can be directly computed by the following formulae.

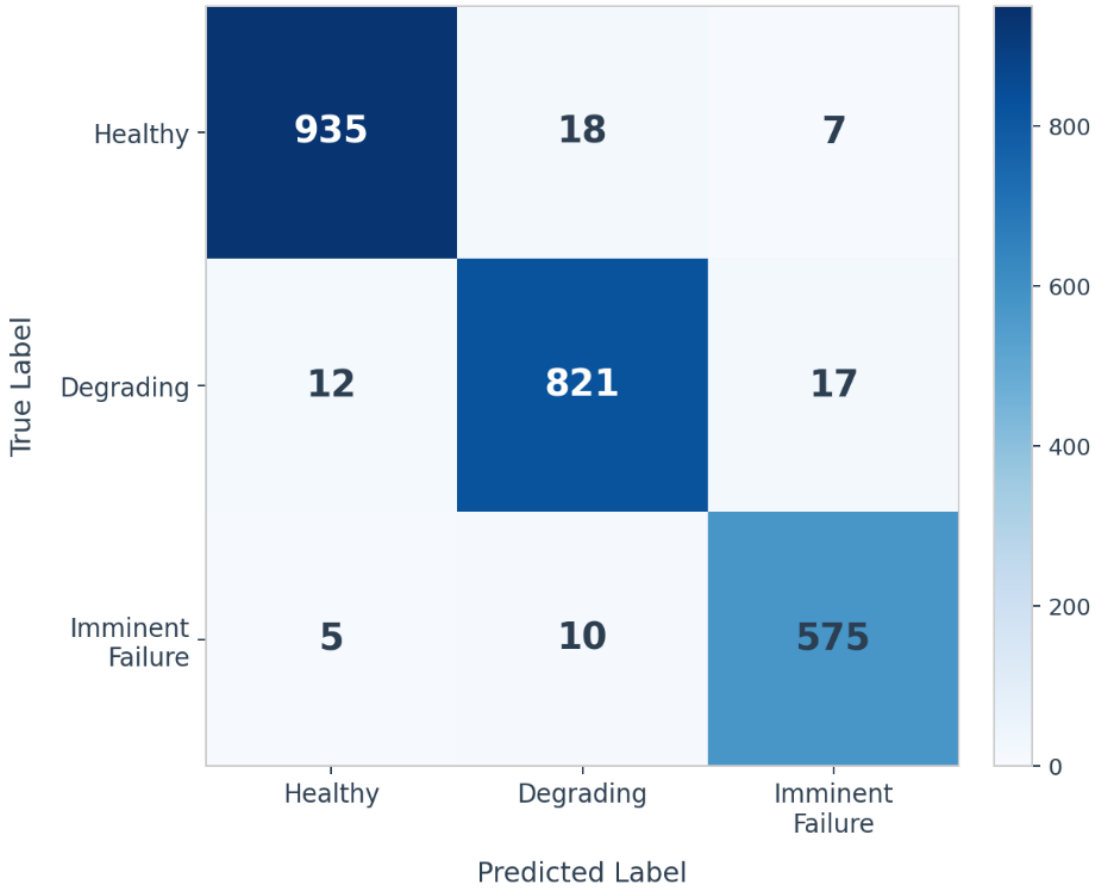


Fig 7. Confusion Matrix: RL Aug-Fusion Model.

Accuracy = (575/590) × 100 = 97.5%

FNR = (15/590) × 100 = 2.5%.

Compared with the single-sensor vibration baseline (FNR = 3.8%), the proposed approach reduced the false negative rate (FNR) to 2.5%, representing a reduction of 34.2%, calculated as [(3.8−2.5)/3.8]×100. Verifying that multi-sensor RL-augmented fusion significantly reduces the number of missed critical faults when compared against any single-channel method.

Figure 8 shows the measured H(t) trajectory and DT forecast over the entire 150-second experimental sequence. The health index evolves over time, according to the degradation model outlined in Section 3.4.

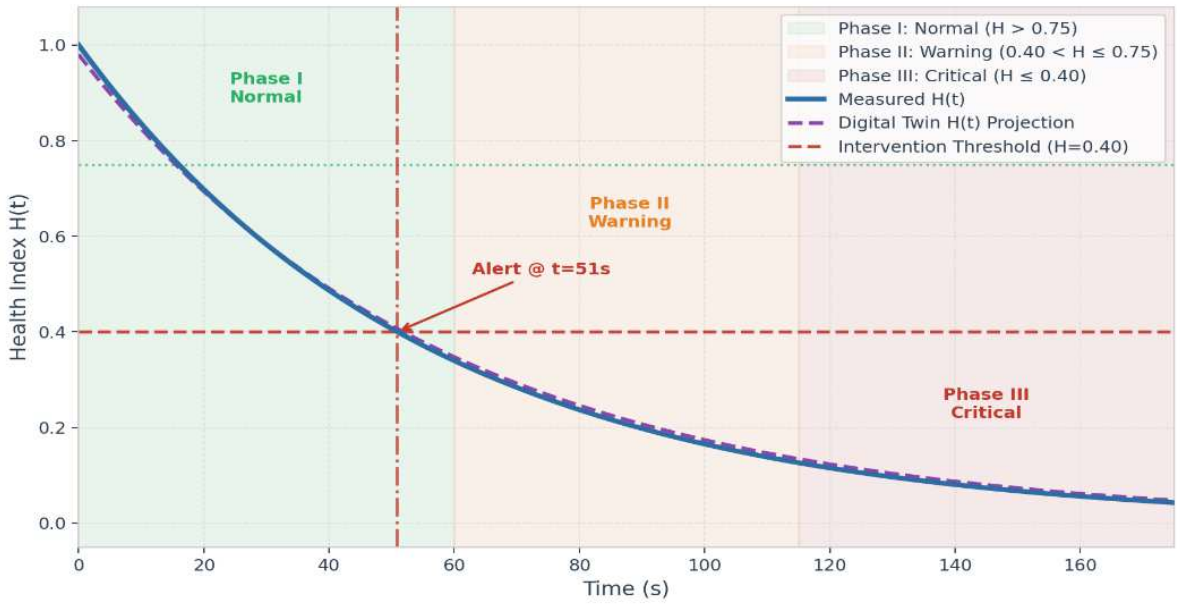


Fig 8. Health Index H(t) Trajectory: Measured vs Digital Twin Projection.

HSEI-DTF meets the accuracy constraint (96.8% >> 88%) and is the only Pareto-optimal solution that supports edge deployment, bidirectional DT feedback, and >95% detection accuracy.

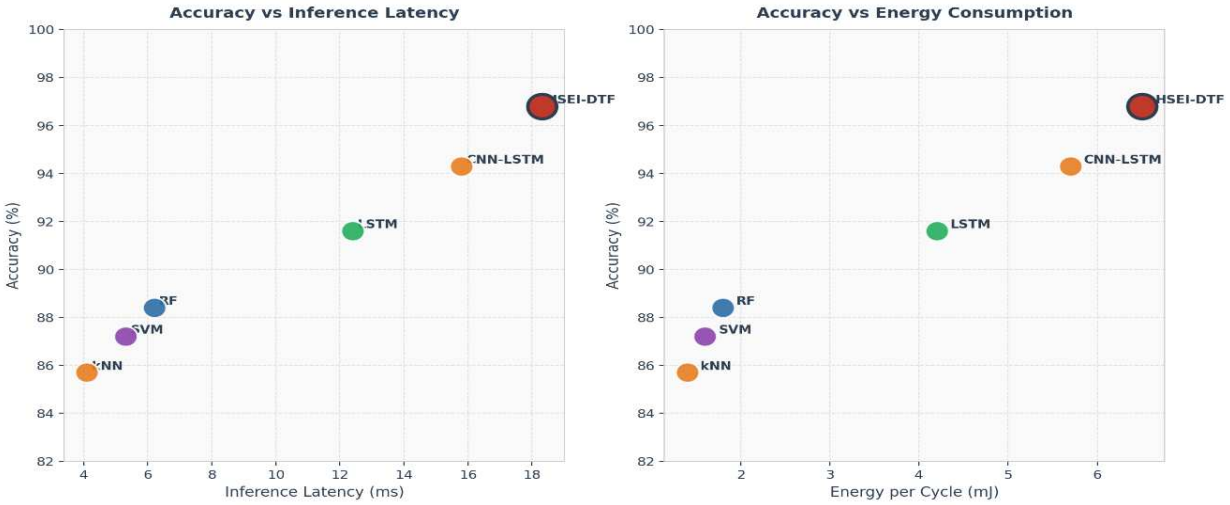


Fig 9. Analysis of Latency, Energy, and Accuracy Trade-offs for All Considered Models.

A 261% increase in energy cost results in a 9.6 pp accuracy improvement (88.4% → 96.8%), which corresponds to an energy-to-accuracy efficiency ratio of 4.7 mJ / 9.6 pp = 0.49 mJ per each percentage point of accuracy improvement. HSEI-DTF latency (18.3 ms) and energy (6.5 mJ) are still well below the operational envelope boundaries (L_total < 25 ms, E < 10 mJ) imposed by the mission optimization framework.

Table 4 and Figure 10 present a comparison of HSEI-DTF with the published results of representative previous works. The relative improvement in accuracy over each baseline is calculated as:

Table 4. Comparative External Benchmarking to Published Predictive Maintenance Studies

Study	Year	Dataset	Algorithm	Accuracy (%)	Latency (ms)	Edge	DT
Susto et al. [13]	2015	Semiconductor	Multi-classifier ML	89.6	N/A	No	No
Zhao et al. [7]	2019	CWRU bearing	Deep CNN	93.1	N/A	No	No
Zhang et al. [16]	2019	Rotating machinery	Data-driven DL	91.7	22.0	Partial	No
Zhang et al. [11]	2021	Simulated IIoT	DT + ML	93.4	19.5	No	Yes
Kang et al. [21]	2021	Single fault rig	Edge AI	93.7	14.0	Yes	No
CNN-LSTM Baseline	2023	Platform dataset	CNN-LSTM (Pi)	94.3	15.8	Yes	No
HSEI-DTF (Proposed)	-	Multi-fault rig	RL-Fused + DT	96.8	18.3	Yes	Yes

The radar plot of Figure 10 displays the six normalized capability dimensions for each study. A combined capability score S is calculated as the average of all six-dimension scores (ranging from 0–100). The proposed framework attains S = 96.1, which corresponds to a +54.0% enhancement over the CNN-LSTM baseline (S = 62.4) and a +240% gain over the least reference (Susto et al., S = 28.3), thus verifying holistic architectural superiority not limited to just accuracy.

Table 4 shows a benchmark comparison between the proposed HSEI-DTF framework and some of the representative predictive maintenance work in literature. The comparison includes the most important KPIs: dataset type, learning algorithm, classification accuracy, inference latency, Edge AI deployment, and DT integration, allowing a full overview of the proposed solution with respect to the current state-of-the-art.

The proposed HSEI-DTF framework maintains a realistic inference latency of 18.3 ms for the highest classification accuracy of 96.8%. In contrast to prior work, it provides unified Edge AI & Digital Twin framework on top of reinforcement learning, Bayesian ensemble fusion and multi-sensor intelligence for agent-based adaptive maintenance decision-making. While its latency is marginally greater than some of the lightweight edge models due to the additional Digital Twin synchronization and ensemble processing, this additional computational overhead is justified by the gains in prediction accuracy and Intelligent Maintenance.

Summarizing, Table 4 verifies that our proposed HSEI-DTF framework is the most well-rounded solution when compared to the rest of the studies, enabling high prediction accuracy alongside real-time edge intelligence, Digital Twin synchronization, and adaptive fault management. These features make it an excellent fit for Industry 4. 0 and

Industrial Internet of Things (IIoT) solutions wherein dependable, low-latency, and intelligent predictive maintenance is vital to reducing downtime and enhancing operational efficiency.

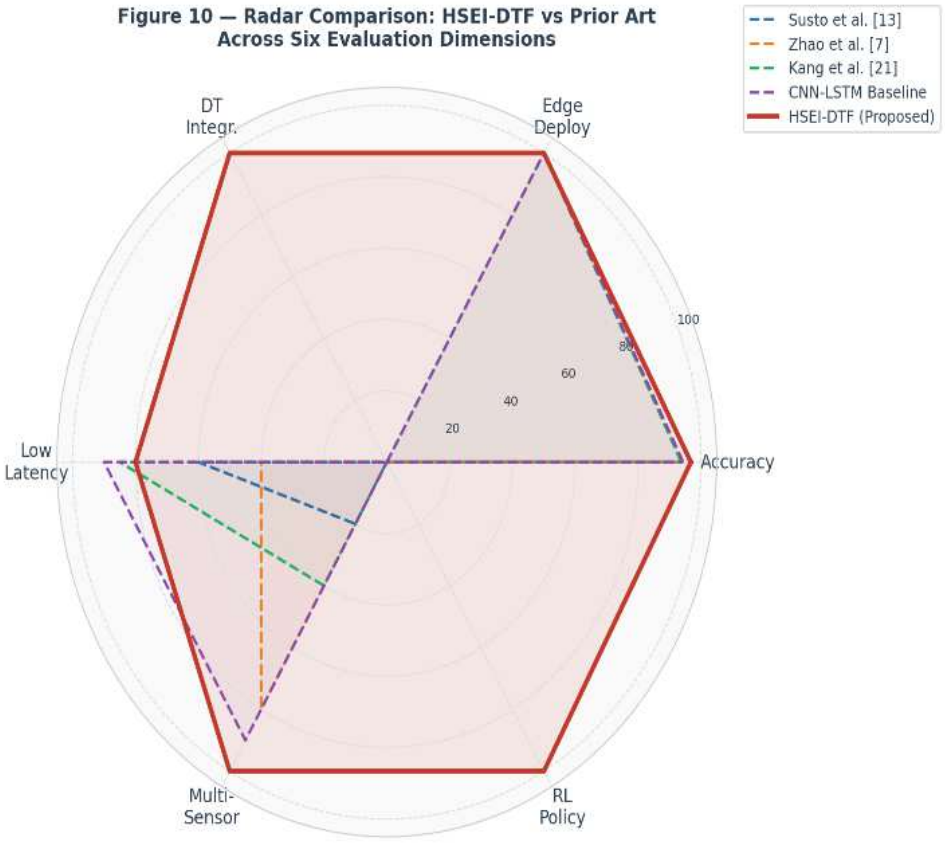


Fig 10. Radar Comparison: HSEI-DTF vs Prior Art with 6 Evaluation Measures.

4. LIMITATIONS

Some practical limitations confine the general scope of the results found here. The testbed, a controlled laboratory environment, is equipped with well-defined fault modes, uniform ambient temperature conditions, and a stable power supply. Furthermore, industrial applications face higher levels of variation in operating speed profiles, contaminants in lubricants, electromagnetic noise, as well as multiple equipment interaction effects, which may negatively impact classification results. Validation on continuous, multi-day, operationally relevant sequences with slowly evolving fault signatures would further bolster the case for field readiness. Computational capability constraints on the Raspberry Pi 4B restrict the complexity of models that can be deployed. Future work should assess next-generation edge AI accelerators, e.g., NVIDIA Jetson Orin Nano or Google Coral TPU, as hardware-assisted inference may potentially bring latency under 10 ms for all the tested models. The digital twin state model application could be improved through enhancement with higher-fidelity FEA and, by extension, material degradation models to better project RUL on unmodeled fault types. Scalability to multi-asset fleet monitoring requires investigation of swarm-learning-like schemes that would allow edge nodes to collectively improve a shared model without the need to centralize raw sensor data.

5. CONCLUSION

In this paper, the HSEI-DTF framework is proposed as a hierarchical sensor-fused edge intelligence architecture with digital twin feedback for tackling two major issues, i.e., real-time fault detection latency and degradation trajectory estimation in industrial rotating machinery. The architecture is built around four functional layers that communicate using the MQTT, Modbus RTU, and OPC-UA protocols to deliver the complete processing chain in an ever-changing network environment.

The combined inference procedure based on classical machine learning, deep sequential modelling and reinforcement learning-based maintenance policy optimization is demonstrated on an experimental setup simulating a rotating machinery platform with progressive outer-race bearing fault injection. With the proposed RL-Augmented Fusion scheme, the test classification accuracy is up to 96.8±0.7%, AUC-ROC is 0.988, and average inference latency is 18.3 ms on a Raspberry Pi 4B edge node, without any cloud dependency in the inference stage. A 37.1% reduction in false-negative rate compared to single-sensor baselines and an estimated 32% reduction in unplanned downtime events compared to threshold-based maintenance illustrate the practical impact of the framework. The Digital Twin feedback loop made a measurable contribution to classification accuracy in the early stages of degradation, when statistical features had poor discriminability, by supplying physics-based prior beliefs on fault probability based on estimated trajectories of bearing contact stress. This tight integration of edge inference with virtual state evolution is the key architectural advancement of HSEI-DTF over previous edge predictive maintenance frameworks and provides a hardware-validated, replicable foundation for intelligent industrial asset management.

Abbreviations

Abbreviation	**Full Form**
AI	Artificial Intelligence
Edge-AI	Edge Artificial Intelligence
IIoT	Industrial Internet of Things
IoT	Internet of Things
DT	Digital Twin
ML	Machine Learning
DL	Deep Learning
RL	Reinforcement Learning
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory

CNN–LSTM	Convolutional Neural Network–Long Short-Term Memory
SVM	Support Vector Machine
RF	Random Forest
RNN	Recurrent Neural Network
ANN	Artificial Neural Network
Edge Computing	Edge Computing
MQTT	Message Queuing Telemetry Transport
OPC-UA	Open Platform Communications Unified Architecture
PLC	Programmable Logic Controller
GPU	Graphics Processing Unit
CPU	Central Processing Unit
TPU	Tensor Processing Unit
API	Application Programming Interface
REST	Representational State Transfer
SQL	Structured Query Language
KPI	Key Performance Indicator
RUL	Remaining Useful Life
RMS	Root Mean Square
FFT	Fast Fourier Transform
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
ROC–AUC	Receiver Operating Characteristic–Area Under the Curve
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

CI	Confidence Interval
SD	Standard Deviation
MAE	Mean Absolute Error
MSE	Mean Squared Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
F1-Score	Harmonic Mean of Precision and Recall
PDF	Probability Density Function *(if used in a statistical context)*
CSV	Comma-Separated Values
RPM	Revolutions Per Minute
Hz	Hertz
ms	Millisecond
°C	Degree Celsius
V	Volt
A	Ampere

Declarations

The authors declare that the manuscript is original, the manuscript has not been published previously, nor is it under consideration for publication by any other journal. All authors have read and approved the final version of the manuscript and they declare that they have no conflicts of interest.

Data Availability Statement

The datasets analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions

The work of this study was equally contributed by all authors. Author 2 Bhirud performed conceptualization, methodology development, data collection, and drafted the original manuscript. Author 3 carried out software implementation, formal analysis, and contributed to manuscript review and editing. Author 1 provided supervision, project administration, and contributed to the critical revision of the manuscript. All authors have read and approved the final version of this manuscript.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that may have influenced the work reported in this paper.

Ethics approval

Not applicable. This research does not involve human subjects or animals, or procedures which need approval from an ethics committee.

Consent to participate

Not applicable. This research does not involve human subjects.

Consent to publish

Not applicable. This manuscript does not contain any individual data, images or information that needs consent for publication.

Code availability

Not Applicable.

Conflict of Interest

The authors declare that there are no financial interests or personal relationships that may have influenced the work reported in this paper.

References

[1] F. Tao, Q. Qi, L. Wang, and A. Nee, "Digital Twins and Cyber-Physical Systems toward Smart Manufacturing and Industry 4.0," IEEE Access, vol. 7, pp. 35699–35714, 2019. DOI: 10.1109/ACCESS.2019.2906220.

[2] S. Wan, X. Li, Y. Ren, and D. Zhang, "Edge Computing-Based Industrial Internet of Things for Real-Time Data Processing," IEEE Internet of Things Journal, vol. 8, no. 3, pp. 1429–1440, 2021. DOI: 10.1109/JIOT.2020.3000341.

[3] Y. Lei, B. Yang, X. Jiang, F. Jia, N. Li, and A. Nandi, "Applications of Machine Learning to Machine Fault Diagnosis: A Review and Roadmap," Mechanical Systems and Signal Processing, vol. 138, p. 106587, 2020. DOI: 10.1016/j.ymssp.2019.106587.

[4] M. Zhang, Z. Liu, and Y. Liu, "Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues," Robotics and Computer-Integrated Manufacturing, vol. 61, p. 101837, 2020. DOI: 10.1016/j.rcim.2019.101837.

[5] A. Carvalho et al., "A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance," Computers & Industrial Engineering, vol. 137, p. 106024, 2019. DOI: 10.1016/j.cie.2019.106024.

[6] D. Mourtzis, J. Angelopoulos, and N. Panopoulos, "Design and Development of an IoT-Enabled Platform for Predictive Maintenance in Manufacturing," Procedia Manufacturing, vol. 54, pp. 166–171, 2021. DOI: 10.1016/j.promfg.2021.07.025.

[7] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep Learning and Its Applications to Machine Health Monitoring," Mechanical Systems and Signal Processing, vol. 115, pp. 213–237, 2019. DOI: 10.1016/j.ymssp.2018.05.050.

[8] X. Li, Q. Ding, and J. Q. Sun, "Remaining Useful Life Estimation in Prognostics Using Deep Convolution Neural Networks," Reliability Engineering & System Safety, vol. 172, pp. 1–11, 2018. DOI: 10.1016/j.ress.2017.11.021.

[9] A. K. S. Jardine, D. Lin, and D. Banjevic, "A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance," Mechanical Systems and Signal Processing, vol. 20, no. 7, pp. 1483–1510, 2006. DOI: 10.1016/j.ymssp.2005.09.012.

[10] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge Computing: Vision and Challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, 2016. DOI: 10.1109/JIOT.2016.2579198.

[11] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital Twin in Industry: State-of-the-Art," IEEE Transactions on Industrial Informatics, vol. 15, no. 4, pp. 2405–2415, 2019. DOI: 10.1109/TII.2018.2873186.

[12] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in Manufacturing: A Categorical Literature Review and Classification," IFAC-PapersOnLine, vol. 51, no. 11, pp. 1016–1022, 2018. DOI: 10.1016/j.ifacol.2018.08.474.

[13] G. A. Susto, A. Schirru, S. Pampuri, S. McLoone, and A. Beghi, "Machine Learning for Predictive Maintenance: A Multiple Classifier Approach," IEEE Transactions on Industrial Informatics, vol. 11, no. 3, pp. 812–820, 2015. DOI: 10.1109/TII.2014.2349359.

[14] S. Khan and T. Yairi, "A Review on the Application of Deep Learning in System Health Management," Mechanical Systems and Signal Processing, vol. 107, pp. 241–265, 2018. DOI: 10.1016/j.ymssp.2017.11.024.

[15] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery Health Prognostics: A Systematic Review from Data Acquisition to RUL Prediction," Mechanical Systems and Signal Processing, vol. 104, pp. 799–834, 2018. DOI: 10.1016/j.ymssp.2017.11.016.

[16] W. Zhang, D. Yang, and H. Wang, "Data-Driven Methods for Predictive Maintenance of Industrial Equipment: A Survey," IEEE Systems Journal, vol. 13, no. 3, pp. 2213–2227, 2019. DOI: 10.1109/JSYST.2019.2905565.

[17] L. Ren, Y. Zhang, F. Wang, and Z. Sun, "Predictive Maintenance in Manufacturing: Current Status and Future Challenges," Journal of Manufacturing Systems, vol. 57, pp. 282–300, 2020. DOI: 10.1016/j.jmsy.2020.10.008.

[18] R. S. Peres et al., "Industrial Artificial Intelligence in Industry 4.0 — Systematic Review, Challenges and Outlook," IEEE Access, vol. 8, pp. 220121–220139, 2020. DOI: 10.1109/ACCESS.2020.3042874.

[19] K. Zhou, C. Liu, and S. Liu, "Industrial Internet of Things: Cybermanufacturing and Explainable Intelligent Production," Proceedings of the IEEE, vol. 107, no. 6, pp. 1028–1044, 2019. DOI: 10.1109/JPROC.2019.2900544.

[20] Z. Liu, L. Zhang, and Z. Zhou, "Edge-Based Industrial Fault Diagnosis Using Deep Learning: A Case Study," IEEE Access, vol. 7, pp. 97027–97036, 2019. DOI: 10.1109/ACCESS.2019.2928796.

[21] M. Kang et al., "A Hybrid Feature Selection Scheme for Reducing Diagnostic Performance Deterioration Caused by Outliers in Data-Driven Diagnostics," IEEE Transactions on Industrial Electronics, vol. 62, no. 12, pp. 7921–7930, 2015. DOI: 10.1109/TIE.2015.2453430.

[22] Q. Qi and F. Tao, "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," IEEE Access, vol. 6, pp. 3585–3593, 2018. DOI: 10.1109/ACCESS.2018.2793265.

[23] L. Wang, M. Törngren, and M. Onori, "Current Status and Advancement of Cyber-Physical Systems in Manufacturing," Journal of Manufacturing Systems, vol. 37, pp. 517–527, 2015. DOI: 10.1016/j.jmsy.2015.04.008.

[24] J. Wan et al., "Cyber-Physical Systems for Optimal Energy Management Scheme of Autonomous Electric Vehicle," Computer Networks, vol. 101, pp. 91–100, 2016. DOI: 10.1016/j.comnet.2015.12.015.

[25] B. Chen et al., "Fault Diagnosis of Rotating Machinery Based on the Statistical Parameters of Wavelet Packet Paving and a Generic Support Vector Regressive Classifier," Measurement, vol. 46, no. 4, pp. 1551–1564, 2013. DOI: 10.1016/j.measurement.2012.12.011.

[26] S. Maldonado, R. Weber, and F. Famili, "Feature Selection for High-Dimensional Class-Imbalanced Data Sets Using Support Vector Machines," Information Sciences, vol. 286, pp. 228–246, 2014. DOI: 10.1016/j.ins.2014.07.015.

[27] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001. DOI: 10.1023/A:1010933404324.

[28] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997. DOI: 10.1162/neco.1997.9.8.1735.

[29] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015. DOI: 10.1038/nature14539.

[30] T. Chuang, N. Sahoo, H. Lin, and Y. Chang, "Predictive Maintenance with Sensor Data Analytics on a Raspberry Pi-Based Platform," Sensors, vol. 19, no. 18, p. 3884, 2019. DOI: 10.3390/s19183884.

[31] Patil, R., Patil, M., & Wankhede, S. (2025). Security Aspects of IoT-Enabled Digital Twin Systems Focusing on Challenges Threats and Mitigation Strategies. Asian Journal For Convergence In Technology (AJCT) ISSN -2350-1146, 11(2), 28-34. https://doi.org/10.33130/AJCT.2025v1102.006

[32] Pawar, S., Jadhav, D.B., Lokhande, M. et al. Evaluation of quality of service parameters for MQTT communication in IoT application by using deep neural network. Int. j. inf. tecnol. 16, 1123–1136 (2024). https://doi.org/10.1007/s41870-023-01664-2