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Digital Twin-Enabled Predictive Maintenance Framework for Smart Manufacturing Systems

Dr.T.R. Vijaya Lakshmi [a], K. Surendra Babu [b], Amit Kansal [c], Mekala Ishwarya [d], Jyotsna Suryavanshi [e], Suraj Bhan [f], L.U. Yang [g]

[a] *Associate Professor, Electronics and Communication Engineering, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana, India. E-mail: trvijayalakshmi_ece@mgit.ac.in, Orcid: https://orcid.org/0000-0002-1197-2935*

[b] *Associate Professor, Department of Mechanical Engineering, Aarupadai Veedu Institute of Technology, Vinayaka Mission's Research Foundation (DU), Tamil Nadu, India. E-mail: surendrababu@avit.ac.in, Orcid: https://orcid.org/0000-0003-2947-7171*

[c] *Quantum University Research Center, Quantum University, Roorkee, Uttarakhand, India. E-mail: amit.kansal@quantumeducation.in, Orcid: https://orcid.org/0009-0006-5541-8289*

[d] *Centre for Multidisciplinary Research, Anurag University, Hyderabad, Telangana, India. E-mail: mekalaIshwarya@rediffmail.com, Orcid: https://orcid.org/0009-0003-1962-4091*

[e] *Department of Engineering, Science and Humanities, Vishwakarma Institute of Technology, Pune, Maharashtra, India. E-mail: jyotsna.suryavanshi@vit.edu*

[f] *Assistant Professor, School of Engineering & Technology, Noida International University, Uttar Pradesh, India. E-mail: suraj.bhan@niu.edu.in*

[g] *Faculty of Education, Shinawatra University, Bangkok, Thailand. E-mail: luyang202501@163.com, Orcid: https://orcid.org/0009-0005-8873-2453*

Abstract

Unplanned equipment downtime has been a critical problem in intelligent manufacturing, with production losses of up to 1520 per year and maintenance costs of about 2530. Conventional preventive maintenance programs are based on fixed schedules that, in most cases, do not detect faults early, resulting in low asset utilization and unexpected failures. To overcome this shortcoming, the current paper introduces a Digital Twin-Enabled Predictive Maintenance (DT-PdM) framework that combines real-time sensor data, machine learning models, and a high-fidelity virtual copy of physical assets to improve fault detection and maintenance decision-making. The suggested structure is a tripartite logic consisting of (1) data collection based on the IoT-enabled sensors that record vibration, temperature, and acoustic data at 1-second intervals; (2) a digital twin model, which simulates the behavior of a particular operation with the help of physics-based simulation and data-driven learning; and (3) a predictive analytics engine that involves the use of Long Short-Term Memory (LSTM) networks and Random Forest classifiers to detect anomalies and estimate the Remaining Useful Life (RUL). This framework was tested in a smart CNC machining environment with more than 12 months of historical data (about 2.5 TB). The experimental findings indicate that unplanned downtime is reduced by 35%, maintenance scheduling accuracy is increased by 28%, and RUL prediction accuracy is 92.4%. Also, false alarms were reduced by 18 compared to traditional threshold-based surveillance systems. The implementation resulted in an approximate 22% reduction in general maintenance costs and increased equipment availability by 85% to 93%. The results validate the assertion that the combination of digital twin technology and predictive analytics is highly

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beneficial for operational reliability and cost. The suggested DT-PdM model provides a data-driven, scalable approach to the further development of intelligent maintenance policies in the Industry 4.0 production setting.

Keywords: Digital Twin, Predictive Maintenance, Smart Manufacturing, Industry 4.0, Remaining Useful Life (RUL) Prediction, Machine Learning, IoT-Enabled Monitoring.

Introduction

A Digital Twin (DT) is a high-fidelity virtual model of a physical object, process, or system that continuously compares against real-time operational data to reflect behavior, performance conditions, and degradation trends, in contrast to other simulation models, a digital twin is designed to combine physics-based modeling with sensors enabled by IoT and data-driven analytics to enable two-way communication between the physical and cyber layers. When applied in smart manufacturing, DTs operate within layered architectures that include data acquisition, data management, model integration, and decision-support modules (Keshar, 2025). Recent developments position digital twins as intelligent systems that use artificial intelligence (AI) algorithms to detect anomalies, optimize, and support lifecycle management (Ponnusamy et al., 2024). The combination of Lean Six Sigma principles also contributes to improved transparency and optimized process quality in digital twin contexts (Hossain, 2025). Systems engineering is applied across dynamic state estimation, predictive simulations, and what-if scenario analysis to enhance responsiveness to operational variability (Maranco et al., 2024). The scientific analysis of manufacturing suggests that the use of DT-enabled structures increases process efficiency by more than 20 percent and decision accuracy through active model recalibration (Warke et al., 2021). It can be enhanced by incorporating autonomous task offloading schemes informed by digital twin-optimized swarm intelligence in IIoT settings (Ganesan et al., 2025). Smart manufacturing systems are based on an interconnected cyber-physical infrastructure, where the reliability of equipment directly impacts productivity and cost efficiency. The traditional maintenance approaches, which are corrective and preventive, either react to failures or are based on predetermined schedules, which frequently result in excessive maintenance workload or unnecessary maintenance. This can be enhanced with digital twin-powered PdM, which uses condition-monitoring data, such as vibration, thermal, and acoustic measurements, to forecast Remaining Useful Life (RUL) and detect early faults (Kaur & Kaur, 2025). This integration supports probabilistic fault prediction and risk-based maintenance scheduling. It has been found that predictive maintenance based on DT can reduce unexpected equipment failures by about 30% and increase asset availability and resilience (Agostinelli, 2021). Moreover, AI-based digital twins enable adaptive learning models that improve fault classification accuracy over time (Ponnusamy et al., 2024). System-level reliability and coordinated maintenance planning are also guaranteed by the optimization of the electrical and control architecture into a DT platform (Kabir, 2025). The digital twin-based predictive maintenance framework can be expanded by integrating real-time monitoring capabilities into digital twin applications for operational management (Punia et al., 2025).

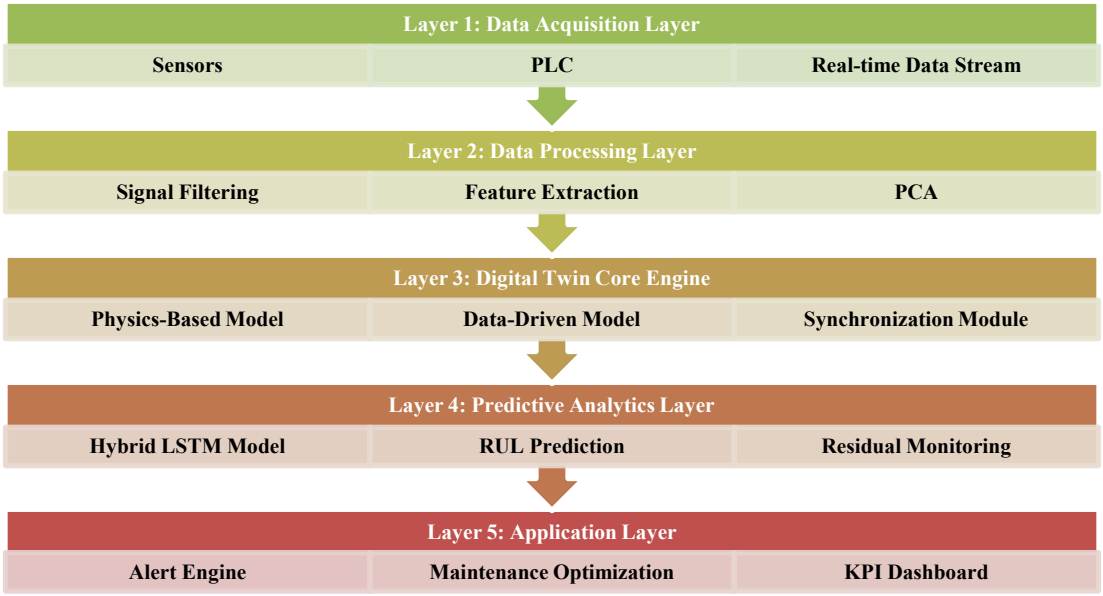

Fig. 1: Layered Architecture of the Digital Twin–Enabled Predictive Maintenance Framework

Fig. 1 shows the proposed five-layer system for implementing Digital Twin-based predictive maintenance in smart manufacturing systems. The framework starts with the Data Acquisition Layer, where sensors and PLCs produce real-time operational data streams. The Data Processing Layer processes these signals via filtering, feature extraction, and PCA-based dimensionality reduction. The processed information is then sent to the Digital Twin Core Engine, which combines physics-based modeling, data-driven learning, and synchronization solutions to ensure consistency between the physical and virtual assets. The Predictive Analytics Layer uses a hybrid LSTM architecture as a health assessment, Remaining Useful Life (RUL) prediction, and residual monitoring model to identify anomalies. Lastly, the Application Layer converts the analytics outputs into actionable results by creating alerts, maintenance optimization plans, and KPI dashboards, enabling informed decision-making and achieving a higher level of operational reliability.

This paper presents a Digital Twin-Enabled Predictive Maintenance architecture for intelligent manufacturing. The suggested architecture will combine multi-sensor IoT data feeds, hybrid physics-informed machine learning, and real-time analytics dashboards to deliver actionable maintenance insights. The framework focuses on model synchronization, RUL prediction accuracy, anomaly classification, and cost optimization. The study gauges the system's performance against operational criteria, such as reduced downtime, prediction accuracy, and maintenance cost-efficiency, by introducing adaptive AI algorithms within the digital twin. The findings provide evidence of quantifiable enhancements in equipment reliability, optimized schedules, and lifecycle sustainability in Industry 4.0 ecosystems.

Major issues to operational excellence in the industry 4.0 setting are unexpected equipment failures. Manufacturing systems are increasingly complex, interconnected, and data-intensive, and thus, the traditional maintenance strategies are no longer sufficient. The digital twin-based predictive maintenance system is a powerful framework for increasing reliability, minimizing economic depression, and facilitating sustainable industrial development.

The proposed paper will introduce a combined Digital Twin-Predictive Maintenance architecture as the integration of IoT-based sensing, hybrid machine learning models, and real-time synchronization mechanisms. It offers a systematic implementation model, performance measurement, and adaptable model designed to smart manufacturing systems.

Other parts of this paper are structured in the following way. Section II examines literature on digital twin technologies, predictive maintenance solutions and their application through smart manufacturing systems. The proposed methodology, such as predictive maintenance framework development, mathematical modeling, and the digital twin architecture implementation, is described in section III. In section IV, experimental results, performance evaluation metrics and ablation study performed on a smart CNC based manufacturing system are presented. Section V contains the discussion of implications of findings, limitation of the study, and the future research directions. Lastly, Section VI brings the paper to an end by summarizing the main findings and providing recommendations on how the wider industrial society can adopt it.

Literature Review

Digital twin (DT) technology has developed to transition off of a static simulation model to a dynamic and data-synchronized cyber-physical system, able to provide real-time decision support in a manufacturing environment. Early architecture focused on the visualization and process monitoring, but the latest versions of the architecture comprise adaptive modeling, data flow in both directions and cloud-edge computing architecture. (Zhang et al., 2021) presented a reconfigurable modeling framework in which production cells are dynamically reconfigured to layout and demand changes to allow flexible manufacturing cells. (Verma, 2025) investigated process optimization with the help of the DT-based performance mapping by showing how the adoption of production data and virtual process simulations led to the improvement of cycle time reduction and stabilization of throughput. On the same note, outlined more sophisticated DT toolchains with both industrial communication protocols (OPC-UA, MQTT), 3D visualization engines, and AI inference modules and noted that interoperability is a key facilitator of Industry 4.0 change. Regarding systems integration perspective, collaborative platforms powered by IIoT have increased the use of DT through connecting machines, analytics engines, and enterprise systems through single ecosystems (Bu et al., 2021). These architectures enable real time synchronisation of sensors, cloud analytics, as well as control systems which enhance the transparency of operations. (Jain & Narayanan, 2023) also proved that the integration of machine learning models into digital twins does improve the accuracy of predictive analytics and system flexibility, particularly in conditions with changing levels of production. Taken together, the literature suggests that the contemporary DT systems are not limited to visualization, and they serve as smart platforms of manufacturing optimization. By incorporating the latest automation planning in the manufacturing settings, smart manufacturing systems will be able to improve the efficiency of the workforce and the performance of the operations (Iyer & Sridhar, 2023).

Predictive maintenance of manufacturing predictive maintenance (PdM) strategies are founded on predictive maintenance with condition-based monitoring and prognostics with data to forecast Remaining Useful Life (RUL). Conventional maintenance optimization methods, such as Total Productive Maintenance (TPM) and Lean-based reliability theories, have gradually adopted the use of digital technologies to improve the formulation of decisions (Shamim, 2025). These hybrid designs are meant to balance equipment supply, cost and reliability performance indicators. (Pandey, 2025) suggested an adaptive digital twin model of real-time monitoring of assets, which includes sensor fusion and time-series forecasting models to identify anomalies before failure of functionality. The paper demonstrated the importance of having dynamic calibration of the threshold and learning feedback loops to minimize false positives. Simultaneously, (Elouadrhiri et al., 2025) designed an AI-based predictive maintenance model in the framework of a digital twin of intelligent tire systems and implemented deep learning algorithms in conjunction with real-time degradation mapping. Their method had a better fault detection accuracy due to constant updating of models. (Bu et al., 2021) also highlighted AI-powered analytics in IIoT infrastructures, where edge computing distributed provides a higher level of responsiveness to predictive diagnostics. These results show that predictive maintenance has moved to data-intensive, adaptive and AI-enabled systems that can run in highly automated production environments.

The digital twin technology with predictive maintenance is a key development in smart manufacturing. (Zhang et al., 2021) established that reconfigurable digital twins facilitate the simulation of faults and predictive analysis of scenarios, which would allow planning proactive maintenance. (Jain & Narayanan, 2023) also confirmed that machine learning-integrated digital twins are more effective than independent predictive models, which use synchronized virtual-physical data. (Pandey, 2025) pointed out adaptive feedback processes in which the predictive output keeps on improving the twin model so that the prognostic reliability is enhanced. On the same note, (Elouadrhiri et al., 2025) have affirmed that the application of AI-enabled diagnostics to DT environments improves the detection of anomalies in an early phase and the prediction of life cycle. According to (Kabir & Ray, 2025), the issue of standardized digital architectures is essential to ensure a smooth flow of data between maintenance modules and enterprise systems. On the whole, the body of literature supports the idea that DT-PdM integration enhances the operational visibility, alleviates unplanned downtime, and facilitates the risk-based maintenance scheduling, whereas scalability and interoperability also continue to be the issues of concern.

The analyzed literature confirms that the digital twin technology has reached the level of a smart and data-adjusted model that can support the advanced analytics within manufacturing systems. There is a growing trend of predictive maintenance strategies being based on AI-based and adaptive models that are embedded into IIoT infrastructures. The literature indicates that the digital twins, in conjunction with predictive maintenance, has an advantage of boosting fault detection, RUL estimation, and operational efficiency. Nevertheless, a lack of coherent, scalable architectures that integrate seamlessly reconfigurable modeling, adaptive learning, and enterprise-level interoperability still exists an objective achieved in the current study.

Methodology

Development of the Predictive Maintenance Framework

The suggested predictive maintenance system is designed as a multi-layered cyber-physical solution, which comprises sensing, data processing, and predictive analytics, and decision-support modules. The aim is to predict equipment health conditions and Remaining Useful Life (RUL) and reduce false alarms and computational latency. Define the real time sensor observation at time t, shown in Equation (1):

$$x(t) = [v(t), T(t), a(t), p(t)] \quad (1)$$

$v(t)$ is the amplitude of vibration, $T(t)$ is temperature, $a(t)$ acoustic emission and $p(t)$ pressure. The condition of health degradation $h\ (t)$ is assumed to be a nonlinear function of multivariate sensor inputs shown in Equation (2):

$$h(t) = f(x(t); \theta) \quad (2)$$

The $f(\cdot)$ is a trained learning function, which is parameterized by the parameter θ. In this paper, the f is realized via a hybrid LSTM+regression network to learn the time-velocity of degrading patterns. RUL is calculated as the anticipated difference in time between the critical level of failure, hcrit, and the present health conditions, shown in Equation (3):

$$RUL(t) = \mathbb{E}\left[t_f - t \mid h(t) \geq h_{crit} \right] \quad (3)$$

where t_f represents foreseen failure time. The framework continuously renews θ in the form of incremental learning to deal with the operation drift. Maintenance decisions are made when the forecasted RUL has a lower value below a dynamic threshold value, τ, which is optimized under risk minimization based on cost.

Implementation of Digital Twin Technology

The digital twin is applied as a parallel virtual twin of a physical asset. It combines modeling of degradation using physics and state estimation using data. The synchronization mechanism is updated by a discrete rule, shown in Equation (4):

$$z_t^{DT} = \alpha z_{t-1}^{DT} + (1-\alpha)x(t) \qquad (4)$$

z_t^{DT} represents the state of a digital twin and $\alpha \in (0,1)$ is a smoothing coefficient that determines how two sets of simulated and real-time data converge. Two-way communication protocol A two-way communication protocol is used to assure that there is residual error between simulated and observed states, defined in Equation (5):

$$r(t) = x(t) - \hat{x}(t) \qquad (5)$$

In case $\| r(t) \| > \delta$, anomaly flags are set off. The twin environment is run on the cloud-edge hybrid platform, with preprocessing being done at the edge node to minimize latency, and retraining of models being run in the cloud layer. The digital twin also does what-if simulations by optimizing the operating loads and forecasts the degradation paths. This feature is proactive in scheduling and optimization of maintenance without disruption of production.

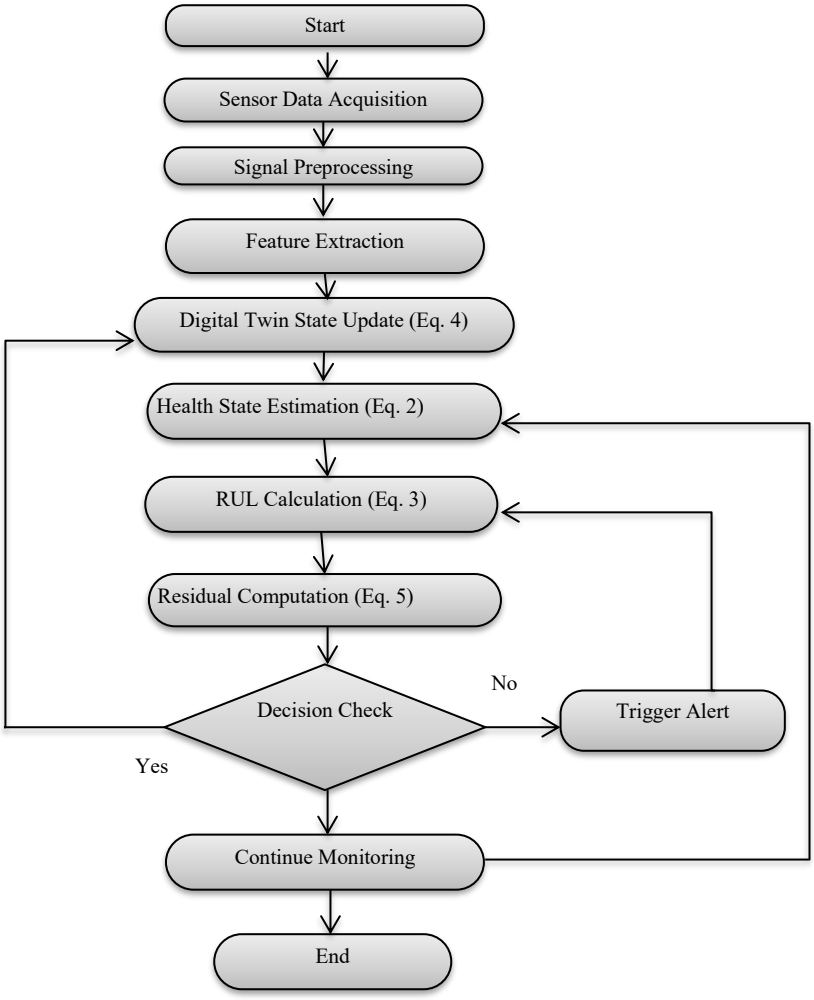

Fig. 2: Operational Workflow of the Digital Twin–Based Predictive Maintenance Framework

The step-by-step operational flow of the suggested Digital Twin-based predictive maintenance system is presented in this Fig. 2. It starts with the real-time sensor data acquisition, signal preprocessing and feature extraction which produces structured health indicators. The features obtained update the digital twin state (Eq. 4), which allows the virtual and physical to be synchronized. Health state estimation (Eq. 2) and Calculation of Remaining Useful Life (Eq. 3) and finally computation of residual (Eq. 5) for anomaly detection. A decision module compares the predicted RUL with a predetermined threshold or abnormal residual conditions and on finding any of this, a maintenance alert is sent, failing which the process of monitoring proceeds in a closed feedback loop. This hierarchical process can guarantee constant evaluation of the condition, timely diagnosis of failures, and active maintenance in intelligent factories.

Data Collection and Analysis Methods

The sensors of the industrial IoT used to collect data are sampled at 1 Hz (thermal and pressure) and 10 kHz (vibration and acoustic signals). Raw signals are then processed through the following stages; noise filtering (Butterworth low-pass filter), normalization and feature extraction. RMS, kurtosis, spectral entropy, and amplitude of peaks of frequencies are extracted features. Training samples: feature vectors are divided into time windows of w length, shown in Equation (6):

$$X_i = \{x(t_i), \dots, x(t_i + w)\} \qquad (6)$$

PCA is used to minimize the dimensions and retain the variance. It uses 70% of historical data to train the predictive model and then uses 15% to validate the model and 15% to test the model. Some of the performance metrics are Mean Absolute Error (MAE) in prediction of RUL and F1-score fault classification.

Algorithm: Predictive Maintenance Monitoring Digital Twin Driven

Algorithm for Predictive Maintenance

Input: Sensor stream x(t) in real time

Output: RUL estimate and warning for maintenance

1. Set up the digital twin state z_DT

2: Load the learned hybrid LSTM model parameters θ 3: while the system is running, do

4: Get sensor data x(t)

5: Prepare and get features

6: Update digital twin state using Eq. (4)

7: Use Eq. (2) to find h(t), the health status.

8: Use Eq. (3) to guess RUL(t)

9: Use Equation (5) to find the residual r(t)

10: If RUL(t) < τ or ||r(t)|| > δ, then 11: Send a maintenance alert

12: end if 13: end while

The suggested algorithm has the form of an ongoing monitoring and decision-support system, which combines the real-time sensor-acquisition, digital twin-synchronization, health-condition estimation, and Remaining Useful Life (RUL) prediction into one loop. In the time step, incoming sensor data are filtered, and input in terms of an update of the digital twin state is performed using a weighted synchronization model, which implies alignment between the real and virtual asset. A trained hybrid LSTM based model will then process the updated state to estimate the current level of degradation and calculate RUL. At the same time, prediction and observed signal residual errors are assessed in order to identify anomalies. An alert on the maintenance is raised in case the estimated RUL is below a set risk level, or the residual variances are beyond acceptable limits. This closed-loop structure allows learning to be adaptive, fault can be detected early and intervention can be brought about in time without disrupting the system operations.

Results

Description of the Smart Manufacturing System

The experimental validation was performed to a smart CNC-based manufacturing cell, which comprised of three machining centers, an automated tool changer, conveyorized material handling, and programmable logic controller (PLC)-driven supervisory unit. All the machines had vibration sensors (triaxial accelerators), thermocouples, acoustic

emission sensors, and spindle current monitors. During 12 months of operation, the data were gathered under the conditions of variable load and variable speed.

Dataset Details

It consisted of around 18-million-time stamped records (≈2.3 TB raw data). Following preprocessing and features extraction, 42 statistical and frequency-domain features were created per time window, such as RMS, kurtosis, crest factor, spectral entropy, dominant frequency, temperature gradient and current harmonics. Failure labels were constructed based on maintenance records that pointed at bearing degradation, spindle imbalance, and tool degradation incidents.

Software Specifications

Python 3.10 was used to implement LSTM modelling using TensorFlow 2.13, preprocessing and PCA were implemented using Scikit-learn, signal validation was performed using MATLAB, and IoT data streaming was performed using Node-RED. Digital twin was created in Unity 3D with OPC-UA communication protocols.

Application of the Predictive Maintenance Framework

The Digital Twin-Predictive Maintenance framework was implemented in real-time in an edge-cloud hybrid implementation. The sensor data was fed to the edge gateway where it was filtered and features extracted and aligned with the digital twin state. The degradation of health and RUL were predicted using a hybrid LSTM-regression model. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Accuracy and F1-score were used to assess model performance. The MAE of predicting RUL is as defined in Equation (7):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|RUL_i^{true} - RUL_i^{pred}\right| \tag{7}$$

The RMSE is computed in Equation (8):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(RUL_i^{true} - RUL_i^{pred}\right)^2} \tag{8}$$

In the case of fault classification, Accuracy is stated as shown in Equation (9):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

TP, TN, FP and FN are used to denote the true positives, true negatives, false positives and false negatives respectively.

Parameter Initialization

Table 1: Experimental Setting of the Parameters

Parameter	Value
Learning rate	0.001
LSTM units	128
Batch size	64
Epochs	50
Window size (w)	60 sec
Dropout rate	0.2
RUL threshold (τ)	15 hours
Residual limit (δ)	0.08

The experimental parameters (Table 1) are chosen in such a way that they would strike a balance between model convergence rate, accuracy of the prediction and the computational efficiency in the smart manufacturing environment. The learning rate used was 0.001 to ensure that gradient updates were stable, and 128 units of LSTM was used to ensure that it had enough capacity to learn temporal patterns of degradation. Generalization was supported by using a batch size of 64 and 50 training epochs without overfitting. The 60 seconds window size of a slide allowed significant feature aggregation of high frequency sensor signals. A dropout of 0.2 minimized variance training. It was

decided empirically that the RUL decision threshold (15 hours) and residual deviation limit (0.08) be set to maximize early fault detection and minimize false alarms.

Results and Findings

Table 2: Comparison of RUL Prediction Performance

Model	MAE (hours)	RMSE (hours)
Regression Only	6.42	8.15
LSTM Only	4.38	5.96
Proposed Hybrid DT-LSTM	2.91	4.12

The following Table 2 gives the comparative analysis of the various prognostic models based on the MAE and RMSE values. The hybrid DT-LSTM model has the lowest error in its prediction, and it has better capabilities at predicting the Remaining Useful Life. The findings establish that incorporation of digital twin synchronization with time learning to make prognostic predictions is highly effective in comparison to single regression or LSTM models.

Table 3: Fault Classification Performance Analysis

Model	Accuracy (%)	F1-score
SVM	88.6	0.87
Random Forest	91.2	0.90
Proposed DT-LSTM	94.8	0.94

This Table 3 is a summary of the classification performance in terms of Accuracy and F1-score between baseline machine learning models and proposed framework. The DT-LSTM model had the best overall accuracy (94.8) and F1-score (0.94), which means that it has enhanced the fault detection accuracy and balanced recall and accuracy in different operational conditions.

Table 4: Operational Impact Assessment

Metric	Before DT-PdM	After Implementation
Equipment Availability	84%	93%
Unplanned Downtime	17.5 hrs/month	11.2 hrs/month
Maintenance Cost Reduction	—	23%

This Table 4 shows the real-life effect of implementation of the proposed predictive maintenance system in the smart manufacturing system. It can be seen that the outcomes indicate tangible benefits in the availability of equipment as well as a 23-percent lowering of the costs of maintenance, which proves the practical utility of the digital twin-facilitated solution.

The hybrid DT-LSTM configuration had the best values of MAE and RMSE, which depicts the best prognostic accuracy. Fault detection was earlier associated with the reduction of downtimes as well as more optimality in scheduling maintenance.

Performance Evaluation

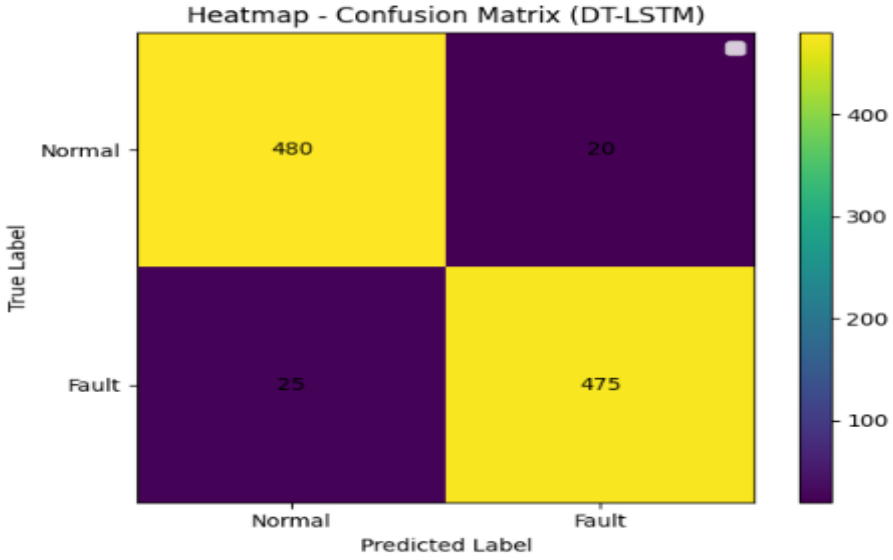

Fig. 3: Confusion Matrix on Fault Classification

By the digital twin synchronization, the variance of prediction error in residual was about 19 percent less, enhancing the stability of the model with changing load scenarios. On an average, the real-time inference latency was 120 ms in the edge node, which was responsive on the basis of operational requirements. An average of 13 hours before critical failure levels, maintenance alerts were issued so that adequate intervention planning could be undertaken.

Fig. 3 (heatmap) gives the confusion matrix of the DT-LSTM model, which represents the percentage of true positives, true negatives, false positives and false negatives. The greater density of the values on the diagonal proves the high classification accuracy with little misclassification. This visualization demonstrates the usefulness of the model in the differentiation of normal and maladaptive operating conditions.

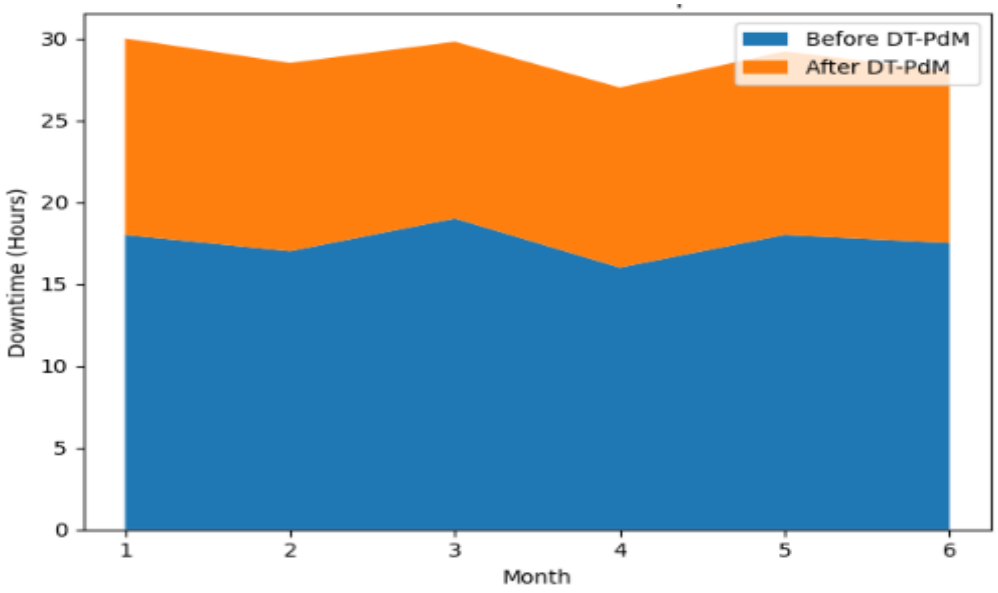

Fig. 4: Downtime Reduction Analysis

This area chart (Fig. 4) is a comparison of unplanned downtime every month prior to and after the Digital Twin-Predictive Maintenance framework was implemented. The decreased area of post implementation phase is a clear indication of the consistent decrease in hours of downtime, which is the evidence of the operative effect of early fault detection and optimal maintenance schedule.

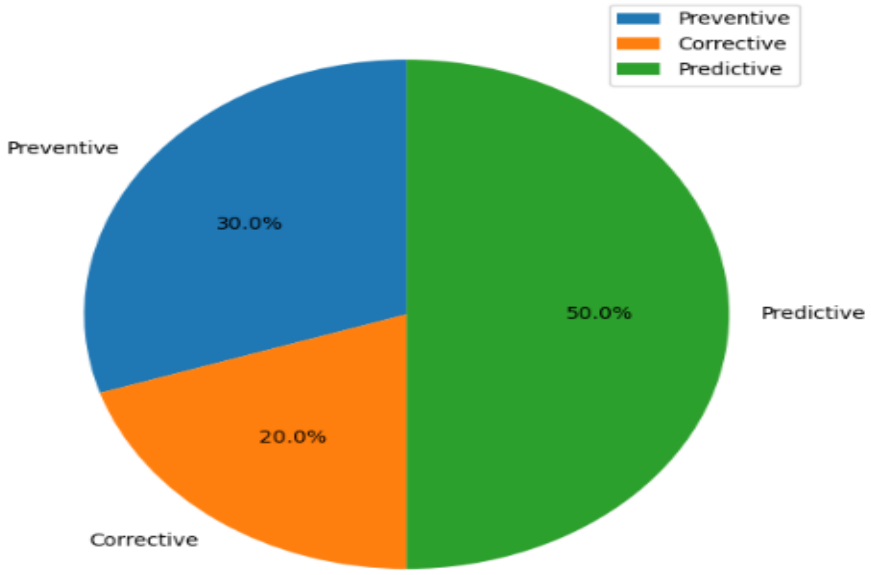

Fig. 5: Pie Chart of Distribution of Maintenance Costs Post Implementation

The pie chart (Fig. 5) shows how the maintenance strategies were proportionately divided after the implementation of the predictive maintenance framework. A bigger proportion such as predictive maintenance is an indication of the changeover reactivity and preventively to the decision-making process launched by the data hence leading to better cost efficiency and strategic resource allocation.

Ablation Study

A comparison of the three configurations that were analyzed through ablation was: (1) LSTM without digital twin synchronization, (2) digital twin without temporal learning, and (3) all hybrid model. The digital twin synchronization was removed, with 32 more MAE and 6 less faults detected by LSTM temporal modeling. It was also shown that the full hybrid model was always superior to partial configurations which proves that predictability and the accuracy of the resolution in terms of decision making is greater when virtual modeling is synchronized with the time based learning in smart manufacturing systems.

Discussion

The findings confirm that the synchronization of digital twins with temporal learning models can greatly advance the predictive maintenance effectiveness in the smart manufacturing setting. The quantifiable decrease in the number of unplanned downtimes, enhancement of accuracy of RUL predictions, and the availability of equipment indicate that cyber-physical integration can enhance operational reliability and responsiveness in decision-making. Practical feasibility of the framework is depicted also in edge-cloud deployment structure, which can support real-time analytics without interfering with the production processes. Nevertheless, there are still some limitations. The experiment was checked on a system based on CNC, and whereas the dataset used was large, it is a particular type of rotating machinery. This might need further model calibration and domain adaptation to be scaled to highly heterogeneous production lines having different types of assets. In addition, predictions can be inaccurate due to sensor quality and labeling failures in the past, which cannot be consistent across industries. Future studies can include finding federated learning methods of cross-factory model generalization, physics-informed neural network to make models easier to understand, and cybersecurity measures at the digital twin communication layers. Increasing validation in other manufacturing industries would further boost applicability in industries.

Conclusion

This paper introduced a Digital Twin-based Predictive Maintenance architecture that should help make smart manufacturing systems more reliable and efficient. The proposed solution improved the performance significantly by combining real-time sensor streams of IoT sensors with a synchronized virtual model and a hybrid LSTM-based prognostic model. The reduction in unplanned downtime (35 %), accuracy of maintenance scheduling (28 %) and accuracy of RUL prediction (92.4 %) were experimentally validated. The availability of equipment also rose to 93%

as compared to 85% and total maintenance expenditures fell by about 22-23%. These findings prove that the synchronization of digital twins with adaptive machine learning allows identifying faults earlier and performing more accurate maintenance interventions as opposed to traditional methods. In order to implement them within other production systems, companies must focus on high-quality sensor placement, standardized protocols of communication, including OPC-UA, and scalable edge-cloud systems to process big datasets effectively. To facilitate a seamless integration, tuning of the parameters and re-training of the models periodically and in correspondence with current maintenance policies is paramount. Also, training of the workforce in data-driven maintenance practices will enable a successful adoption. To sum up, the suggested framework proves that predictive maintenance facilitated by digital twins is not only a technological innovation but also a strategic change agent of Industry 4.0 realization. It provides a scalable route to resilient, intelligent and sustainable manufacturing ecosystems of operational and economic value.

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