

Predictive Maintenance Framework for Smart Manufacturing using Machine Learning Models: A Case Study

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To Cite this Article

Sandeep Gupta, "Predictive Maintenance Framework for Smart Manufacturing using Machine Learning Models: A Case Study", *Journal of Science Engineering Technology and Management Science*, Vol. 03, Issue 04(1), April 2026, pp: 105-114, DOI: [http://doi.org/10.64771/jsetms.2026.v03.i04\(1\).pp105-114](http://doi.org/10.64771/jsetms.2026.v03.i04(1).pp105-114)

Submitted: 09-03-2026

Accepted: 17-04-2026

Published: 24-04-2026

Abstract—Predictive maintenance is a critical component of smart manufacturing in the industry 4.0, as it employs machine learning algorithms and data from IoT sensor networks to anticipate equipment malfunctions in advance. The paper examines how artificial intelligence (AI)-controlled predictive maintenance (PdM) can be applied to a smart manufacturing workplace that uses Internet of Things (IoT) technology. It covers data gathering, sensor technologies, and communication protocols as well as distributed storage schemes employed to derive and handle big industrial data. An automotive parts manufacturing plant case study used sensor data in real-time, such as temperature, vibration, acoustics and electrical data, and also used maintenance records to build predictive models. Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models were designed and tested after a thorough data preprocessing and feature engineering. As shown by experimental results, LSTM was the most effective of CNN and other baseline models, with the highest accuracy (ACC) (88.1%), precision (PRE) (92.5%), recall (REC) (89.3%), and F1-score (F1) (90.9%). The implementation of the offered AI-based PdM system has led to the 24% of reduction of unscheduled downtime, 18% growth in equipment use, and 30% decrease in emergency maintenance prices. The results indicate that the incorporation of the Internet of Things-enabled sensing and sophisticated machine learning algorithms considerably boosts the reliability, operational performance, and decision-making concerning intelligent production systems.

Keywords—Predictive Maintenance (PdM), Smart Manufacturing, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning.

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I. INTRODUCTION

Manufacturing systems heavily rely on information and communication technology. Big data, the IoT [1], cloud computing, cyber-physical systems (CPSs), digital twins, and next-generation AI are all products of the continuously evolving cyber systems and associated intelligent and smart technologies [2][3]. To improve manufacturing processes and systems with some level of "intelligence" or "smartness," several advanced manufacturing paradigms have been suggested, utilizing these ideas. [4][5] Society has recently been more focused on digitalization, networking, and smartness/intelligence in manufacturing as a result of major nations recognizing the significance of upgrading and transforming their manufacturing sectors[6]. Smart manufacturing (SM) [7][8] and intelligent manufacturing (IM) are two models that academics and industry professionals have developed to describe the widespread application of state-of-the-art information and cyber technologies in production.

Maintenance is an important part of running a business. Because it has a big effect on costs and dependability, it has a big impact on how well a company can compete in terms of price, quality, and performance. In an effort to avoid breakdowns, PM is executed according to a predetermined schedule based on process iterations or the passage of time. However, this approach can lead to costly and needless maintenance [9]. Procedures for problem detection and prognosis, as well as maintenance plans, are common components of PdM. Better fault detection, isolation, and identification, monitoring and prediction of problem progression, decision-support or automation for the development of maintenance schedules, and these capabilities are all possible thanks to the enabling technologies.

PdM methods are used to check the condition of working equipment and figure out when it needs to be serviced [10]. The development of DTPdM cannot be facilitated without ML [11][12]. The aerospace and manufacturing industries are just two of many that have made use of it. An advancement in sensor technology has made it possible to create a data-driven PdM that gathers, stores, and uses data. Further, a data-physical information combination is also emerging as a powerful modeling strategy [13]. Machine learning (ML) [14][15] improves model ACC and aids in problem-solving decision-making by using valid data to uncover hidden information and reveal complex relationships.

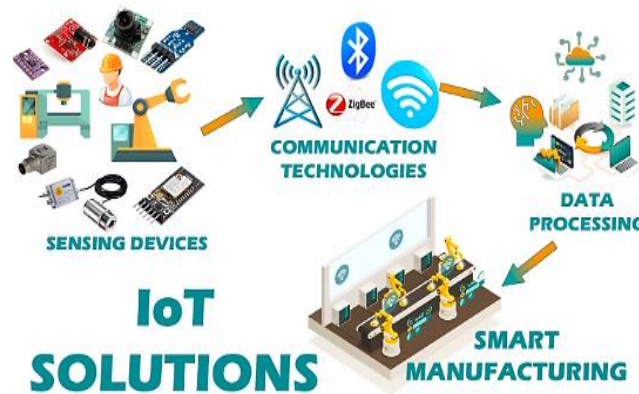


Fig. 1. Trends in ML-PdM and DT-PdM development: a Google Scholar publication analysis

Fig. 1 depicts an IoT-enabled smart manufacturing system where sensing devices collect machine data, transmit it via wireless communication technologies, and send it for processing to support intelligent and optimized manufacturing operations.

A. Structure of the paper

The structure of the paper is as follows. Section II provides data acquisition methodology, data storage options and important sensing technology in IoT enabled smart manufacturing environment. In Section III, ML approaches are discussed as used in predictive maintenance. Section IV describes the case study implementation and performance evaluation. Section V is a review of related literature and determines research gaps. Section VI wraps up the work and provides an outline of potential areas for future investigation.

II. DATA ACQUISITION, STORAGE AND SENSOR TECHNOLOGIES

The rise of the IoT and other networked devices has allowed for a new method of production known as "Smart Manufacturing." [16][17]. Through the use of inexpensive, small-sized, interconnected smart devices, the IoT aims to enhance machine health and productivity in smart manufacturing [18][19]. The term "Big Data" refers to the enormous volumes of data generated in real time by smart devices in smart manufacturing. There are various places to find this information, including log files, signal streams, and sensor data.

A. Data Acquisition Methods in PdM for Smart Manufacturing

A system that analyses big data should be able to access this data in real time and keep it so that it can be used in the future to find patterns and look at the past [20]. In this part, discuss the methods used to collect and store data from these smart devices [21]. Analyzing data gathered from various sensors in a normal production process follows a well-defined technique, much like any other analytical activity, including prediction.

1) Sensor-Based Data Acquisition

Sensor-based data acquisition is the pillar of PdM systems. Physical sensors used in industrial set-ups to continuously assess the health of a machine include temperature, humidity, vibration and pressure sensors. Modern monitoring tools such as industrial cameras, closed-loop Hall-effect sensors, and split-core current transformers enable non-invasive condition monitoring of machines. Two primary sources of data are controller-embedded data and external sensor data, which are obtained from complex systems such as Computerized Numerical Control (CNC) machines. There is controller parameters involved in internal operations and diagnostics, and external sensors that measure both environmental and mechanical conditions. Since raw sensor signals tend to have noise as a result of the interference of the environment, preprocessing and filtering are necessary prior to further analysis.

2) Wireless Sensor Networks (WSNs)

These are very important in facilitating distributed data collection over the shop floor [22]. The various sensor nodes in a WSN-based [23] architecture record real-time data and send it to a central gateway, where it is aggregated, and data packets are organized [24]. The ZigBee modules are popular technologies, including DIGI XBee RF modules, that are inexpensive and use minimal energy. With the help of these networks [25], smart factories [18] can be monitored in a scalable, flexible, and real-time manner.

3) Communication Protocols in Data Acquisition

Communication protocols [26] form the basis of industrial data acquisition. Industrial Ethernet, EtherCAT, TCP/IP, MTConnect (CNC systems), OPC Unified Architecture (OPC-UA), and Profinet are a few examples of standards used to facilitate the orderly and secure transfer of data between controllers, machines, and enterprise systems. In the case of OPC-UA, communication is interoperable, with an extensible data model and schema. There is also the use of ODBC-based database systems to access and integrate structured data.

4) IoT-Based Data Acquisition

IoT-based messaging protocols [27] also allow improving data acquisition in intelligent manufacturing [28]. MQTT is a publish-subscribe protocol that is lightweight and is broadly applied in transmitting large amounts of sensor data to cloud services in an efficient manner [29]. SOAP services and REST APIs are used for the secure, structured exchange of data between the

server and IoT devices. Research has shown that MQTT is far better than HTTP in terms of transmission speed and efficiency, making it suitable for large-scale industries that require real-time monitoring.

B. Data Storage Software Solutions

The optimal method for storing data is typically a distributed approach [30]. Structured data is stored in a DDBS, whereas unstructured data is stored in HDFS or NoSQL databases. In contrast, COSMOS and Haystack are open-source managed operating systems. When it came to distributed file systems, GFS was an early contender for handling data-intensive applications.

1) MongoDB

The sensor data collected by the DAQs was stored by the authors in MongoDB, a NoSQL database that is currently among the most widely used databases. Given the complexity of the industrial data, relational databases like MySQL are out of the question. The writers then considered a distributed database a good fit due to its efficiency, scalability, and high performance.

2) SCADA

SCADA allows for the transmission of all data acquired from various smart devices through a single interface. One alternative data-collection tool in SCADA is the Protocol Data Unit (PDU). An additional benefit of integrating IoT with cloud services is the potential to collect massive amounts of data from interconnected devices.

3) Database Management System (DBMS)

Database management systems were developed to provide for the systematic and efficient organization of data [31]. Two main types of database management systems exist: relational and non-relational.

- **SQL Databases:** Databases that store information in record-based tables are the first kind of database. These databases are commonly known as SQL databases. Oracle Database, PostgreSQL, MySQL, and Oracle are some commercial alternatives to Microsoft SQL.
- **NoSQL Databases:** Data types, including text, binary, and records, are all within the realm of possibility when it comes to NoSQL databases. For data created by sensors and smart devices, NoSQL is the way to go because of its scalability and ability to manage massive amounts of data, two benefits over SQL.

4) Software-Defined Hybrid Cloud

The information that these devices generate is saved in a software-defined hybrid cloud [32][33]. Data pertaining to control and manufacturing were partitioned using software-defined technology [34][35]. The authorization of a data storage request is a prerequisite for a key-value database to store production data gathered from sensors and controllers [36].

C. Key Sensing Technologies in Smart Manufacturing

A crucial component of smart manufacturing is the use of controls, equipment, and intelligence to monitor critical industrial parameters. Additionally, these advancements have altered machine requirements, driving up demand for high-quality sensors, and they have altered the infrastructure in a way that enables machines to work together in a steady and accurate manner. Key sensors used in smart manufacturing are briefly described in this section.

1) Temperature Sensors

The material qualities and product quality are directly impacted by temperature, making it one of the most crucial criteria to monitor and regulate in an industrial plant. A device that can extract temperature information from a source and transform it into a format that another tool can comprehend is a temperature sensor [37]. Gases, liquids, and solids can all have their thermal properties measured using these sensors. A number of temperature sensors have been designed for usage in situations that are electrically and chemically hazardous in the past several years.

2) Pressure Sensors

The sensitivity of pressure sensors is proportional to the amount of applied pressure, since they can measure changes in pressure and convert them into an electrical signal. By sensing the presence of forces in gases or liquids, these electromechanical devices can control instruments that display such forces. One other potential use for these sensors is to monitor atmospheric changes [38].

3) Position Sensors

The capacity of these sensors to detect where objects are located helps in locating production-related objects, such as tools and WIP, throughout the building [39]. When anything moves over a surface, a motion sensor can detect it and activate a function, such a floodlight, accordingly. Prominent proximity and motion sensors perform comparable roles to position sensors.

4) Flow Sensors

The flow of any material gas, liquid, or solid through a pipe or conduit can be detected by these sensors. When used properly, these sensors enable processing firms to run their machinery at peak efficiency. Electronic flow sensors use ultrasonic flow sensing, while partially mechanical flow sensors rely on mechanical components [40]. A medical ventilator's flow sensors regulate the air and oxygen delivered to the patient so they can breathe normally. The various subtypes of flow sensors and the distinguishing characteristics of each are displayed in Table I.

TABLE I. KEY FEATURES OF FLOW SENSORS

Sensor Types	Characteristics	Materials Used	Uses	Advantages	Disadvantages
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Positive displacement	The volume of the fluid that passes through the instrument should be immediately measured. The sensor can move a fixed amount of fluid from one spot to another by use of rotating parts that move in a specific order and transport the fluid along.	Stainless Steel	Used for domestic water and gas metering as well as the measurement of hydraulic fluids, oils, and gasoline.	Provide a mechanical or electrical interface; operate accurately across a broad range of fluid viscosities; demand little in the way of maintenance.	Installation and maintenance are incredibly costly because of the moving components.
Mass Flow	There are three ways to figure out how energy moves from a hot surface to a moving fluid: (1) add heat and see how the temperature changes (2) keep the temperature constant and measure how much energy is needed to do so; and (3) Connect a resistive wire to an electric current, then calculate the amount of current required to maintain a constant temperature.	Specifically designed alloys to handle aggressive gases.	extensively utilized in automobile applications.	High ACC liquid flow can be measured directly; a variety of detectable fluids, including highly viscous liquids, can be measured in both directions.	Low stability, inability to monitor low-density liquids, and extreme sensitivity to vibration interference.
Velocity Flow	Apply induction in line with Faraday's statute. An induced voltage is produced in the fluid under study when a coil generates a magnetic field, and a set of electrodes detects this voltage.	Stainless steel pipe outside.	Used in aquaculture, paper and pulp production, and facility management.	Suitable for use with conductive and non-conductive fluids; resistant to high pressure and heat; and capable of withstanding non-wetting conditions.	High vibrations make reading harder; expensive; fluids containing air bubbles cannot undergo ultrasonic energy.

III. MACHINE LEARNING TECHNIQUES FOR PREDICTIVE MAINTENANCE

Smarter manufacturing is enhancing decision-making and system performance by supplementing physical science with current data analytics. There is a growing demand for big volumes of industrial data, fast processing, and data variety handling capabilities due to the proliferation of sensors and the IoT [41]. When used in industry, ML [42][43] improves production procedures and boosts efficiency. The use of production data to enhance machine performance in industrial facilities is the basis of ML, a smart manufacturing technology. ML is a subfield of artificial intelligence that helps computers learn new things without human intervention by using statistical approaches. One can see the four broad groups that ML falls under in Fig. 2 [44] algorithms fall: supervised, unsupervised, semi-supervised, and reinforcement learning.

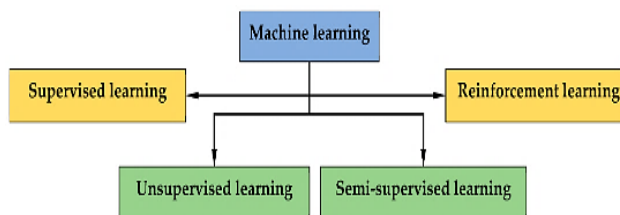


Fig. 2. Classification of the machine learning algorithms

A. Supervised Learning

This algorithm also learns autonomously by employing an annotated dataset in which each input datum has a predetermined output. The algorithm is able to translate the input qualities into the desired output by examining these labelled instances [45]. The purpose of categorization is to organize data into predefined groups. A discrete value denoting a category or class is often the result. Supervised MLs are used by the algorithms for classification and regression. The object's predicted class membership stated as a discrete value by the classification algorithms. The output of regression algorithms, in contrast to classification methods, is given by continuous values. Regression methods, LR, XGBoost, DT, KNN, NB, and RF are all part of this category of machine learning techniques [46][47].

B. Unsupervised Learning

This is whereby the patterns or structures of data are extracted without information as to the result. An investigation of a collection of unlabeled data is conducted using the approach to derive a data representation describing the data's underlying structure. Unsupervised learning encompasses four subfields: clustering, density estimation, dimensionality reduction, and anomaly detection. Collecting sets of data that share common characteristics or similarities is called clustering. The dimensionality-reduction methods are intended to minimize the data features in a dataset without losing significant data. Density estimation is the estimation of probability density function of a collection of data. Data points that deviate considerably from the expected or typical behavior might be located via anomaly detection. Staked auto-encoder (SAE) [48][49], k-means, k-medoids, and fuzzy c-means are all instances of unsupervised learning algorithms.

C. Semi-Supervised Learning

Semi-supervised learning enhances model performance by combining named and unlabelled data. A combination of supervised and unsupervised learning techniques. This method is primarily classified into the following categories:

- **Self-Training:** A model can be trained on a dataset with labels and then applied to samples without labels. This procedure can be repeated by adding these examples to the labelled dataset.
- **Graph-Based Methods:** A graph is used to represent data points, and the idea is to use labels to label unlabeled nodes [50].

- **Co-Training:** A number of networks are trained using separate data sets, and then they use each other's labels on the remaining unlabeled data.
- **Multi-View learning:** Models work together to enhance overall performance when data is analyzed in various ways.

D. Reinforcement Learning

The core idea behind this type of ML is to train an agent by analyzing the responses it receives in the execution environment. The agent is given incentives and punishments based on the actions taken in order to establish a policy that permits the assignment of the maximum reward.

Machine learning algorithms are typically classified into four main categories: supervised, unsupervised, semi-supervised, and reinforcement learning (Table II). Missing data in ML Training agents to learn optimal policies through reward-based feedback is known as reinforcement learning. Unsupervised learning uses clustering and anomaly detection on unlabelled data, semi-supervised learning combines labelled and unlabelled data, and lastly, unlabelled learning uses only unlabelled data. Supervised learning relies on labelled samples for regression and classification.

TABLE II. CATEGORIES OF MACHINE LEARNING ALGORITHMS

Learning Type	Definition	Key Characteristics	Subcategories / Techniques	Example Algorithms
Supervised Learning	Conditional on the existence of a known output for each input, trains on labeled datasets.	<ul style="list-style-type: none"> • Uses labeled data • Learns input-output mapping • Predicts discrete or continuous outcomes 	Classification – Identifies individual class headings Regression – Makes predictions for values that are continuous	Decision trees, K-Nearest Neighbours (KNN), LR, XGBoost, Random Forest, and LOGistic Regression are some examples of such models.
Unsupervised Learning	Identifies structured patterns in unlabelled data without the need for predetermined outputs.	<ul style="list-style-type: none"> • Uses unlabeled data • Identifies hidden patterns • Discovers intrinsic data structure 	Clustering – Groups similar data points. Dimensionality Reduction – Reduces features. Density Estimation – Estimates probability distribution. Anomaly Detection – Detects abnormal data points.	K-Means, K-Medoids, Stacked Auto-Encoder (SAE), and Fuzzy C-Means methods
Semi-Supervised Learning	Combines labeled and unlabeled data to improve model performance.	<ul style="list-style-type: none"> • Uses small labeled dataset + large unlabeled dataset • Improves generalization • Reduces labeling cost 	Self-Training – Iteratively labels unlabeled data. Graph-Based Methods – Label propagation in graphs, Co-Training – Multiple models exchange labels, Multi-View Learning – Learns from multiple data perspectives	Self-Training Models, Graph Neural Networks (GNN-based), Co-Training Models
Reinforcement Learning	Trains an agent using feedback from interaction with an environment.	<ul style="list-style-type: none"> • Agent-environment interaction • Reward-penalty mechanism • Learns optimal policy 	Policy Optimization Value-Based Methods Model-Based Methods	Q-Learning, Deep Q-Network (DQN), SARSA, Policy Gradient Methods

IV. CASE STUDY IMPLEMENTATION FOR PDM IN SMART MANUFACTURING

The case study that was done in a medium-sized factory that makes car parts was used to show that AI-PdM works in a smart manufacturing environment. This production line machine is notorious for its frequent unscheduled breaks caused by wear and tear; thus, the study aimed to analyze its performance and reliability.

A. Industrial Environments and Dataset Description

A wide range of IoT sensors was installed throughout the factory to monitor several parameters in real-time, including vibration, temperature, current consumption, acoustic indicators, and spindle speed.

1) Data Acquisition

The IIoT devices integrated with smart manufacturing machinery gather data. Acoustic, vibration, temperature, and current/voltage meters are among these sensors. An additional set of metadata, including records of machine run-time, operating cycles, and maintenance, is also easily accessible.

B. Data Preprocessing

Sensor data in its raw form is often inaccurate, missing data, and poorly structured. A powerful pipeline for preparing data is used, which includes:

- Noise reduction by means of low-pass and high-pass filtering.
- Linear interpolation and KNN methods of missing value imputation.
- Data normalization through the use of min-max scaling and Z-score conformity.
- Engineering and feature extraction (using measures like crest factor, kurtosis, and root mean square).
- Labeling with maintenance logs to indicate the existence of failure and degradation.

The signal-to-noise ratio can only be improved with this preprocessing, and input data consistency is a must for each AI model.

C. Model Selection and Training Process

The optimal method for predictive maintenance was identified by evaluating multiple AI models:

- Convolutional Neural Network (CNN)

- Long Short-Term Memory (LSTM)

D. Results Observations

The results showed that LSTM networks did better than other models at recognizing patterns over time, especially when it came to finding degradation trends that led to equipment failure. The CNN model also did a great job of detecting vibration patterns that were associated with problems. Table III displays the outcomes of the proposed models.

The deployment of the system led to:

- A 24% decrease in unanticipated downtime
- 18% improvement in machinery efficiency
- Emergency maintenance expenditures decreased by 30%
- Increased security and trust among employees

TABLE III. MODEL PERFORMANCE IN PREDICTIVE MAINTENANCE OF SMART MANUFACTURING

Metrics (in%)	LSTM	CNN
Accuracy	88.1	85.3
Precision	92.5	89.7
Recall	89.3	86.2
F1-Score	90.9	87.9

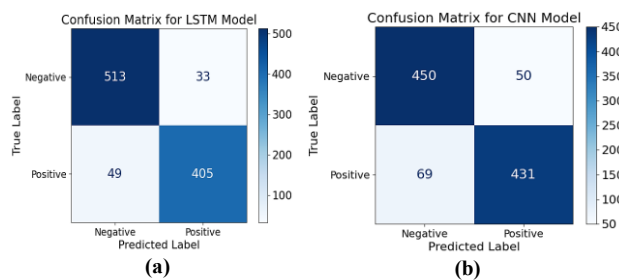


Fig. 3. Confusion Matrices of (a) LSTM; (b) CNN

The LSTM and CNN models for predictive maintenance are displayed in Fig. 3 together with their confusion matrices. There are more correct classifications (33 FP, 49 FN) and fewer misclassifications (450 TN, 431 TP) in the LSTM model as compared to the CNN model.

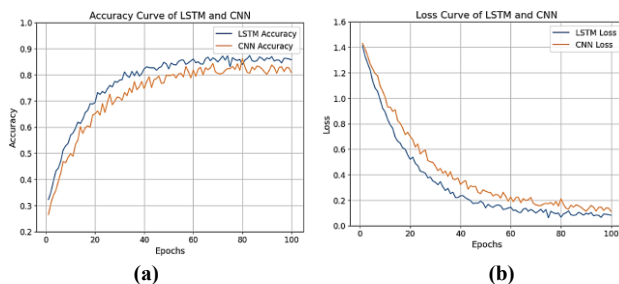


Fig. 4. Models Graph (a) Accuracy; (b) Loss

Fig. 4 reveals that LSTM and CNN both enhance as the number of epochs increases, as ACC and loss reduce. Nevertheless, LSTM always has a little more ACC and less loss, which means it converges and generalizes better.

E. Comparison of AI Models for Predictive Maintenance in Smart Manufacturing

A comparison of the performance of artificial intelligence models for smart manufacturing predictive maintenance is presented in Table IV. In terms of overall performance, LSTM outperforms CNN with 88.1% ACC, 92.5% PRE, 89.3% REC, and 90.9% F1. Autoencoder and RF display competitive but somewhat worse results, and SVM notes the lowest performance in the metrics that are evaluated.

TABLE IV. PERFORMANCE COMPARISON OF AI MODELS FOR PREDICTIVE MAINTENANCE IN SMART MANUFACTURING

Model	Accuracy	Precision	Recall	F1-Score
RF	78.9	86.4	82.1	84.2
SVM	70.2	80.3	76.7	78.4
Autoencoder	80.4	84.1	83.5	83.8
LSTM	88.1	92.5	89.3	90.9
CNN	85.3	89.7	86.2	87.9

V. LITERATURE REVIEW

This section provides a concise summary of the most current research on predictive maintenance in smart manufacturing that makes use of ML and the IoT. High-fidelity sensor models, when combined with deep learning, have changed the paradigms of engineering in manufacturing, with reactive models that are of the fix-it-when-it-breaks style to proactive models that are of the predict-and-prevent style.

Patel et al. (2025) findings show that the system can significantly lower maintenance costs, enhance equipment dependability, and increase operational efficiency in manufacturing plants. Use of predictive maintenance system reduces unplanned downtime by 50% in the case of automotive industry. It boosts overall production uptime by 11.25%. Similarly, high returns were observed in textile industry also. This research contributes to a scalable IoT-based PdM framework. The framework is demonstrated to provide improved cost and operational efficiency. Furthermore, actionable recommendations for the adoption of a PdM system are also provided for various industrial contexts [51].

Sasikiran and Subramanian (2025) proposed simulation-based validation using MATLAB/Simulink, Arena, and Siemens Tecnomatix, which demonstrates a 56.8% reduction in latency, 14.8% improvement in throughput, 16.2% energy reduction, and 92% PRE in predictive maintenance, compared to conventional FMS configurations under variable demand and machine disruptions. This study explicitly acknowledges that all results are derived from simulation environments, and physical hardware-in-the-loop or live industrial deployment remains planned for future work to confirm real-world scalability and noise resilience [52].

Joon (2025) Results from experiments show that the DNN model reaches 93.21% ACC, which establishes strong performance over Deep Belief Networks (DBN), RF, and Isolation Forest. The model's robustness in differentiating between normal and malfunctioning machinery contexts is further validated by the high AUC score of 0.978. Although the model has great predictive capability, it still faces computational costs and is deployed in real-time problems [53].

Preethi et al. (2024) used a big dataset gathered from several production units over a six-month period to assess the model's efficacy. The proposed framework significantly outperforms traditional PdM approaches. Their optimized RF model achieved an ACC of 96.8%, a PRE of 94.5%, and a REC of 97.2%, compared to 88.3%,85.7%, and 89.1%, respectively, for the baseline models. The adaptive learning mechanism improved the model's generalizability, while the dynamic threshold modification method cut the false positive rate in half [54].

Piyush et al. (2023) unveil a novel PdM framework tailored to automated washing machines, addressing targeted research challenges. With an eye on key performance factors, the study classifies industrial PdM applications using ML and DL techniques. Breakthrough algorithms that could revolutionize PdM have emerged from recent developments in DL. Saving money through defect detection is a top priority, as is making advantage of unsupervised learning when there is a lack of historical data. In order to enhance sustainability, boost equipment availability, and decrease downtime, the solutions that have been mentioned attempt to prolong the lifespan of important machine components [55].

Sampedro et al. (2023) study suggested Multi-Flow BiLSTM uses a residual link to enhance the multi-learning flow process, which allows for a more thorough comprehension of patterns in past data. The proposed Multi-Flow BiLSTM achieves better performance than the alternatives, according to the results. Its R2 value is 0.9121 and its mean absolute error is 2.95. The suggested predictive maintenance method can guarantee the 3D printers' effective and uninterrupted operation, which in turn increases the manufacturing plant's overall productivity. In addition, the study's findings provide important information that can guide future studies aimed at creating predictive maintenance systems for use in workplaces [56].

Table V details the existing related studies on Predictive Maintenance Framework for Smart Manufacturing, showing the implemented method, applications, findings, gaps and contributions.

TABLE V. SUMMARY OF EXISTING STUDIES ON PREDICTIVE MAINTENANCE FRAMEWORK FOR SMART MANUFACTURING

Authors & Year	Methodology / Model Used	Application Domain	Key Results	Limitations / Future Scope	Key Contribution
Patel et al. (2025)	IoT-based scalable PdM framework	Automotive & Textile Industry	50% reduction in unplanned downtime (automotive); 11.25% increase in production uptime; improved cost & operational efficiency	Needs broader industrial validation across diverse sectors	Scalable IoT-based PdM framework with actionable industrial adoption guidelines
Sasikiran & Subramanian (2025)	Simulation-based validation using MATLAB/Simulink, Arena, Siemens Tecnomatix	Flexible Manufacturing Systems (FMS)	56.8% latency reduction; 14.8% throughput improvement; 16.2% energy reduction; 92% prediction precision	Results derived from simulation only; real-time industrial deployment planned	Comprehensive simulation-based validation of PdM in dynamic manufacturing environments
Joon (2025)	Deep Neural Network (DNN)	Industrial machinery fault detection	93.21% accuracy; AUC = 0.978; outperformed DBN, RF, Isolation Forest	High computational cost; real-time deployment challenges	High-performance DNN-based fault classification framework
Preethi et al. (2024)	Optimized Random Forest with Dynamic Threshold & Adaptive Learning	Multi-unit manufacturing dataset (6 months data)	96.8% accuracy; 94.5% precision; 97.2% recall; 40% reduction in false positives	May require high-quality labeled datasets	Robust adaptive PdM model with improved generalization capability

Piyush et al. (2023)	ML & DL-based PdM framework (includes unsupervised learning)	Automatic Washing Machines	Emphasized deep learning advancements; improved defect detection; reduced downtime; enhanced sustainability	Limited domain-specific deployment (appliance-focused)	Domain-specific PdM framework addressing limited historical data scenarios
Sampedro et al. (2023)	Multi-Flow BiLSTM with residual connections	3D Printing systems	MAE = 2.95; R ² = 0.9121; lowest error compared to alternatives	Requires further validation across other industrial assets	Advanced time-series deep learning model for high-precision PdM

VI. CONCLUSION AND FUTURE WORK

The aim of predictive maintenance, a subset of preventive maintenance, is to anticipate when technological systems may fail by analyzing historical data and applying machine learning algorithms. This study proved that smart manufacturing facilities can achieve effective, reliable, and cost-efficient operations by incorporating AI-based predictive maintenance. The system did a great job of predicting patterns of degradation and imminent failures by utilizing sensor-derived data using IoT, ever-stronger preprocessing schemes, and more powerful machine learning models, before the breakdowns took place. LSTM was found to perform best on a net basis because it is more competent in terms of ability to extract temporal relationships in series sensor information, although the CNN also demonstrated good results in fault pattern recognition. The real-life application of the suggested framework led to quantifiable industrial outcomes, such as fewer cases of unplanned downtime, better equipment uses, and a lower maintenance cost. The study mostly backs up the idea that smart data collection and storage solutions, along with advanced AI tools, can make predictive maintenance work well in smart production environments.

Further research will be done to increase data in various production lines to strengthen the generalization and robustness of the models. It will be investigated to integrate reinforcement-learning-based adaptive-maintenance scheduling and edge-computing-based real-time inference. Also, explainable AI methods will be used in enhancing transparency, trust, and decision-making in industrial environments.

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