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Original Article

ERP-Enabled Predictive Maintenance in Manufacturing: Leveraging Machine Learning for Fault Detection and Production Continuity

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Abstract *- Predictive Maintenance (PdM) Enabled ERP on fault-detection and product-community of machine learning (ML) has emerged as a significant facilitator towards the establishment of machinery dependability, reduction of downtime, and optimization of operation performance in the modern world of manufacturing. PdM can capture faults at an early stage and make proactive maintenance choices, out of the scope of traditional reactive and preventive mechanisms, using ML, Internet of Things (IoT) sensors, and advanced data analytics. This review of the predictive maintenance systems that are based on ERP, with a specific emphasis on the architectural integration of ERP, MES, and SCADA platforms, with the help of digital twin technology. The paper reviews data collection on the shop floor, water, and the IoTs; data synchronization and interoperability issues; and the use of supervised, unsupervised, semi-supervised, and deep learning methods for the detection and classification of faults. Moreover, the paper compares the effects of predictive maintenance on production continuity and operational resilience, and the contribution of ERP-enabling planning and rescheduling to reduced downtime and enhanced decision-making.*

Keywords *- Predictive Maintenance, Machine Learning, ERP Integration, Internet of Things (IoT), Fault Detection.*

1. Introduction

The manufacturing industries are taking a leap of faith towards a digital transformation, where the usage of Industry 4.0 technologies like intelligent automation, real-time data analytics, and digital integrations has become the core for the industry to retain its competitiveness along with operational efficiency [1][2]. Unexpected failures in the equipment can lead to long downtime, losses of finances, and supply chain interruptions, therefore, in this case, the most essential performance measures include continuous production and maintenance reliability [3]. The old forms of maintenance, like reactive and time-oriented preventive maintenance, are not adjusting well to the complexity and dynamic nature of the current manufacturing systems.

Predictive Maintenance (PdM) is a game-changer in equipment maintenance that uses the power of ML to monitor and analyze the status of important equipment. The traditional maintenance processes such as the preventive and reactive maintenance have been reported to create unnecessary downtime, high maintenance costs and inefficient allocation of resources [4][5]. On the other hand, Predictive Maintenance is a method that utilizes advanced analytics and machine learning software to predict when equipment will fail and take cost-efficient repairs at the most appropriate times.

Machine learning identifies critical patterns amidst the huge amounts of sensor data and operational data generated by monitoring the shop floor that result in predictive maintenance. Real-time data enables making maintenance decisions, and it is possible with the assistance of the ML-based PdM systems that rely on the supervised, unsupervised, and deep learning methods to recognize the problems, detect abnormalities, and provide an estimate of the remaining usable life [6]. Consequently, predictive maintenance has become a major factor in ensuring manufacturing continuity in data-centric production environments.

Machine learning (ML)-based PdM systems may detect problems, identify abnormalities, and estimate remaining usable life using supervised, unsupervised, and deep learning techniques. This allows maintenance choices to be made based on real-time data. Therefore, in data-centric production environments, predictive maintenance has become an important component for manufacturing continuity [7]. The discussion of the synergy between Predictive Maintenance and Machine Learning will cover the main concepts, data roles, machine learning algorithms[8], and strategies for real-world implementation [9][10]. Although the features of Predictive Maintenance are well proven, the integration of the same within an ERP platform, namely QAD ERP, has been almost unexplored. Embedded capabilities for predictive Maintenance can be installed within ERP systems and provide a single platform for managing business processes without any hassles[11].

As such, strong control of processes and early detection of faults are the most important issues for manufacturers who want to maintain a competitive edge, minimize downtime, and ensure product reliability [12]. Conventional maintenance programs, which are usually responsive or time-scheduled, are ineffective in dealing with the dynamic, complex nature of PCB manufacturing environments [13]. These conventional methods tend to incur higher costs and lower efficiency because they neither predict failures in advance nor optimize maintenance actions based on real-time conditions.

The timeline for 6G is expected to follow the previous timeline patterns of previous generations. We observed a time gap of almost 10 years between two mobile generations starting from 2G to 5G. A similar time gap is expected in order to reach a preliminary version of 6G. As expected, 5G will not be rolled out all over the world in 2021. Actually, only some cities across the world will have it. Around 2025, 5G will be used widely across the world. Rural deployment in the developing countries may take even longer. Thus, the incremental versions of 5G will be developed after 2025 which are expected to be better than 5G and inferior to 6G. This gradual process of innovation would make 6G ready for deployment around 2030. As it happened with the previous generations, large-scale deployment of 6G will not be immediate; rather, it is expected that 6G will be adopted gradually. It is also true that 6G may not be attractive for many developing countries as 5G itself would be too advanced for them. The individual communication demands can be easily met by the 5G specifications. Thus, 6G and its subsequent versions may remain limited only to the business and high-performance applications. By applying continuous delivery (CD), companies are able to deploy application changes to the customer rapidly and reliably-ably from the software repository to the customer's hands By applying continuous delivery (CD), companies are able to deploy application changes to the customer rapidly and reliably-ably from the software repository to the customer's hands By applying continuous delivery (CD), companies are able to deploy application changes to the customer rapidly and reliably-ably from the software repository to the customer's hands.

1.1. Structured of the paper

This paper is structured in the following way. The ERP-integrated predictive maintenance system architecture is provided in Section II. Section III contains the discussion of machine learning methods used to detect faults. Section IV deals with continuity of production and resiliency of operations. Lastly, in Section V, the literature has been summarized in the form of concluding the reviewed literature, summarizing the study, and presenting possible future research directions in the form of Section VI.

2. Architecture of ERP-Integrated Predictive Maintenance Systems

The conceptual framework presented in this study combines digital twin (DT) technology with enterprise resource planning (ERP) systems to facilitate predictive maintenance for intricate mechanical systems within decomposition facilities[14]. A cyber-physical environment is formed by the architecture's design, which integrates real-world machinery with digital models and smart analytics through a structured data and control framework. Integrating these systems creates a closed-loop system that can monitor machines in real-time, anticipate their conditions, and make maintenance decisions automatically, all of which are crucial in today's robot design and industrial automation [15]. Figure 1 shows the three interconnected levels of the framework, which represent the various tiers of machine data management responsibilities.

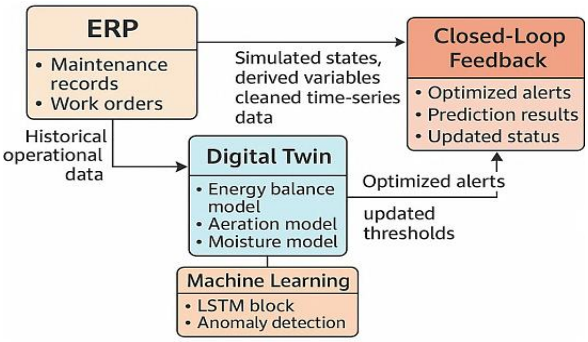

Fig 1: Architecture of the Integrated ERP–Predictive Maintenance System

The proposed system differs primarily in its integration mechanism and the type of information flow, even though many DT-ERP-PdM research uses comparable three-layer designs. While previous research has focused on one-way data exchange or simple alerts as the only means of communication between DT and ERP, this study designs a two-way mechanism where the digital twin model can impact ERP performance, change maintenance policies, and direct the decision-making loop using real-time predictions [16]. Problems with physical models not working together, noisy data being difficult to handle, decision-economic impact tracking not being possible, and real-time analysis not being very strong are all addressed by this method..

2.1. ERP–MES–SCADA integration framework

The integration between ERP, MES, and SCADA systems enables seamless data flow from shop-floor operations to enterprise planning (See figure 2). ERP systems manage business processes, MES handles production execution, and SCADA provides real-time control and monitoring[17].

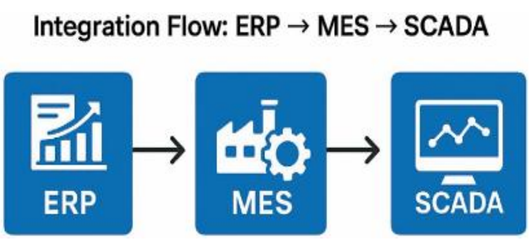

Fig 2: Integration Framework for ERP-MES-SCADA

Here are the Emerging Trends based on ERP, MES, and SCADA are as follows:

- AI-driven MES: Uses machine learning models to correlate historical production data with maintenance logs, enabling predictive analytics.

- Edge Computing: SCADA systems process data locally to enable faster decision-making and lower latency.
- SaaS-based ERP: Offers scalable, remote access to enterprise functions with real-time integration.
- Digital Twins: Simulation and diagnostics are made possible by virtual versions of physical assets.
- IIoT Connectivity: Real-time data sharing across systems enhances responsiveness and diagnostics.

The combination of the two systems presents a rather impressive pointer of bridging the gap between the real-time readings of the physical surroundings, as offered by SCADA, and the real-time management of the production process, as offered by MES. Constant communication of data is an opportunity that can enhance decision-making, operational effectiveness, and reduce resource wastage [18]. The integration should be able to work with different data formats, communication protocols, and system architectures [19][20]. This paper provides the integration of SCADA and MES systems, their relevance, difficulties, methods, and the advantages they offer to modern manufacturing through comprehensive research.

2.2. Data acquisition from IoT sensors and shop-floor systems.

The IoT is a revolutionary paradigm in which everyday objects and industrial devices are connected and intelligent, enabling them to gather, share, and act on data. Some of the most common IoT sensors in use include temperature and humidity sensors, which are important in climate control in smart homes and condition monitoring in logistics; motion sensors (such as PIR) which are critical to security systems and lighting that conserves energy; proximity sensors, which are essential in automation and touchless interface; and ambient light sensors, which are important in maximizing the brightness of devices. Sensors are devices that produce an output signal based on the quantification of a physical property in the environment [21]. These devices are used to provide quantitative and qualitative measurements of an environmental factor to monitor data, either to record it or to take action.

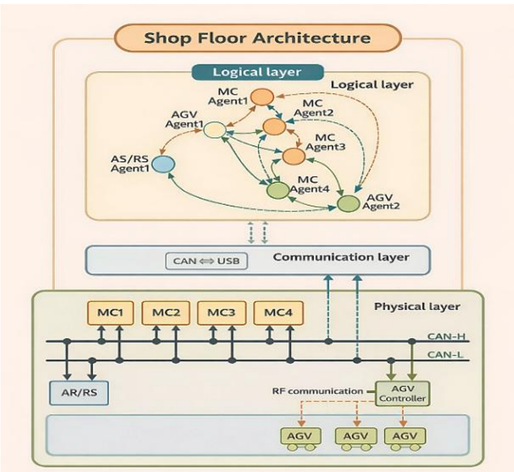

Fig 3: Architecture of the Shop Floor

In addition to smart shop floor, the idea is that CPSs would watch over the physical activities on the shop floor, make a virtual copy of the real world, and make decisions without being centralized [22]. The physical, communication, and logical layers form the backbone of smart shop floor architecture via the Internet of Things (Figure 3) [23].

2.3. Data synchronization and interoperability challenges

The IoT is huge, and interoperability remains a challenge within the ecosystem. The existing complexity and challenges in the interoperability of different systems are increasing due to the billions of connected IoT devices and the predicted exponential growth [24]. Interoperability in the IoT context means that different IoT systems and devices, even if not from the same manufacturer and/or running on different OS, can communicate, share data, and interpret it. This is an indispensable part of the appearance of efficient, scalable, and sustainable IoT ecosystems[25]. However, interoperability has to be put in place by addressing a range of issues (Figure 4):

- Diverse Hardware and Standards: The variety of IoT devices from different manufacturers, with distinct hardware configurations and standards, is a major challenge for intercommunication.
- Fragmentation of Communication Protocols: The protocols used for data transmission in Internet of Things (IoT) devices include Wi-Fi, Bluetooth, Zigbee, and LoRaWAN, among others. The lack of standardized protocols further complicates interoperability.
- Data Format and Semantic Differences: Even though a majority of devices are now capable of communicating to some extent, they have to deal with inconsistencies in data formats and semantics during communication.

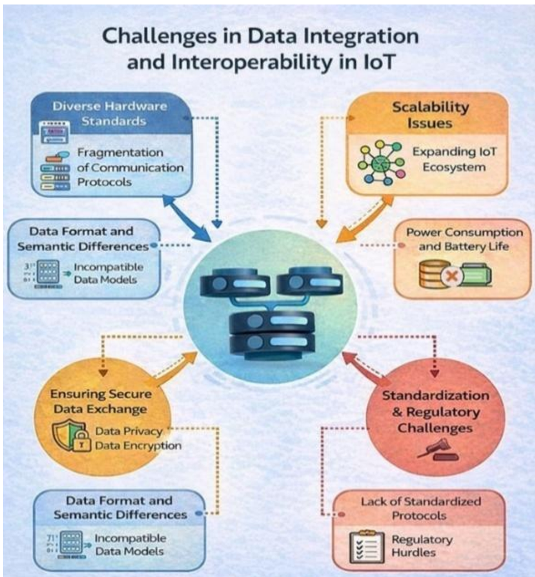

Fig 4: Challenges in Data Integration and Interoperability in IoT

3. Machine Learning Techniques for Fault Detection

The effectiveness of methods for defect identification, classification, and mitigation has been greatly enhanced by combining ML with AI models. This literature review highlights recent advances and methods in smart grid defect detection using machine learning, deep learning, and generative AI [26]. Table I illustrates the Comparison of ML Algorithms for Fault Detection in ERP-enabled systems, as shown below:

Table 1: Comparison of Machine Learning Algorithms for Fault Detection in ERP-Enabled

Algorithm	Data Need	Strength	Limitation	Industrial Suitability
Decision Tree (DT)	Labeled historical sensor data	Simple interpretation; fast training; easy rule extraction	Prone to overfitting; limited accuracy for complex patterns	Suitable for small to medium manufacturing systems requiring transparency
Random Forest (RF)	Large labeled datasets	High accuracy; robust to noise; handles nonlinear relationships	High computational cost; reduced interpretability	Widely used in large-scale industrial PdM with sufficient data availability
Support Vector Machine (SVM)	Labeled feature-engineered data	Effective for high-dimensional data; good generalization	Sensitive to kernel selection; scalability issues	Suitable for precision-critical equipment with moderate data volumes
Artificial Neural Network (ANN)	Large labeled datasets	Models complex nonlinear relationships; flexible architecture	Requires extensive tuning; limited explainability	Applicable to complex machinery with stable data pipelines
Isolation Forest (IF)	Unlabelled operational data	Efficient anomaly detection; scalable for high-dimensional data	Limited interpretability; threshold sensitivity	Highly suitable for real-time anomaly detection in ERP-integrated environments

3.1. Supervised learning models for failure classification

Supervised learning models are also used in ERP-integrated predictive maintenance architectures that classify equipment failures using the labeled historical data collected by IoT sensors, shop-floor machines, PLCs, and SCADA systems [27]. The data streams are processed in advance and converted into useful features, namely, machine health conditions. The operational patterns are then processed by supervised algorithms, including DT, RF, SVM, and NNs, which are trained to categorize the patterns into predefined failure types[28]. The models that have been trained are then connected with the ERP systems for instant identification of faults, automatic maintenance notifications, and decision-making based on data, which in turn improve the reliability of the system, decrease unplanned downtimes, and allow the production flow to run without interruptions.

3.2. Unsupervised and semi-supervised anomaly detection

Unsupervised learning approaches have become increasingly popular for addressing these problems. The models work without labels and detect anomalies by identifying patterns that differ from normal transaction behavior. The most famous techniques include Isolation Forest, which partitions the data into groups in such a way that one of the groups is the anomaly; Local Outlier Factor (LOF), which looks at and compares the density of the point with its neighbors; and OCSVM, which takes the surrounding points of the data as the boundary of normal points[29]. In addition, the studies highlighted the use of clustering methods, such as DBSCAN and GMM, for fault detection [30]. Similarly, probabilistic models, such as GMM, can capture complex data distributions, offering a flexible framework for anomaly detection when the data exhibit multimodal characteristics[31]. There are some mentioned below:

- Isolation Forest (IF) identifies anomalies through recursive data partitioning. Anomalies are instances that can be isolated with fewer splits. Optimal for massive transaction streams, this approach excels with high-dimensional data.
- Local Outlier Factor (LOF) compares one data point to its neighbors and finds the standard deviation. When it comes to detecting little changes in density, which could be signs of fraud, it works well.
- One-Class Support Vector Machine (OCSVM) forms a hyper spherical or hyperplanar boundary around the normal data points, applying kernel transformations to pull away the outlying anomalous points from the decision boundary.
- Gaussian Mixture Model (GMM) estimates the data distribution by summing up the Gaussian components, weighted according to their contribution. The transactions that are least likely under the fitted mixture are marked as potential anomalies.
- DBSCAN Anomalies are being recognized as points that do not fit into any of the high-density clusters. This method is especially helpful in pointing out irregularities based on groups, without any prior assumptions about the distribution of data.
- Autoencoder (AE) uses reconstruction learning to train a neural network to learn a concise representation of typical transactions. Anomalies are transactions that cause significant reconstruction mistakes.

Unsupervised learning techniques have gained increasing attention to overcome these challenges. These models identify anomalies by detecting patterns that deviate from normal transaction behavior without requiring explicit labels. Fraud Detection Using Unsupervised Learning PREPRINT Among the most notable techniques are Isolation Forest [Liu et al., 2008], which isolates anomalies through recursive partitioning; Local Outlier Factor (LOF) [Breunig et al., 2000], which measures local density deviation; and One-Class Support Vector Machines (OCSVM) [Schölkopf et al., 2001], which construct a boundary around normal data points .

Recent research has concentrated on semi-supervised anomaly detection, a method for labeling unlabelled data with high-confidence pseudo-labels. There is a lot of literature on semi-supervised learning, which often divides into two types: methods with one stage and methods with multiple stages [32]. A few single-stage semi-supervised learning methods boost the trustworthiness of threshold-based pseudo labels; these methods typically use high thresholds for unlabelled samples to avoid false pseudo labels. Another option is contrastive learning, which uses a combination of pseudo-labeling and consistency regularization to promote similar predictions between two perspectives on an instance, strengthening the model.

4. Role of ERP-Enabled Predictive Maintenance in Production Continuity

The word "operational performance review" (OPR) has two current meanings: first, as a feature unique to the banking industry; and second, as a type of tactical, lower-level planning and execution of business continuity procedures. Operational performance requirements (OPR) in the financial industry often center on maintaining the availability of mission-critical processes in the face of interruptions[33].

In the context of cybersecurity, business continuity refers to the protocols and measures put in place to maintain product or service delivery in the event of a cyber incident, as well as to limit harm and get operations back to normal as soon as possible. To guarantee that recovery and resilience strategies take into consideration the cyber environment, it is important for business continuity management to think about particular risks and weaknesses linked to IT [34][35]. It is essential to establish Business Continuity Management (BCM) strategies that prioritize cybersecurity and information technology in order to prevent unforeseen interruptions to an organization's activities, such as cyber events, technological failures, and process errors [36]. When planning for disaster recovery and restoration, it is critical to keep the cyber context in mind, as well as the unique risks and weaknesses linked to IT.

4.1. Impact of predictive maintenance on downtime reduction

The lack of investment in predictive technologies and the aging infrastructure in developing economies causes average downtime durations to be much higher. In India, for example, factories estimate 6 to 8 hours of machine downtime every month, which adds up to over 15% in lost output every year. Unscheduled equipment failures and power outages cause Brazilian textile companies to incur an average of 7 hours of downtime every month [37]. The importance of developing maintenance skills and finding cost-effective Internet of Things solutions is highlighted by these extended outages. Machine learning (ML) predictive maintenance is the process of using algorithms to assess data collected in real-time from equipment in order to predict when faults may happen [38][39]. Reduced downtime by 30% in pilot trials and more accurate maintenance schedule were both made possible by regression models' estimates of equipment remaining useful life. By spotting anomalies in operation, early action can reduce average monthly downtime to 2.5 hours.

4.2. ERP-enabled production planning and rescheduling

The goals of making decisions about ERP implementation in production planning and control are discussed in this section. The primary objectives are to enhance responsiveness, transparency, and efficiency, as illustrated in Figure 5. Underscoring the centrality of both financial performance and reliable information management in ERP-supported PPC, the primary objectives are Information Integration, Real-time Control, and Process Visibility (16%), followed by Cost Reduction and Data Quality (10%) [40]. The high implementation cost of enterprise resource planning (ERP) systems, particularly for SMEs, and the difficulty of integrating new technologies like the internet of things (IoT) and artificial intelligence (AI) are two of the biggest obstacles to ERP adoption [41]. However, as these technologies are spreading, the ability to create smart, autonomous factories is increasingly becoming a possibility.

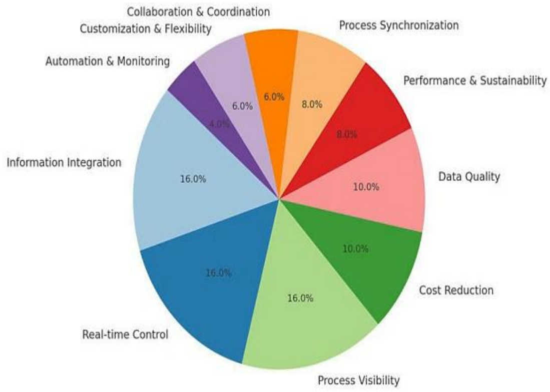

Fig 5: Key Factor in Process Optimization with the ERP System

ERP implementation is directed at efficiency in operations, in terms of automation and real-time responsiveness. This enables prompt decision-making and the entire picture of activities in areas like finance, production, and procurement [42]. There is no time to think too much, and the strategic integration of data is very important in situations when the demand is highly unpredictable, which is provided by ERP. BI-supported and predictive analytics demand forecasting tools and automation offer flexibility and adaptability.

5. Literature Review

The literature reviewed states that predictive maintenance and machine learning in the context of fault detection in software and industrial systems are popular among researchers. In this paper, it is observed that ML- and AI-based solutions are very useful in facilitating early fault detection, anomaly detection, and preventive maintenance, thus minimizing downtime and improving the overall reliability of a system. Table II indicates the important machine learning methods, fields of application, and comparative advantages that have been noted in the considered studies.

Elugbadebo, (2025) In the light of the growing complexity of modern software systems, reliability and constant operation are the most important ones. The idea of predictive maintenance (PdM) pervasive in the manufacturing and the industrial systems is now being implemented to the software systems. Predictive maintenance helps forecast and prevent failure while repair systems can be automated using machine learning (ML) to identify faults at an earlier stage and enact preemptive preventive actions. The paper discusses the practice of predictive maintenance in software applications, with consideration of machine learning techniques in fault detection and prevention. The paper covers the literature in depth, offers frameworks on predictive software maintenance, considers real-world applications, identifies challenges, and provides guidelines for future research. A table of comparison shows different ML approaches, their advantages and weaknesses [43].

Torshin, (2025) The advent of Industry 4.0 has made the incorporation of ML in the manufacturing process one of the primary strategies of increasing the efficiency of production and reducing the time spent on downtimes. Predictive maintenance, as well as fault detection in Printed Circuit Board (PCB) manufacturing are very important to ensure that the yield, quality, and reliability of equipment is maintained at high levels. This paper will explore how various machine learning methods, including the deep learning algorithm, supervised learning, and unsupervised clustering, could be applied to automate fault classification, predictive diagnostics, and real-time monitoring in PCB fabrication process, through data sets obtained by sensors mounted on surface-mount technology (SMT) lines, drilling machines, as well as automated optical inspection (AOI) devices [44].

Sandhya Sadashiv Mahure, Deharkar and Yadav, (2024) present the current understanding of machine learning (ML) approaches, uses, and issues concerning industrial predictive maintenance practices. This is a valuable source of information to people in industrial sector to understand how, what, and what challenges there are in integrating machine learning in predictive maintenance strategies. This study analyzes the literature, case studies, and practical applications in order to identify the effectiveness of machine learning in enhancing the maintenance processes and general equipment reliability. Other material introduced in the article involves supervised learning, reinforcement learning, and unsupervised learning which are machine learning (ML) tools that can be used in predictive maintenance in the business world [45].

Owen, Axel and Nelson, (2023) Client trust and satisfaction necessitate guaranteeing the stability of Automated Teller Machines (ATMs) during their operation, which contributes greatly to contemporary banking. In the situation when one has to cope with the sudden breakdowns and inefficiencies, the traditional approaches to maintenance such as the reactive and preventive maintenance often become ineffective. In this case, consider the possibility of application of ATM predictive maintenance by means of the IoT and ML algorithms. This approach aims at decreasing the cost of maintenance and downtime through combining Internet of Things sensors, real-time data gathering, and sophisticated analytics to anticipate and avert potential issues. They introduce a full methodology that involves IoT device data collection, preprocessing, and the use of suitable machine learning models for predictive analytics [46].

Sheriffdeen (2022) analyzes different AI methods, such as supervised, unsupervised and deep learning models, their advantages, difficulties and their practical uses. It also explores how various industries, such as manufacturing, energy, transportation, and many others are enjoying the fruits of AI-guided anomaly detection in the form of operational effectiveness, cost-saving, and asset life. Lastly, the paper predicts the future of AI-enabled predictive maintenance systems with an emphasis on the necessity of constant innovation, incorporation with IoT, and the possibility of the development of fully autonomous systems capable of transforming the way maintenance strategies are developed to allow industrial operations to be smarter, more efficient, and more resilient to disruptions [47].

Parmar, (2021) Utilizing the data that is gathered by Internet of Things (IoT) sensors in predictive maintenance (PdM) can completely transform the process of semiconductor production by obtaining more reliable equipment and simplifying the process. The impact of Internet of Things (IoT) sensor networks, sophisticated analytics, and MES integration on predictive maintenance strategy deployment in semiconductor production is the subject of this review. In order to lay the groundwork for predictive maintenance, IoT sensor networks allow for the complete collection of real-time data on equipment performance and ambient conditions. Machine learning-based methods, ARIMA, and exponential smoothing are some of the time series forecasting algorithms used to foretell when machinery will break down [48].

Table 2: ERP-Enabled Predictive Maintenance in Manufacturing for Fault Detection and Production Continuity

Authors (year)	Focus Area	Key Findings	Approaches	Objectives	Futherwork
Elugbadebo (2025)	Predictive maintenance in software systems	ML-based PdM improves early fault detection, fault resilience, and system availability while reducing downtime in complex software environments.	Supervised and unsupervised ML, fault prediction models, and automated repair frameworks.	Adapt PdM principles from manufacturing to software engineering for reliability and continuity.	Develop autonomous self-healing systems and scalable PdM frameworks for cloud-native software.
Torshin (2025)	PCB manufacturing fault detection	ML models accurately predict equipment failures and detect PCB defects, improving yield and product quality.	Supervised learning, clustering, deep learning, and real-time sensor analytics.	Enable real-time monitoring and predictive diagnostics in PCB fabrication lines.	Integration of advanced deep learning and digital twins for end-to-end PCB optimization.
Mahure; Deharkar; Yadav (2024)	ML-based predictive maintenance in manufacturing	ML enhances maintenance efficiency, reduces unplanned downtime, and improves equipment reliability.	Supervised, unsupervised, reinforcement learning; literature review and case studies.	Analyze ML techniques and their effectiveness in industrial predictive maintenance.	Address data quality issues and develop hybrid ML models for industrial scalability.
Owen; Axel; Nelson (2023)	Predictive maintenance for ATMs	IoT-enabled PdM significantly reduces ATM downtime and maintenance costs.	IoT sensors, real-time data analytics, ML-based failure prediction.	Improve ATM operational reliability and customer satisfaction.	Expansion toward AI-driven autonomous maintenance and large-scale banking networks.
Sheriffdeen (2022)	AI-driven anomaly detection	AI-based anomaly detection enables early failure identification and optimized maintenance scheduling.	Supervised, unsupervised, deep learning, and real-time sensor monitoring.	Enhance operational efficiency and asset longevity through AI-enabled PdM.	Fully autonomous PdM systems integrated with IoT and edge computing.
Parmar **(2021)**	Semiconductor manufacturing PdM	IoT sensor data combined with analytics improves equipment reliability and production efficiency.	Time-series forecasting (ARIMA, exponential smoothing), ML, MES integration.	Optimize semiconductor manufacturing through predictive maintenance.	Adoption of AI-driven forecasting and tighter MES–IoT integration.

6. Conclusion and Future Work

Predictive maintenance and fault detection based on ERP in current manufacturing systems, specifically how Industrial Internet of Things (IIoT), machine learning, and digital twin technologies are integrated into ERP, MES, and SCADA systems. The studies reviewed all point towards the fact that predictive maintenance is much superior to the traditional reactive and time-based preventive maintenance approaches, where early fault identification, preventing unplanned downtimes and enhancing the reliability of equipment in the production process and its continuity are possible. Machine learning models like supervised classification, unsupervised anomaly detection and deep learning time-series models have been demonstrated to be capable of modeling complex machine behavior and support real-time monitoring of conditions.

The QAD ERP software and predictive analytics can be used to directly relate the maintenance insights with the production planning, production scheduling, inventory control, and optimization of resources. Such interconnection among the entities enhances the quality of the enterprise-level decision-making process along with the operational resilience since the maintenance activities are aligned with the manufacturing objectives. Their future focus is likely to be on developing data models that are standardized and semantic-based interoperability frameworks to enable the seamless integration of IoT devices, digital twins, and ERP systems. This will also have to focus more on the application of the methods of explainable and hybrid artificial intelligence, which include supervised, unsupervised and reinforcement learning to the industrial decision-making.

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