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Predictive Maintenance in Industrial Automation and Smart Manufacturing Applications using Artificial Intelligence

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Abstract

Recently, with the advent of Industry 4.0 (I4.0), intelligent systems, Machine Learning (ML) within Artificial Intelligence (AI), and Predictive Maintenance (PM) methodologies have been widely implemented in industries to manage the health state of machinery in the workplace. Owing to the shift in technology regarding 14.0, information technologies, computerized control, and networked communications, it is feasible to amass extensive data on working and process circumstances generated by various equipment. This data can be utilized for automated fault identification and evaluation to reduce downtime, enhance component use rates, and prolong their remaining valuable lifespans. PM is essential to long-term smart manufacturing in I4.0. AI approaches have become a viable instrument in project management systems for intelligent production in I4.0, attracting significant interest from writers in recent years. This paper seeks to thoroughly review recent developments in AI techniques extensively utilized for predictive maintenance in smart manufacturing within I4.0. It categorizes the research based on AI methods, categories, the technology employed, collecting data devices, information organization, dimensions, and type. It emphasizes the principal contributions of investigators, thereby providing rules and a foundation for future studies.

Keywords: Predictive Maintenance, Industrial Automation, Smart Manufacturing, Artificial Intelligence

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Introduction

Companies are presently experiencing "The Fourth Industrial Revolution," commonly referred to as Industry 4.0 (I4.0) (Mayer & Oosthuizen,2020). I4.0 primarily integrates physical and digital technologies within manufacturing environments. The emergence of I4.0 has rendered Prognostics and Health Monitoring (PHM) (Kwon et al., 2017) an essential trend within the context of commercial big data and intelligent production while simultaneously providing a dependable solution for managing the health state of machinery in factories. I4.0 and its pivotal technologies are crucial for rendering industrial systems independent, hence facilitating automated data collecting from industrial machinery and elements. Machine Learning (ML) (Diez-Olivan et al., 2019) can be employed for automatic fault identification and diagnosis according to the type of acquired data. Identifying suitable ML methodologies, data types, data volumes, and equipment for implementing ML in industry systems is exceedingly challenging. Selecting an unsuitable Predictive Maintenance (PM) (Achouch et al., 2022) technique, a database, and data volume results in time inefficiencies and impractical maintenance planning. This study seeks to provide a thorough literature analysis to identify existing literature on and applications for Artificial Intelligence (AI) (Secinaro et al., 2021), thereby assisting researchers and practitioners in selecting suitable AI algorithms, data dimensions, and information types for viable AI applications.

PM for industrial machinery can detect performance decline, as it is engineered to attain near-zero concealed hazards, mistakes, pollutants, and accidents inside the production setting. The extensive data amassed for AI encompasses significant knowledge and valuable insights that can enhance overall productivity in producing procedures and dynamics of systems and facilitate decision-making in various domains, particularly in condition-based upkeep and health tracking. Recent technological advancements in information methods, electronic oversight, and communications networks have enabled the collection of extensive volumes of working and processing condition data from various equipment, facilitating automated Fault Detection and Diagnosis (FDD) (Halmetoja,2022). The gathered data sets can be utilized to formulate more efficient techniques for bright, proactive upkeep, commonly called PM. AI applications offer several advantages, including lower servicing costs, decreased repair downtime, minimized machine faults, extended spare-part lifespan, diminished inventory, enhanced operator safety, a rise in output, improved repair confirmation, and a general boost in profit, among others. These benefits are significantly linked to maintenance methods. Fault finding is a crucial element of preemptive upkeep, and organizations need to identify issues in the early phases.

Industrial Automation

2.1 Industrial Revolution

The industry has seen four significant revolutions. The First Industrial Revolution (I1.0) occurred from 1785 to 1865, characterized by the advent of mechanization, coal utilization, and the steam locomotive's advancement. The Second Industrial Revolution (I2.0) introduced mass production at reduced costs with the advent of electricity and advancements in transportation. I3.0 transpired between 1975 to 2015. It emphasizes emerging information technology, gadgets, and communications. The Hannover Exhibition initially introduced the I4.0. The definition of

I4.0 varies based on the area of use and study.

2.2 Strategies for Industrial Repair

European regulations define maintenance as a synthesis of actions and administration approaches to guarantee the machine's optimal operation over time. Corrective Maintenance (CM) (Erkoyuncu et al., 2017) refers to the actions taken whenever a machine experiences problems or malfunctions. No work will commence until the malfunction is rectified. PM seeks to diminish the likelihood of components failing. It is executed at particular rates or intervals. PM and Condition-Based Management (CBM) (Zou et al., 2019) solutions have recently garnered increased interest from manufacturers. Predictive maintenance is a methodology employed to anticipate a machine part's imminent breakdown or operational lifespan before its malfunction. The research can use extensive data to train AI algorithms to optimize production systems. The algorithms can identify patterns associated with defects, malfunctions, or early-stage deterioration to provide suitable remediation.

2.3 Categories of Control in Industrial Repair

There are four primary inspection categories for physical production systems in industrial upkeep. The initial form, visual inspection, involves an in-person or regular examination of the entire system (I1.0). The second category comprises instrument checks, which involve a combination of physical assessments and regular equipment utilization to evaluate the system's state (I2.0). The third sort of inspection is real-time condition tracking, which

involves continual assessment by enabling specialists to provide insights into the system's status or health (I3.0). The final form is proactive upkeep, enabling professionals and data researchers to utilize acquired data to forecast the operational lifespan of devices.

Background

The PHM system has now established itself as a reliable approach for ensuring the safety status of machinery, including fault detection and Remaining Usable Life (RUL) assessment. The methodical use of contemporary testing results in AI and Information Technology (IT) technologies achieves this.PM can reduce maintenance expenses and extend the RUL.

Emerging issues resulting in catastrophic failures can be accurately anticipated, allowing for the implementation of suitable measures to prevent such shortcomings based on predictive results. Industrial machinery can be changed or restored at any suitable period before a malfunction, potentially restoring the system or appliance to its previous condition following each service completion. The health state of the machinery, part, structure, or machine can be assessed at any moment. Their inability can be anticipated to provide a non-zero downtime efficiency. The project manager primarily employs predictive information to organize forthcoming repair tasks precisely.

The objective of PM is to gather not only process information and its variables but also physical wellness metrics of the machinery, device, or element, including stress, tremors, temperatures, viscosity acoustics, and flow rate information, among others. This acquired information is currently extensively utilized for identifying issues, early defect detection, machine health evaluation, and forecasting the future condition of the equipment.

ML is a subset of AI characterized by algorithms or programs capable of learning with minimal or no external assistance. AI addresses numerous challenges, including vision, extensive data, automation, and speech recognition. AI approaches are engineered to extract knowledge from existing data. The PM technique and technology that facilitate PM are illustrated in Fig. 1. Essential technology for PM includes intelligent sensors, networking, data mining, AI, and cloud computing platforms.

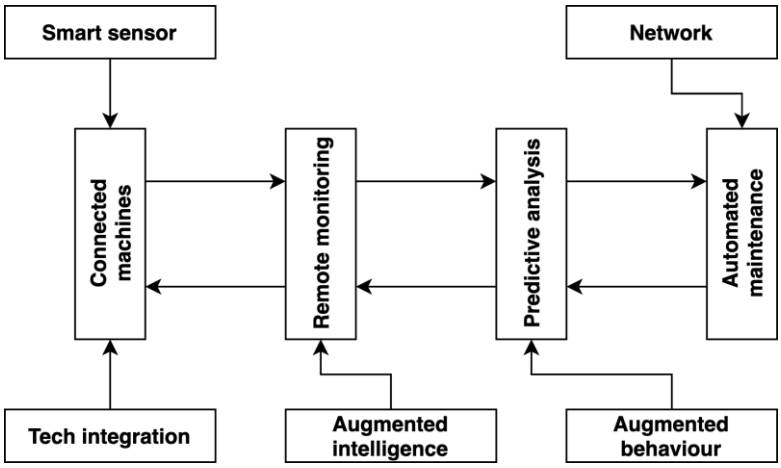


Fig. 1: PM Process Technologies

The study categorizes the tools that facilitate PM into five classifications. These encompass sensors, networking, integration, AI, and enhanced behavior. Intelligent sensors collect machine data through integrated or environmental data via outside sensors. The system facilitates the storage of information and transmission using Bluetooth and WiFi. Technology integration facilitates data collection and management through the Internet of Things (IoT), while AI enhances data processing and analysis. Enhanced behavior enables virtualization, calculating, and service platforms through applications and tickets to support the operator.

AI methods are classified into three distinct categories: (1) supervised learning, (2) unsupervised training, and (3) Reinforcement Learning (RL) (refer to Fig. 2). The objective is to demonstrate the complexity of the structure and the often employed learning methodologies. Other algorithms can be integrated to enhance categorization efficacy. Several AI methods are suitable for unsupervised and supervised training.

In unsupervised AI methods, input is absent from an external instructor or informed expert. The program identifies groups based on accessible information. The primary objective of supervised education is to ascertain the unknown categories of things through clustering, while classification pertains specifically to supervised training. Unsupervised ML is any AI technique that seeks to discern patterns without a specified output, as seen in supervised learning or feedback, as in RL.

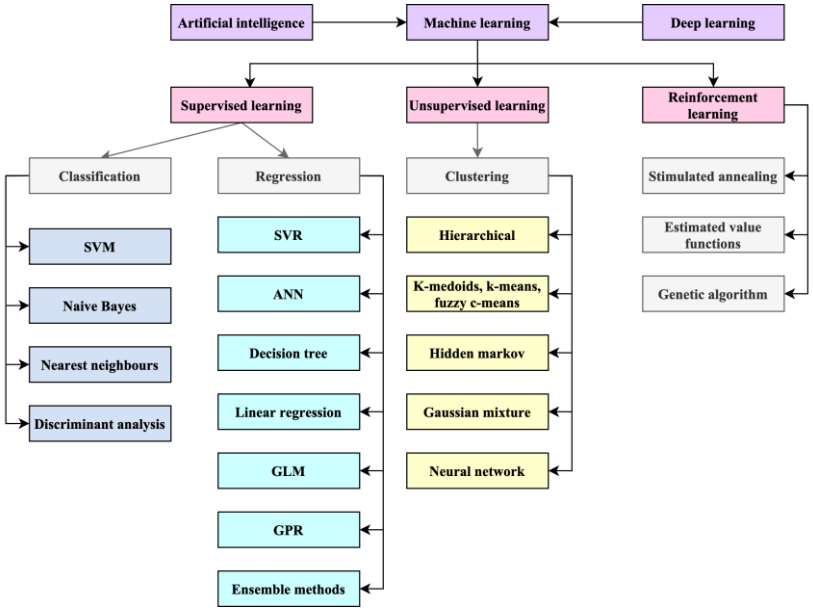


Fig. 2: Classification of Methods

Clustering, self-organizing maps, and relationships represent the three fundamental examples of learning without supervision. This research categorizes the examined publications into three AI groups: regression, classification, and grouping, as seen in Fig. 2. The data employed in research publications is classified into two categories: genuine data, derived from actual machinery, and simulated and synthetic data, produced to fulfill specific requirements such as validation of models in AI.

RL is disseminating training knowledge to the general public. In RL, the learner must ascertain which activities yield the most favorable results (quantitative reinforcement signals) through experimentation rather than instruction. Certain scholars regarded RL as a distinct form of guided learning. As articulated by RL, issues in RL diverge from those in controlled learning, as they are characterized by the lack of labeled instances of "positive" and "negative" behavior.

Conclusion

The literature is organized according to AI approaches, classifications, equipment utilized, devices employed for data acquisition, descriptions of the applicable data, data size, and data type. A thorough research evaluation indicates that proactive upkeep remains a crucial strategy for enhancing efficiency in contexts with machines subject to wear over time. The potential for producing and deploying inexpensive, interconnected sensors will continue to expand with the advancement of IoT. As the volume of data escalates with the proliferation of sensors, the potential for employing AI techniques for maintenance planning will expand.

This study thoroughly examines AI approaches in predictive maintenance by focusing on the most prevalent methods, the industrial sectors where these methods are implemented, and the data types employed for AI applications. It proposes a pathway for future research and establishes a basis for further investigation. Subsequent observations are provided to encourage authors and practitioners in their research endeavors.

- Collecting real-time data through an intelligent data-gathering system can facilitate the automation of proactive upkeep.

The amalgamation of multiple AI models can yield superior predictions compared to using a singular model.

- Further investigation of cloud-based AI model deployments is necessary.

Categorization and algorithms for detecting anomalies can be integrated to preserve the accuracy of categorization models while retaining the benefits of identifying anomalies. Thus, PM can be implemented on devices or networks lacking extensive datasets.

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