DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE FOR PREDICTIVE MAINTENANCE IN INDUSTRY 4.0

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Bentham Books

Data Analytics and Artificial Intelligence for Predictive Maintenance in Industry 4.0

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ISBN (Online): 979-8-89881-087-0

ISBN (Print): 979-8-89881-088-7

ISBN (Paperback): 979-8-89881-089-4

Published by Bentham Science Publishers Pte. Ltd. Singapore, in collaboration with
Eureka Conferences, USA.

First published in 2025.

Bentham Science Publishers Pte. Ltd.
No. 9 Raffles Place
Office No. 26-01
Singapore 048619
Singapore
Email: subscriptions@benthamscience.net

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FOREWORD

The convergence of Data Analytics and Artificial Intelligence (AI) has unlocked transformative possibilities across industries, and their application in predictive maintenance within the Industry 4.0 framework stands as a testament to this progress. The chapters in the book *Data Analytics and Artificial Intelligence for Predictive Maintenance in Industry 4.0* comprehensively explore the intersection between cutting-edge technology and maintenance practices, offering invaluable insights for researchers, practitioners, and industry leaders.

This anthology begins by establishing a foundational understanding of predictive maintenance, detailing how Industry 4.0's enabling technologies—such as the Internet of Things (IoT), cloud computing, and big data analytics—pave the way for smarter, data-driven decisions. Subsequent chapters delve into innovative methodologies, showcasing machine learning, deep learning, and generative AI implementation in predictive maintenance systems. These techniques address challenges such as real-time monitoring, fault detection, and optimization of resources, significantly reducing downtime and improving operational efficiency.

The book emphasizes technical advancements and contextualizes them within diverse applications, ranging from agriculture and manufacturing to disaster resilience and healthcare. Unique perspectives on federated learning, bibliometric analyses of AI innovation, EEG-based IoT for human-machine interaction, and optimization strategies further broaden the scope of discussion. Integrating novel approaches like homomorphic encryption in healthcare predictive analytics highlights the commitment to balancing technological progress with ethical considerations like privacy and security.

Readers will also find forward-looking perspectives in chapters discussing quantum computing, augmented and virtual reality, and blockchain as potential disruptors in predictive maintenance. This book equips readers to navigate the complexities of implementing predictive maintenance systems in dynamic industrial environments by addressing challenges such as interoperability, workforce upskilling, and data governance.

This book represents the collective expertise and forward-thinking vision of its esteemed editors—Dr. Tanu Singh, Dr. Vinod Patidar, Dr. Arvind Panwar, and Dr. Urvashi Sugandh—and its contributors. Together, they provide a robust academic and practical framework to harness the potential of predictive maintenance in shaping the future of Industry 4.0.

With the advent of Industry 4.0, the industrial landscape is undergoing a significant transformation, driven by the integration of data analytics and artificial intelligence into predictive maintenance. *Data Analytics and Artificial Intelligence for Predictive Maintenance in Industry 4.0* captures this dynamic shift, offering a balanced mix of foundational knowledge, pioneering advancements, and innovative perspectives. This book is a vital resource for academics, industry professionals, and policymakers aiming to navigate and shape this evolving field.

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PREFACE

The rapid technological advancement in the era of Industry 4.0, led by the integration of cutting-edge technologies such as data-driven systems, smart factories, the Internet of Things (IoT), big data analytics, artificial intelligence, and machine learning, is revolutionizing manufacturing and industrial processes. The adoption of such technologies has innovated a diverse range of solutions, such as predictive maintenance, directing a shift from a reactive and preventive maintenance approach to a highly proactive maintenance approach. The predictive maintenance approach is a key enabler of efficiency in Industry 4.0 due to its ability to anticipate equipment failures, optimize maintenance schedules, and reduce downtime, leading to cost savings and overall increased productivity along with the improvement in safety measures. Artificial Intelligence and data analytics have emerged as crucial technologies in predictive maintenance due to their capabilities of processing vast amounts of data, identifying patterns, and providing actionable insights that improve overall maintenance processes.

The book *Data Analytics and AI for Predictive Maintenance in Industry 4.0* offers a thorough overview of how data analytics and artificial intelligence are applied to predictive maintenance across various industries. The chapters in this edited book offer in-depth analyses of the fundamental principles, practical resources, optimization methods, and smart uses of AI and machine learning algorithms, advanced sensor technologies, and resilience against natural disasters for predictive maintenance. These contributions also include real-world case studies on predictive maintenance ensuring that readers gain theoretical as well as practical insights into the application of these technologies.

The book is divided into 13 chapters. Each chapter highlights a key aspect of predictive maintenance and has been carefully selected and peer-reviewed, ensuring that the book offers both theoretical insights and practical applications. The first few chapters offer core principles and knowledge on data analytics, machine learning, and IoT technologies, preparing readers for in-depth exploration of the challenges and opportunities in predictive maintenance. The later chapters provide a thorough overview of big data analytics integration, federated learning techniques for the advancement of agriculture, healthcare predictive analysis, and advanced optimization methods, demonstrating their potential to revolutionize maintenance strategies and improve decision-making. Overall, the book provides a comprehensive summary for a broad audience that includes academics, professionals, and researchers keen to apply data analytics and artificial intelligence for predictive maintenance in a wide spectrum of industries, from agriculture and healthcare to disaster management and manufacturing.

We are grateful to all the authors who have shared their expertise in the form of contributed chapters in this edited volume. Their expertise, diverse experiences, and practical insights offer readers a comprehensive view of the emerging landscape of predictive maintenance.

As editors of this book, our role has been to oversee the organization and compilation of the chapters and to ensure coherence across the content. The responsibility for the integrity, accuracy, and reliability of the scientific material rests with the respective authors. The views and findings expressed in the chapters are those of the authors and do not necessarily reflect those of the editors.

We would like to extend our gratitude to our institutions for their support, resources, and encouragement, without which this book would not have been possible. Special thanks go to our editorial team for their meticulous work in ensuring the quality of this publication.

As the industry undergoes digital transformation, we are sure that this book will inspire innovative ideas and applications in predictive maintenance, leading to more intelligent and resilient industrial operations in the future.

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CHAPTER 1

Understanding the Basics of Data Analytics and AI for Predictive Maintenance in Industry 4.0

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Abstract: Industry 4.0 marks a transformational era in industrial practices, defined by the merging of cutting-edge technologies such as the Internet of Things, cyber-physical systems, extensive data examination, cloud computing, artificial intelligence, and machine learning. This chapter, entitled "Understanding the Basics of Data Analytics and AI for Predictive Maintenance in Industry 4.0," offers an inclusive exploration of how data examination and AI are revolutionizing predictive servicing strategies to improve functional efficacy, decrease expenses, and enhance safety. To commence with an outline of Industry 4.0 and the evolution of servicing strategies—from reactive and preventative to predictive—the chapter underscores the pivotal role of data-driven decision-making in modern industrial operations. It delves into the basics of data examination, analyzing the kinds of industrial data, methods of obtaining information, and preprocessing techniques. Core analytical techniques, like descriptive, diagnostic, predictive, and, briefly, prescriptive analytics, are inspected to demonstrate their applications in servicing contexts. The chapter further examines the joining of AI in predictive servicing, detailing machine learning algorithms. It also highlights the instruments and platforms usually used in data examination and AI, together with programming languages like Python and R, specialized software, and data visualization instruments. The advantages, like reduced downtime, servicing cost savings, extended equipment lifespan, and enhanced decision-making capabilities, are balanced against challenges, for example, data quality management, scalability, cybersecurity concerns, skills gaps, cultural resistance to change, and investment considerations. The chapter also explores emerging developments and future directions, like edge computing, digital twins, comprehensible AI, merging with other Industry 4.0 technologies, and the concept of Predictive Servicing as a Service (PMaaS), analyzing their possible influence to further transform servicing practices and contribute to sustainability. By providing foundational knowledge and practical insights and highlighting both oppor-

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tunities and challenges, this chapter aims to provide readers with the understanding necessary to leverage data examination and AI for innovative and efficient predictive servicing in the evolving landscape of Industry 4.0.

Keywords: Artificial intelligence (AI), Data analytics, Industry 4.0, Internet of things (IoT), Machine learning (ML), Predictive maintenance.

INTRODUCTION

The dawn of Industry 4.0 has transformed how industries function, communicate, and conceive [1]. This section intends to offer a thorough comprehension of the fundamental principles of data examination and synthetic consciousness for anticipatory servicing in Industry 4.0. In this section, we will plunge into the overview of Industry 4.0, its progression, and the importance of predictive servicing at this time. Additionally, industries must leverage novel technologies to optimize operations whilst ensuring worker safety through automation. While change can inspire apprehension, an open mind to emerging tools may reveal opportunities to enhance productivity, quality, and outcomes [2].

OVERVIEW OF INDUSTRY 4.0

Industry 4.0 and the fusion of cyber systems will revolutionize manufacturing like never before. While companies scramble to integrate networks of intelligent devices and technologies capable of autonomous action, profound transformation lies ahead. Already, robots work alongside workers on factory floors, communicating in real time through IoT platforms to autonomously complete tasks. Machines learn from vast torrents of big data, enabling precision and customization at scale. Human and artificial intelligence will cooperate as never before to realize smart factories envisioned since the dawn of computational might, though challenges remain to full realization [3]. Optimists point to skyrocketing productivity and emancipation from dreary tasks, while others fear widespread economic upheaval and profound social changes as old jobs become obsolete. One thing is clear - a new industrial age defined by sentient systems and omnipresent information looms on the horizon, for good and for bad [4].

The Evolution of Industrial Revolutions

The novelty concept of Industry 4.0 does not exist alone and is deeply rooted in the flow of industrial revolutions that took place in a certain chronological order. The first industrial revolution took place in the late 18^{th} century and tended to associate with the transition from manual labor to the operation of machines [5]. The second revolution unfolded in the late 19^{th} and early 20^{th} century and involved the further development of machinery, as well as the new concept of mass production, which was represented by conveyor belts. The third industrial revolution started in the mid-20th century and was based on the vastly spread computer, automation, and mechanization of production. The fourth industrial revolution, which is sometimes called Industry 4.0, is fuelled by the integration of digital, physical, and biological systems, which provides for the creation of levels of automation, service, and innovation that were not experienced before by the manufacturing industry. The fundamental transformation of Industry 4.0 is not only in industrial facilities' widespread adoption of modern and highly efficient technologies but also in the development of an entirely new ecosystem where machines, humans, and data interact with each other harmoniously and effectively [6]. Industry 4.0 ecosystem is built on interconnectivity, automation, and the ability to exchange data for the foundation of smart factories, which create smart products and carry out smart services.

In the next sections, the basics of data analytics and AI in predictive maintenance will be discussed. These will include types of data and data analytics techniques, AI algorithms, integration of these technologies in Industry 4.0, benefits, and challenges of the implementation.

Key Technologies Driving Industry 4.0

The hallmarks of Industry 4.0 are the convergence of a number of essential technologies that revolutionize manufacturing. The technologies are the foundation on which smart factories, smart products, and smart services are built. It can be said that the key technologies of Industry 4.0 are:

- **Internet of Things:** The term Internet of Things refers to the interconnection of devices and machines using sensors to collect data and exchange it. In other words, IoT refers to the connection of anything from house appliances and motor vehicles to the entire factory and networks, enabling their communication. For example, in the case of predictive maintenance, IoT sensors can be used to monitor equipment and detect and possibly predict undesired anomalies and failures. Other uses for IoT devices are keeping track of inventory levels, monitoring the supply chain, and optimizing logistics [7].
- **Cyber-Physical Systems (CPS):** Cyber-physical systems amalgamate computational and physical mechanisms to generate ingenious infrastructures. CPS combines the tangible with the digital, permitting live observation, administration, and optimization of corporeal processes. In prescient servicing, CPS can monitor hardware performance, distinguish anomalies, and foresee failures. CPS can furthermore optimize fabrication techniques, diminish energy usage, and improve merchandise quality [8].
- **Big Data and Analytics:** Vast data alludes to the expansive and intricate

CHAPTER 2

AI-Enabled Industrial Intelligence: From Data Engineering to Predictive Modeling

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Abstract: The application of artificial intelligence, combined with advanced data gathering, processing, and analytics, has revolutionized industrial operations and elevated predictive maintenance in Industry 4.0 to a new level. Cutting-edge big data analytics platforms, cloud computing, and IoT-enabled enhancements in data collection have made predictive machine learning models accessible, cost-effective, and feasible for industrial applications. The chapter illustrates the importance of a well-structured data architecture and details steps from data collection and pre-processing to training and deploying machine learning models. Integrating real-time data streams with historical data allows for a comprehensive view of equipment health, enabling timely and accurate maintenance decisions. These enhancements have improved accuracy and increased effectiveness in several central aspects. The key techniques discussed include supervised learning and unsupervised learning, deep neural networks, and time series forecasting. In this chapter, such developments are shown for the aerospace, manufacturing, and transportation industries. The chapter deals with issues like data collection, streaming, storing and processing large amounts of data, and construction of more sophisticated models based on contemporary AI and ML algorithms and, therefore, provides development towards enhancing predictive maintenance in the era of Industry 4.0.

Keywords: Cloud computing, Data streaming, Deep neural networks, Edge computing, ETL processes, IoT, Supervised learning, Time series analysis, Unsupervised learning.

INTRODUCTION

With advancements in industrial operations, predictive maintenance has come into play as a paradigm shift. It is an approach where technologies predict failures before they occur and thus improve the maintenance regimes. This chapter aims to elaborate on some of the cutting-edge analytic tools and methodologies, including machine learning, deep learning, pattern recognition, and others, that constitute a

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critical part of the predictive maintenance revolution. The way predictive maintenance works includes performing data analysis to perform ML modeling to prevent breakdowns, Irregularities, and faults arising in industrial machinery based on patterns learned and monitored from data gathered from IoT sensors, environment, maintenance logs, and so forth [1]. Such forms of data analytics in predictive maintenance systems usually require a step-by-step combination of supervised, unsupervised, and deep learning, as well as anomaly detection and time series analysis methods to be used [2]. Equipment failure prediction and lifespan estimation are usually performed under supervised learning, and the former includes anomaly detection, which utilizes unsupervised learning and state machine modeling [3]. Deep learning models are utilized to analyze sensor data patterns, while time series analysis is applied to forecast equipment performance trends [4].

With the inclusion of these techniques, predictive maintenance systems achieve high accuracy and reliability, which enhances the effective utilization of operations and increases the reliability of equipment [5].

These complex models are trained on a high volume of datasets that are formed from the combination of operational data from equipment sensors that give monitored parameters such as vibrations, pressure, and temperature. Such big data analytics are useful in converting these insights into interventions [6]. It helps to manage the time-series data and facilitates the analysis of the data stream without restoring it; instead it identifies important features to guide data interpretation [7]. Advanced computing resources, especially those supported by cloud systems, can maintain the management of large amounts of data captured within a short time period and make accurate forecasts. Such a robust data processing architecture increases the accuracy of predictive maintenance models and enables their application efficiently and cost-effectively, which overall has a great impact on improving the efficiency of operations and reliability of the equipment. Apart from issuing alerts about impending failures, the models are also capable of forecasting the future state of the machinery. These forecasts improve maintenance through process improvement and re-engineering, supply chain control, Remaining Useful Lifetime (RUL) evaluation, and planning downtime properly. This chapter aims to demonstrate the trends in the field of predictive maintenance and management using AI systems in the context of Industry 4.0, highlighting advanced predictive maintenance methods, optimization strategies, risk management techniques, and big data technologies.

ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML) ALGORITHMS IN INDUSTRY 4.0

With the integration of the AI (Artificial Intelligence) models, the evolution and development of various techniques of predictive maintenance became faster and more efficient by making use of large volumes of operational data to foresee the drawbacks of the equipment and improve maintenance scheduling. It is possible to review the historical and current data obtained from sensors on IoT, data and control systems SCADA, and maintenance logs by using advanced techniques like supervised learning for predicting faults and unsupervised learning for detecting anomalies. These models identify trends and relationships, both of which are critical for predicting distress and the need for maintenance. The integration of Artificial Intelligence and Machine Learning (AI and ML) in predictive maintenance has a great impact on reducing unplanned equipment downtime, increasing the life span of the equipment, and facilitating effective operations. Additionally, the learning capabilities of these models are not static as they also evolve with time; thus, even as the environment changes, the maintenance approaches continue to be effective, which will, in turn, realize savings and improved performance in many sectors.

This section will discuss the main features of the ML approaches relevant to predictive maintenance, the usage of these methods for different tasks, and the description of real-world applications of these methods in multiple industrial sectors.

Supervised Learning Overview

In supervised learning, a model is trained with the help of labeled data. In such instances, the input data is related to the output that is already known. In various industries, supervised learning methods are widely deployed to forecast equipment breakdowns based on past records.

Applications

- **Failure Prediction:** Identifying when equipment is likely to fail.
- **Anomaly Detection:** Classifying normal *versus* anomalous behavior on the basis of historical patterns.

Example: Manufacturing Industry

Within the manufacturing factory, devices are used to monitor certain parameters such as temperature, vibration, and pressure of machines. There are certain devices in the manufacturing factory that serve the purpose of taking readings of parameters such as temperature, vibration, and pressure of the machines. The

CHAPTER 3

Big Data Analytics for Predictive Maintenance in Industry 4.0.

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Abstract: This chapter presents a design for a Situation-Based Maintenance Model (SBMM) that explains different statistical approaches to predict maintenance. It also gives some example applications to help grasp predictive maintenance before exploring the possible big data models that can predict when maintenance work is most needed. The high-level architecture that reflects the big data predictive maintenance model is presented for the proven potential of future industrial predictive maintenance systems. The growing interest in Industry 4.0 has driven the creation of systems that are capable of real-time data generation. Many different industrial areas can benefit from this grand concept, and analytics is an important area of Industry 4.0. Whether it is structured data from Enterprise Resource Planning (ERP) or Customer Relationship Management (CRM) systems, unstructured data from sensors and machines, or new types of data generated from Radio Frequency Identification (RFID) devices or the Internet of Things (IoT), processing and analyzing extremely large datasets is a challenge that needs to be mastered. This transformation can be achieved through Big Data Analytics. These analytics combine statistical data analysis techniques, models, and algorithms with human ingenuity to yield new insights and optimized decisions.

INTRODUCTION

The term "Industry 4.0" was coined in Germany, and in recent years, it has been intensively used as a label for several technologies and trends in automation and data exchange in the manufacturing field, including industrial robotics, Internet of Things (IoT), digitally connected technologies, smart manufacturing, *etc*. The development of Industry 4.0 and smart manufacturing concepts is a result of technological advancements in several fields, including nanomaterials, regene-

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rative and regenerable off-grid energy conversion systems and other products, automation engineering, cloud computing techniques, cyber-physical systems, cognition and decision-making processes, smart services, business models, and the need to increase competitiveness for profit maximization. The Industry 4.0 concept includes several major technological aspects. The major core, revealing the main technology and performance, is related to continuous information exchange among technologies, *i.e*., cloud computing, Cyber-Physical Systems (CPS), the Internet of Things (IoT), and the related Digitization (DI) in a manufacturing context.

Big data has become the cornerstone of predictive maintenance technologies, and it can be said that all industries are somehow engaged with some kind of predictive maintenance research and development. Big data analytics technologies can allow the prediction of failures and breakdowns in an efficient manner, thus ensuring less downtime, anomalies reduction, and losses of the expected lifecycle as well as lower maintenance costs with spare parts and on-manpower. According to the Industry 4.0 quest, precision engineering of the spare part supply chain is also affecting the maintenance cost. At present, however, only a few industries can collect data regarding the equipment through their entire quality life cycle, from design to actual operation, selecting adequate predictive algorithms trained with the utilization data collected through the equipment in the operation phase and any additional relevant data. This subject aims to outline the most recent achievements in the field of predictive maintenance implementation in the Industry 4.0 context.

OVERVIEW OF BIG DATA ANALYTICS

Big data analytics refers to collecting, processing, analyzing, and interpreting a large number of data from different sources. The main challenges of big data analytics are data modeling and data processing in terms of volume, speed, timing, ingenuity, reliability, *etc*. These qualities are determined by what role big data plays in people and the value they can create. The realization of these values can help businesses make better decisions. Mobile Internet devices are also growing rapidly. The massive and increasing data sets generated by networked devices are the basis of big data. Big data and the powerful data mining methods developed by various disciplines, such as data analysis, database systems, data storage, information retrieval, machine learning, and pattern recognition, allow significant knowledge discovery in business and research.

In the era of digital transformation, various types of machines, electronically controlled devices, manufacturing facilities, and processes in manufacturing enterprises generate a great deal of structured and unstructured data, and the amount of this data becomes the key criterion for business success. Business success depends on the capability to cope and be profitable in an environment flooded with Industry 4.0 [1]. Technologies such as big data, the Internet of Things, cloud manufacturing, cloud computing, *etc*., are the main driving forces of the transformation from traditional manufacturing to Industry 4.0. These technologies have a significant effect on predictive maintenance methods. More digital data-based work on predictive maintenance and related big data application models is the main direction for future KD machinery.

Importance of Predictive Maintenance in Industry 4.0

Predictive maintenance is also essential for high-value assets. The overview of predictive maintenance is shown in Fig. (**1**). If any of the production lines or equipment goes down, it can cause a loss of business. A given production line equipment will produce a large part of the production volume for a specific product. By performing predictive maintenance and making up time, equipment and/or machines can spend more time producing what they should have produced, leading to increased operational productivity. The maintenance planning and scheduling costs in the predictive application are significantly reduced. Because PdM relies on the predictability of a piece of equipment, PdM does not have timely interventions that are characteristic of new tools/trackers required for advanced asset failures, which also reduces the cost of the deferred repair schedule [2]. Fig. (**1**) shows the overview of predictive maintenance.

Efficiently managing a maintenance program with a large amount of data results in optimal efficiency and cost savings. Because the condition of the factory equipment is always desirable, Predictive Maintenance (PdM) is the maintenance of the physical condition and is not planned and performs maintenance according to the actual state of the piece of equipment to maximize the life of the equipment.

Minimize maintenance costs. There are significant benefits as follows: By properly maintaining the service life of parts, equipment, and machines, maintenance costs are minimized, which helps to minimize the all-inclusive manufacturing cost over time. Traditional maintenance programs can only estimate when the machine fails. By creating unnecessary replacements/parts maintenance costs, predictive maintenance eliminates the potential for poor performance/equipment reliability [3]. The steps for predictive maintenance in Industry 4.0 are shown in Fig. (**2**).

CHAPTER 4

Hardware Security Enhancement with Generative Artificial Intelligence

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Abstract: In today's society, which is heavily influenced by technology, it is crucial to prioritize the security and integrity of computer systems and their underlying hardware components. As advancements in hardware technologies continue to progress rapidly, new vulnerabilities emerge, posing significant risks to the confidentiality and integrity of sensitive information. Therefore, it is essential to proactively identify and mitigate potential threats to hardware. Traditionally, threat modeling tools have primarily focused on software vulnerabilities, neglecting the exploration of hardware vulnerabilities. However, with the increasing complexity of hardware architectures, there is an urgent need for effective methodologies to assess and address potential threats at the hardware level. Currently, state-of-the-art approaches in hardware threat modeling rely on static analysis techniques and knowledge of known hardware vulnerabilities. The existing approaches are considered cumbersome since they require computer validation experts and engineers to perform manual inspection, simulation-based testing, and formal verification. These approaches face increasingly difficult challenges these days when hardware architectures continuously evolve, rendering them more advanced and complicated. In order to cope with these challenges, it is therefore essential to seek alternative and more reliable approaches that are capable of improving the efficacy and accuracy of threat identification and analysis. Since generative Artificial Intelligence (AI) is equipped with the tool to model and generate complex data patterns, it can be considered an alternative approach for hardware threat modeling. With the aid of generative AI, the restricted scope faced by threat modeling can, therefore, be expanded. By incorporating generative AI into hardware threat modeling, hardware vulnerabilities that are hard to be detected and analyzed by conventional approaches can be identified. Hence, the overall security and integrity of computer systems can also be significantly enhanced, resulting in the formation of a more secure environment for protecting sensitive information.

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Keywords: Artificial intelligence, Hardware security, RAG approach, RISC-V architecture, Threat modeling.

INTRODUCTION

The lifestyle of mankind has been interwoven seamlessly with advanced and ever-evolving technology nowadays. As such, computer systems and their corresponding auxiliaries have become an indispensable asset to society. For this reason, it is important to safeguard the security and reliability of computer systems and their hardware components. As the technology continues to evolve, more atrocious threats that defy the confidentiality and integrity of data are deemed to emerge. There is thus an urgent need to develop hardware security enhancement approaches to suppress the potential threats.

In order to develop approaches that can effectively mitigate threats, the security issues inherently associated with computer systems are to be identified and understood. Throughout the years, computer validation aficionados have focused their efforts and resources on coping with software threats and vulnerabilities. As technology continues to march inexorably towards a whole new realm, there exist threats in hardware architectures that have turned out to be a critical issue that can no longer be neglected.

Indeed, all of the latest hardware threat modeling approaches were developed on the basis of established hardware vulnerabilities, and they also emphasize primarily static analysis. Some of these popular approaches include manual inspection of hardware designs, testing *via* simulation, and formal verification. Though effective in certain aspects, all these approaches possess inherent limitations. In particular, these approaches have a high possibility of failing to detect threats that fall beyond the scope of well-recognized hardware vulnerabilities and static analysis.

It is apparent that there is a pressing need to look into existing hardware threat modeling approaches and find ways to cover the deficiencies in them. One of the solutions is to adopt generative Artificial Intelligence (AI) and to fuse it with existing approaches. The incorporation of AI technology may introduce a quantum leap in existing hardware threat modeling approaches, increasing their efficiencies and accuracies considerably. By using generative AI as a catalyst in threat modeling, new and subtle threats and vulnerabilities that are not archived in existing databases and are also undetectable by static analysis may be identified. This is because generative AI is capable of self-learning. By feeding it with an extensive amount of datasets, it can then study and recognize patterns and subsequently generate synthetic scenarios that emulate potential attack vectors. In other words, generative AI provides an avenue for threat modeling approaches to iteratively enhance their efficiencies and develop more sturdy countermeasure strategies.

Taking the RISC-V architecture as an example for proof-of concept, this chapter shall delineate how generative AI can be incorporated into current approaches to identify and mitigate threats and vulnerabilities in the hardware framework. Python programming language shall be used as the tool for embedding generative AI into the approaches.

LITERATURE REVIEW

In a paper [1], a study to gauge the impact of few-shot prompting on Codex was conducted. The study made use of the CodeXGLUE code and it incorporated cross-project and same-project datasets. The results strongly suggested that Codex was superior over fine-tuned foundational models such as CodeBERT, CodeT5, GraphCodeBert, *etc*., in cross-project scenarios. It is worthwhile noting that Codex achieved a 12.56% increase in the BLEU-4 score in comparison with the foundational models.

In a study [2], Khadija, Aziz, and Nurharjadmo proposed an automated approach for information retrieval *via* a chatbot. Their approach classified PDF documents according to characters, headers, and tokens and subsequently stored segmented classes into a Pinecone vector database. The chatbot made use of cosine similarity to evaluate the similarities between the user prompt and document classes within the vector database when responding to users' queries. The efficacy of this approach is convincingly reflected in the measured metrics – it attained a unigram BLEU score of 0.84, a bigram BLEU score of 0.87, and a low negative log-likelihood ratio loss of 0.19.

Zhang *et al*. introduced a customized framework designed for resolving code queries named EcoAssistant [3]. EcoAssistant parsed code compiler outputs, unsuccessful execution traces, and error messages. EcoAssistant utilized various types of Large Language Model (LLM) assistants and implemented a response-reference mechanism—successful queries and responses were saved for future reference. By employing these strategies, the success rate allegedly surpassed that attained by GPT-4 by 10 points.

In another study [4], an expand-guess-refine approach was used to develop an LLM specifically tailored to answer medical-related queries. The USMLE dataset was used in the LLM, and Multiple-Choice Questions (MCQs) were employed in interactions with users. The LLM used zero-shot prompting, and the received document was segmented *via* a recursive text splitter. Its embeddings were saved in the Facebook AI Similarity Search (FAISS) vector database. When providing

CHAPTER 5

Fundamentals of Predictive Maintenance Using Machine Learning, Deep Learning, and IoT in Industry 4.0

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Abstract: The term "digital age" refers to the 21st century, characterized by the widespread use of digital platforms for data and information sharing. This era is marked by critical technologies such as sensor networks, Machine Learning (ML), Deep Learning (DL), Predictive Maintenance (PDM), and the Internet of Things (IoT), which are pivotal in driving the Industry 4.0 revolution. Today, industrial operations encompass pre- and post-production, quality control, and supply chain management, all fully automated. Physical tasks are handled by intelligent robots equipped with machine learning capabilities, freeing humans to focus on cognitive activities. These robots perform diverse tasks while real-time sensor networks collect environmental data, ensuring efficient and adaptable industrial operations 3.5. This study aims to highlight the pivotal roles of ML, DL, and IoT within the framework of Industry 4.0, leveraging historical performance data for real-time decision-making. The chapter critically evaluates a multitude of tools, models, protocols, and cutting-edge technologies deployed in Industry 4.0 settings. It identifies areas requiring further investigation and provides recommendations to steer future advancements in Industry 4.0.

Keywords: Deep learning, Internet of Things, Industry 4.0, Machine learning, Predictive maintenance.

INTRODUCTION

The latest industrial revolution is termed Industry 4.0, commonly known as the Industrial Internet of Things (IIoT) and smart manufacturing. It primarily focuses on automation, interconnection, cyber-physical systems, machine learning, and big data [1, 2], as well as smart manufacturing and the Industrial Internet of

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Things (IIoT) [3, 4]. Additionally, it incorporates both physical operations and smart procedures that are guided by artificial intelligence and automation. Here, instead of using their bodies to operate industries, people use their intellect. Industry 4.0 has transformed into a cutting-edge production system that ensures efficient output while keeping costs to a minimum. Furthermore, blockchain technology is essential for establishing a safe, interconnected, and competitive environment, facilitating swift societal development. A shift in production away from rural areas and toward urban centers was ushered in with the invention of the steam engine in 1760, starting the first industrial revolution [5, 6].

Trains were the main means of transportation, and coal became the main source of energy. The introduction of combustion engines and the widespread use of oil marked the beginning of the Second Industrial Revolution, which promoted mass manufacturing and quick industrialization [7, 8]. Global industry automation was a result of the Third Industrial Revolution, which began in the 1960s with advances in electronics and information technology [9, 10]. The German government started a project in 2011 that served as the inspiration for Industry 4.0 [11]. The main objectives of this revolution are decentralized decision-making, technology decisions, information transparency, and interconnection.

Computing power, computational resources, cyber-physical systems, and the Internet of Things are driving this change [12]. These advanced technologies enable seamless communication and efficient operations by integrating IoT nodes with cyber-physical infrastructure. In this new era, humans remain essential for monitoring and controlling every operation [13, 14]. Moreover, it enables the real-time detection of any problems with machinery or their early detection to prevent total failure and save maintenance costs [15, 16]. Fig. (**1**) depicts the revolutions in industry. Because 3D printing technology makes product design more efficient, it is a major force behind the Fourth Industrial Revolution. It enables customized manufacturing, enhances flexibility, and promotes ecological sustainability [17 - 19]. Intelligent machinery and automated enterprises rely on smart sensors for their operations. These sensors are crucial components in automated control systems and monitoring devices within the context of Industry 4.0 [20 - 22]. In agriculture, they revolutionize practices by enabling real-time crop monitoring, leading to savings in labor, costs, and time [23]. These sensors are highly accurate in identifying damage and pests, and they are also crucial to irrigation control [24, 25]. However, Industry 4.0 presents several challenges. The most critical factor is security [26 - 28]. Companies can mitigate the burden of higher initial costs by adopting low-cost machinery and equipment designs [29, 30]. Continuous surveillance in some companies raises privacy concerns [31, 32]. The convergence of ML with the IoT has enabled a significant industry shift. Cost containment must be a top priority across all industries without compromising product quality. Human error remains a constant risk in manual industries.

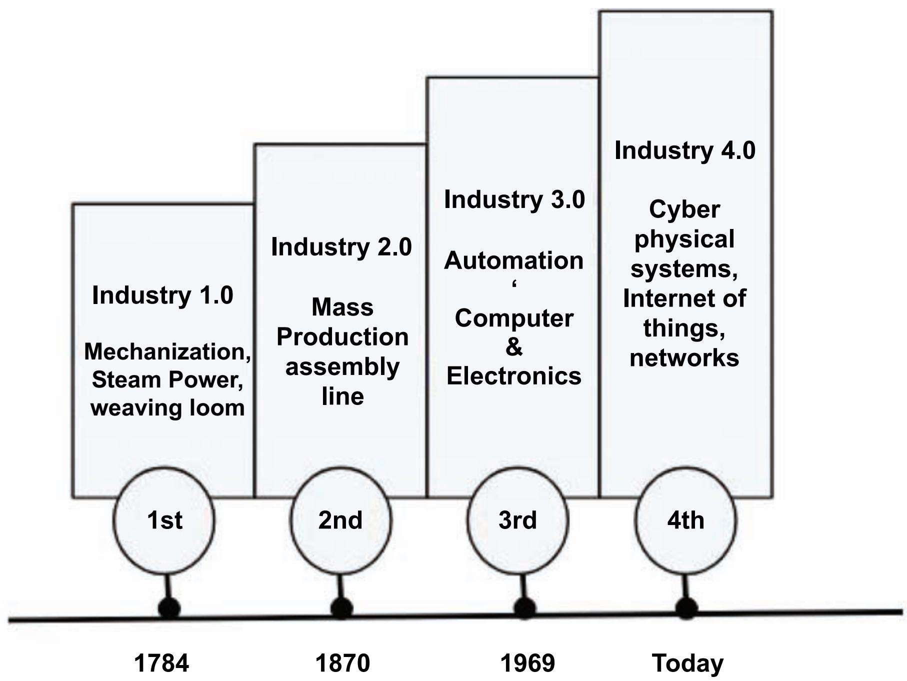

Fig. (1). Revolutions in industry. It illustrates the changes and their primary causes from Industry 1.0 to Industry 4.0.

The integration of ML and IoT devices has elevated system automation to unprecedented levels. Tasks such as post-manufacturing quality checks and equipment maintenance are now efficiently managed by these technologies. IoT sensor nodes monitor product and equipment performance during manufacturing, while machine learning algorithms detect potential anomalies [33]. Moreover, the requirement for human work may be greatly decreased by this automation. Machines have developed into extremely intelligent beings with the capacity to see their environment and make judgments based on past data. IoT devices are used to inspect products after they are manufactured. These devices track and label things, and they frequently contain ML-powered sensors like cameras. Furthermore, AI techniques are combined with IoT sensors and devices. Studies on ML and the Internet of Things (IoT) in the context of Industry 4.0 frequently omit protocols, technology, sensors, and algorithms as they pertain to the IoT [34, 35].

CHAPTER 6

Predictive Maintenance for Enhanced Resilience in Natural Disasters

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Abstract: Disasters occur frequently around the world, affecting structures and people, thus resulting in massive disruption of services. This is particularly the case with the increasing frequency and intensity of disasters, leading to the necessity of more proactive steps to improve the critical systems' resiliency. Predictive maintenance (PM), which uses data to predict when equipment might fail, provides a solution in this sense as it enables organizations to plan for repairs that will prevent major failures. This chapter aims to discuss how PM can be incorporated into disaster management plans to mitigate the impact of natural disasters and enhance the durability of structures. This chapter provides an overview of applications of information methods mentioned previously, including descriptive, diagnostic, predictive, and prescriptive analytics. It also reveals the issues of data quality, data accessibility, and multi-disciplinary data fusion from weather forecasts, seismic data, and Internet of Things (IoT) sensor data. Besides, it also describes how PM can improve risk evaluation and assessment solutions, early warning systems, infrastructure health, and disaster management solutions. The chapter outlines how predictive maintenance redefines disaster planning and management based on real-life case studies. The relevance of data integration and availability can be a barrier, but PM is a strong positive lever for enhancing the protection of critical infrastructure in disaster-sensitive areas.

Keywords: Climate change, Climatological disasters, Data analytics, Data integration, Disaster management, Geophysical disasters, Hydrological disasters, Meteorological disasters, Predictive maintenance.

INTRODUCTION

A natural disaster is a catastrophic occurrence caused by natural processes or events that lead to the loss of lives, property, and structures [1]. In light of the

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effect of global warming and climate change that has contributed to the rise in the frequency and intensity of occurrence of natural disasters, there has never been a greater need to embrace innovation in managing such disasters [2]. Disaster management paradigms in the past have largely been of a reactive nature, in which the response to catastrophic disasters is to restore and reconstruct after the occurrence [3]. However, this approach always has a profound consequence of causing vast destruction, loss of lives, and high costs of repairing in society caused by the destruction. Thus, in recent years, there has been more concentration on risk assessment, risk prevention, and ways to minimize the effects of natural disasters [3].

Predictive maintenance (PM) is one approach that uses dated technologies to check the functionality and health of infrastructure or equipment before a failure happens [4]. Traditionally practiced in specific fields like manufacturing and aviation, this concept is now in focus to be an excellent mode of tackling disasters. Besides mitigating the likelihood of infrastructure failure during a catastrophe, PM improves the ability of essential systems to compensate for change and uncertainty in the environment [5, 6]. Consequently, this chapter focuses on explaining what PM is and why it is necessary for natural disaster management in data analytics to integrate PM in the management of natural disasters.

PM - AN OVERVIEW

PM is a preventive maintenance technique that involves the assessment of the status of a given asset, equipment, structure, or machine with the intention of assessing when they should be maintained [7]. This method depends on the acquisition of real-time data that enables organizations to decide the appropriate time to conduct maintenance, thus minimizing incidences of downtime due to equipment failure. The concept of PM revolves around the condition or state evaluation of infrastructures with real-time monitoring. It includes gathering information from various sources, which include sensors, records, and the environment, among others, to forecast future breakdowns. PM involves the following, as shown in Fig. (**1**).

- **Data Collection:** This is achieved through the use of IoT sensors, smart gadgets, and other devices that constantly check the conditions of infrastructure.
- **Data Transmission:** Once collected, the data is either stored in centralized storage or, more specifically, in cloud servers for processing. Relaying this data through dependable means, such as Wi-Fi and Bluetooth, is done effectively and without much interference in the PM cycle.

- **Data Analysis:** The gathered data undergo flow analysis with sophisticated algorithms, such as machine learning (ML) algorithms for pattern recognition, to forecast risks.
- **Prediction and Failures:** The predictive models simulate possible equipment breakdowns according to current and previous conditions. Such predictions allow organizations to schedule maintenance activities so that unnecessary idle time is eliminated, thereby guaranteeing the continuity of operations. In other words, it is possible to use ML to elaborate forecasts regarding certain values changing over time.
- **Decision-Making:** If a possible problem is observed, the maintenance crew plans the correction or overhaul when they make their decisions, hence reducing interference.
- **Maintenance and Feedback:** After maintenance, the system always receives feedback, which enhances the next predictions. This way, the algorithms are continuously educated and supplemented by the input that makes the PM and, consequently, the accuracy of the algorithms a constant learning process.

Fig. (1). Steps of PM.

In the aspect of disasters, through constant assessment of structures like bridges, power, and water companies, this concept of performing regular check-ups, especially on the mechanical structures, will prevent them from failing during

CHAPTER 7

Advancing Agriculture 4.0 through Federated Learning Techniques: Collaborative Analysis of Distributed Agricultural Data

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Abstract: Agriculture 4.0 is evolving by combining traditional farming methods with advanced technologies from Industry 4.0, offering farmers new opportunities to improve their agricultural practices. However, implementing Agriculture 4.0 through the incorporation of these innovative technologies and evidence-based strategies is facing challenges. Moreover, data is proven as one of the most significant assets in the era of big data. Analyzing massively distributed agricultural data while ensuring its privacy, security, and scalability concerns is also an important challenge. This chapter presents the state-of-the-art by leveraging the applications of federated learning methods to handle the aforementioned challenges and promote collaborative analysis of distributed agricultural data. In this work, we utilize the publicly accessible Rice Dataset Cammeo and Osmancik, which comprises 3,810 instances, with 2180 instances of Osmancik and 1,630 instances of Cammeo. This study presents a federated learning-based rice variety classification (AgriFedClassifier) framework for analyzing distributed agricultural data while safeguarding the privacy and security of clients' local data. We simulate the framework with Multilayer Perceptron models at each client, training the models for a fixed number of local epochs using local data and aggregating model updates at the server employing Federated Averaging (FedAvg) and Federated Proximal (FedProx) methods. We evaluate the effectiveness of federated learning techniques on horizontally distributed agricultural data under two scenarios: IID and non-IID datasets. Experimental results demonstrate that in non-IID data distributions with 80% of stragglers (nodes encountering delays), FedProx achieved a classification accuracy of 89.33%, whereas FedAvg achieved only 50% accuracy. The results section presents an analysis of the effectiveness of federated and centralized models. Overall, we observe that FedProx effectively managed data heterogeneity, mitigated delays, and improved efficiency compared to FedAvg.

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Keywords: Aggregation methods, Agriculture 4.0, Collaborative machine learning, Distributed machine learning, Federated learning, Federated optimization, IID, Industry 4.0, Non-IID.

INTRODUCTION

The evolution from Industry 4.0 to Agriculture 4.0 [1, 2] investigates the incorporation of innovative, cutting-edge solutions, including IoT, big data processing, AI-driven systems, and robotics into agricultural activities, enhancing crop productivity, efficient resource utilization, and sustainable development. This emphasizes essential technologies such as IoT for real-time monitoring [3], AI and big data for predictive analytics [4], robotics for automation [5, 6], and blockchain for ensuring supply chain transparency [7]. Although these advantages exist, there are barriers that hinder the practical implementation of Agriculture 4.0 [8 - 10], such as small-scale farmers investing a high-cost technology, gap between farmers and AI researchers, managing and analyzing the vast amount of heterogeneous agricultural data, and need for robust infrastructure and expertise. Moreover, there is a lack of skills, as farmers need training to use these advanced technologies [11]. Ensuring data security and addressing security are other significant challenges.

Federated learning (FL) has the capacity to offer practical approaches to many of the problems encountered in Agriculture 4.0. FL [12] is a distributed machine learning approach that enables decentralized data processing. It promises benefits to micro farmers by allowing them to leverage advanced AI and machine learning applications without investing in high-cost infrastructure [13, 14]. This approach utilizes the computational power of client machines, which may reduce the need for expensive centralized data centers. Additionally, FL is capable of promoting collaboration between farmers and AI researchers, filling the skill gap by allowing farmers to use refined models developed from a wide pool of agricultural data. This decentralized method also promises data privacy and security, as data remains local, mitigating the risk of data theft [15]. Moreover, FL has the ability to handle heterogeneous data from various sources, which helps manage and analyze vast amounts of distributed agricultural data. Distributing the processing workload makes AI more accessible, promoting the larger adoption of innovative technologies like big data and IoT [16 - 18] in agriculture and empowering the sustainable development of Agriculture 4.0.

This work aims to analyze the performance of federated learning techniques [19, 20] for distributed agricultural data analysis. We introduce a federated learning-based rice variety classification (AgriFedClassifier) framework to demonstrate the practical implementation of FL. To verify the stability of the proposed framework in defiance of heterogeneous agricultural data and stragglers, we distribute the data in two scenarios: IID and non-IID datasets. We also compare the effectiveness of federated and non-federated models. Based on the analysis

results, we observe that FedProx effectively manages data heterogeneity, mitigates delays, and outperforms FedAvg.

FEDERATED LEARNING APPROACH

FL involves a ML method where several decentralized devices jointly train a common model void of transferring their data off local devices [21 - 23]. This feature allows us to perform machine learning in those locations where previously it was not possible. To implement this client server approach in agriculture, several steps will need to be followed sequentially. Firstly, the server establishes a global machine learning model and transmits it to all engaged clients. Secondly, each client trains this commonly received model locally using their own data. Once local training has been concluded after several iterations, the clients revert the revised model parameters relayed to the server to complete the third step. In the fourth step, the server aggregates these parameters using aggregation techniques to update the global model. Steps 1 to 4 continue iteratively until the model converges to an optimal state. Throughout this process, raw data remains local, maintaining its privacy and reducing the risk of data theft [24, 25]. It also promotes collaboration among remote clients without revealing their identities to one another.

Federated Learning Methods: Federated Averaging (FedAvg)

This method in federated learning is used to train a global model by averaging the model updates from multiple client devices. In the k^{th} communication round, the server does global aggregation by applying the rule:

$$\bar{\omega}k = \frac{1}{N}\sum_{i=1}^{N} w_i^k \quad (1)$$

where $w_i^k, \omega\bar{k}$ represents a client's local weight as well as the aggregated weight.

Generally, the aim of this method is to minimize the global loss for which the following global loss function will be utilized.

CHAPTER 8

From Data to Insights: A Bibliometric Exploration of AI Innovations in the Fourth Industrial Revolution

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Abstract: The Fourth Industrial Revolution, which is hallmarked by the convergence of digital, biological, and physical systems, has placed AI at the heart of all technological advancements. In turn, this chapter uses bibliometric techniques to provide an in-depth analysis of AI innovations in such a transformative era. Moreover, due to the use of the Len.org database, we have an opportunity to highlight various trends in the field of AI, determine research areas that require more profound analysis, and identify the emergent topics within the domain. To provide a more sophisticated review of bibliometric data, one may apply different techniques of analysis, such as co-citation analysis and network mapping. Together, the implemented methods expose an intricate web of knowledge that impacts current developments in AI research. In this study, the authors search for the links between technological advancements and changes in the role of AI. It is of paramount importance to identify the influence of certain regions, institutions, and scholars on the AI field of study. For this reason, the reflection on the latest trends allows the authors to compare different studies, note the difficulties in the field, such as data availability and methodology, and derive new insights for other researchers. The latter is critically vital since it is essential to comprehend a path researchers may follow to understand the implications of technological advancement in different periods. In such a way, bibliometric techniques may also determine the current path of AI research and outline emergent trends of future studies.

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Keywords: Artificial Intelligence (AI), Bibliometric analysis, Emerging trends, Fourth industrial revolution, Industry 4.0, Innovation ecosystem, Len.org database.

INTRODUCTION

Background of Industry 4.0 and AI

The Fourth Industrial Revolution, also known as Industry 4.0, is a transformative era in the ever-evolving history of industries. The central premise of the Fourth Industrial Revolution is that it is fundamentally different from how other industrial epochs worked and continue to function [1, 2]. The convergence of the physical, digital, and biological spheres of life and the advent of new computational paradigms have marked the establishment of Industry 4.0. Implementing the new model is Artificial Intelligence, self-evidently, with its main characteristic, which is the simulation of the human mind [3, 4]. The guideline function of AI in the Fourth Industrial Revolution is immutable; it powers automation, produces vast amounts of data as a result, and facilitates progress across industries, from healthcare and finance to transportation and manufacturing [5, 6].

Industry 4.0 makes it evident that AI is not only a tool to advance it but, essentially, a cause of its continuance [7, 8]. Moreover, AI increases the number of tasks the machines can carry out autonomously and is used to monitor, track, and observe details of machine performance. Thus, notions such as the “smart factory” have become a reality with the guidance of AI. The movement toward innovative products is opposite to the stagnant products of the earlier Industrial Revolutions, which could not interact with or respond to their environment. Last but not least, the use of AI in industrial processes leads to a significant increase in efficiency, productivity, and ability to customize products [9, 10].

Importance of Bibliometric Analysis in Understanding Research Trends

The bibliometric analysis represents an effective tool for understandingthe development and future tendencies of AI and Industry 4.0. With the development of AI, its study has also developed. As a result of this, the number of publications devoted to the development and application of AI has reached its peak [11]. In this regard, it has become somewhat problematic to trace common tendencies or to understand in what directions it is possible to expect further development in this sphere of studies. Bibliometric analysis represents a quantitative approach to studying academic literature that presents information about the structure and dynamics peculiar to a particular field of study [12, 13]. As a result, by analyzing the information contained by citing references, the network of co-authors, and the keywords, it is possible to understand the intellectual space of the sphere of studies [14]. This article presents the importance of bibliometric analysis for understanding AI and Industry 4.0 development and tendencies.

Drawing attention to the above, one should admit that bibliometric analysis helps to understand AI and Industry 4.0 as instruments that are aimed at fostering the development of certain spheres interested in supporting productivity, effectiveness, and quality [15 - 17]. Additionally, the information presented in this article presupposes that bibliometric analysis helps researchers, policymakers, and industry representatives to understand which way AI is used in separate sectors and which common tendencies can be followed in the future [18 - 20]. Furthermore, conducting such analysis helps to understand which aspects need to be additionally studied to facilitate the development of certain spheres using AI and Industry 4.0.

Objectives of the Chapter

The aim of this chapter is to provide a detailed bibliometric examination of the artificial intelligence innovations in the context of the 4th Industrial Revolution. By drawing on data from the Len.org database, the chapter has the following objectives:

- **Explore Publication Trends:** Examine the rising pace of AI publications, identify the period when AI publications experienced the most significant growth, and draw some inferences from these trends.
- **Identify Key Research Areas:** Map the major themes within AI and the topics of its publication. It will shed light on the AI research focus and potentially hot ***topics*** in development in the future.
- **Analyse Geographic and Institutional Contributions:** Explore which countries and ***especially*** institutions were leading in the particular publication years. It will help to identify implicit regional specializations.
- **Identify Emerging Trends:** Specify those papers/areas that are relatively new in AI research, are gaining attention, and have the potential to rapidly develop in the future.
- **Discuss Implications for Future Research:** Discussing implications for future research and providing recommendations. It is a very crucial part of the chapter in which the future development of the study is discussed.

The central recommendation is the necessity of further research in the areas thathave not been studied well, supported by inferences based on the completed bibliometric analysis results. Overall, the data in the chapter aims to provide a deeply elaborated insight into the impact of AI on the 4th Industrial Revolution, which is of interest to researchers, industry professionals, and decision-makers.

CHAPTER 9

Application of IoT-Based EEG Sensors in Industry 4.0

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Abstract: Human-Machine Interaction (HMI) is definitely considered to play a pivotal role in advancing smart manufacturing systems in today's Industry 4.0 age. In this context, the chapter considers how IoT technologies are converging with EEG-based interfaces to refine HMI within Industry 4.0 frameworks. The introduction gives a thorough overview of the 4th industrial revolution (*i.e.*, Industry 4.0), focusing on its transformative influence on automation and data exchange within manufacturing processes. Real-time knowledge of cognitive states is essential to maximize human-machine collaboration, and EEG technology is presented as a key means for monitoring brain activity. The recognition of the relevance and impact HMI has in the context of smart manufacturing is demonstrated, evincing how it facilitates efficiency on factory floors, secures operations, makes them safer, and reinforces business decisions to be taken in real-time. The chapter also provides an explanation of how the Internet of Things can contribute to Industry 4.0 by connecting devices and exchanging data almost effortlessly. Incorporating EEG with IoT even allows formonitoring and analysis of human cognitive states in real-time, thus creating adaptive manufacturing environments where machines respond immediately based on updated human intent and condition. It also increases efficiency during operation hours by keeping workers in an optimal working condition. Machines look for factors that induce stress or fatigue and set them straight before they occur. Integrating EEG and IoT technologies represents a paradigm shift in HMI, offering manufacturers unprecedented insights into human cognition and behavior. By leveraging EEG data through IoT-enabled systems, manufacturers can optimize task allocation, personalize user interfaces, and even predict maintenance needs based on cognitive workload. This chapter argues that such advancements are critical for achieving higher productivity, quality, and safety standards in modern manufacturing. To sum up, this chapter elucidates EEG-based IoT-integrated interfaces for revolutionizing HMI from an Industry 4.0 perspective. These technologies improve operational confidence by facilitating real-time monitoring and adaptive responsiveness, making them ideal enablers for future smart manufacturing.

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Keywords: Cyber-physical systems, Cognitive state monitoring, Data analytics, EEG sensors, Electroencephalogram, Human-machine interactions, Operational efficiency, Industry 4.0, Internet of Things, IoT sensors, Smart manufacturing.

INTRODUCTION

An Overview of Industry 4.0 and its Dependence on Human-Machine Interaction

Industry 4.0 is the fourth industrial revolution, primarily identified as a fusion of digital automation systems and physical processes necessary in biological environments. The role of EEG technology is shown in Fig. (**1**). This change has been possible thanks to technologies like artificial intelligence (AI), robotics, big data analytics, and the Internet of Things (IoT), thus giving birth to new-age smart factories and cyber-physical systems. At the heart of this revolution is Human-Machine Interaction (HMI), which emphasizes the incorporation of human operators with automated systems, ensuring a smooth transition. Good HMI is imperative in smart manufacturing. Human operators must be able to oversee, control, and cooperate with machines quickly, boosting productivity and safety.

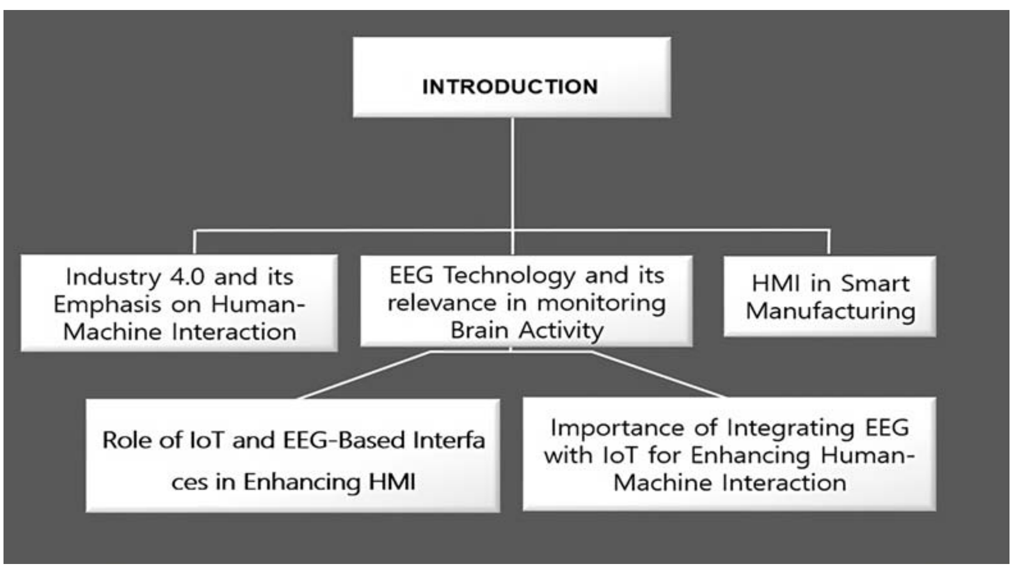

Fig. (1). Role of EEG technology.

Introduction to EEG Technology and its Relevance in Monitoring Brain Activity

EEG is a non-invasive way of tracking and recording electrical activity in the brain. By putting electrodes on the scalp, EEG measures electrical signals in the brain, thus informing about cognitive and emotional conditions. It is a technology that is used in a myriad of medical and psychological research, leading to advances ranging from the understanding of brain function to the diagnosis of neurological disorders and exploration into mental processes. From the perspective of Industry 4.0, EEG technology is a newer way to approach how HMIs perform within an industry by providing real-time data on the mental state and mental processes of workers/operators. It allows a more adaptive and responsive interaction with machines.

Importance of Human-Machine Interaction (HMI) in Smart Manufacturing

HMI is very important in smart manufacturing, and its efficiency and effectiveness have become more critical for various reasons. Human operators can operate complex automated systems in a natural manner, which reduces the risks of errors and improves operational safety. Secondly, it allows operators to make more informed decisions by making sure the right information is there and that they have control. It finally enables the amendment and improvement of manufacturing practices, facilitating changes in real-time due to human instruction and environmental variation. In this sense, industry 4.0 ambitions that strive to boost performance, quality, and customization levels are simply impossible without improved HMI capabilities.

Role of IoT and EEG-Based Interfaces in Enhancing HMI

The IoT bridges the gap in Industry 4.0 by interconnecting systems and devices to collect, process, and exchange real-time data. By integrating it with EEG-based interfaces, IoT can dramatically improve HMI by giving a live data stream of an operator's cognitive and emotional conditions. This real-time data can be used to alter the behavior of machines, human-machine interfaces, and systems, creating a more intuitive and responsive interaction environment. For instance, an EEG-based interface can detect fatigue in machine operators to change the pace of operation or notify the operator that they need a break, which would prevent incidents and promote greater efficiency overall.

Importance of Integrating EEG with IoT for Enhancing Human-Machine Interaction

When combined with IoT for the sake of HMI (Human-Machine Interface), EEG yields a few essential advantages. It allows the production of resilient systems that can react to the present mental states of the people operating them, leading to enhanced safety, performance, productivity, and user pleasure. Secondly, it enables the creation of customized HMI solutions that can match unique requirements and preferences of different operators. It can monitor and

CHAPTER 10

Optimization Techniques for Predictive Maintenance in Industry 4.0

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Abstract: In Industry 4.0, "intelligent factories" collect and analyze data to keep tabs on the production process. Machine learning, data mining, and other statistical AI technologies can identify and forecast possible manufacturing procedure abnormalities, improving productivity and dependability. Nevertheless, the information retrieved from manufacturing information is sometimes presented in a complex structure due to the heterogeneous nature of the data. This puts up the semantic gap problem, which is shorthand for the reality that various production systems are incompatible. In addition, a unified knowledge model of physical assets and the ability to think in real time about analytical activities are essential for automating the decision-making process of Computerized Physical Systems (CPS), which are growing more data-intensive. Using symbolic AI in predictive maintenance could be a promising solution to these problems. Through numerous examinations, predictive upkeep offers a comprehensive review of the identification, localization, and identification of malfunctions in associated machinery. RAMI4.0 provides a structure to analyze the several initiatives that comprise Industry 4.0. The hierarchical structure, functional classification, and product life cycle are all encompassed. The Corporate Data Space, currently known as the International Data Space, is an online database that allows for the safe transfer and simple linking of data between corporate ecosystems using shared standards and governance frameworks. It guarantees data owners' online privacy while laying the groundwork for developing and using intelligent services and novel business procedures. In light of Industry 4.0, this article investigates potential ways to bolster maintenance prediction. Data exchange between businesses with varying security needs and the subsequent modularization of relevant functions are outcomes of implementing the RAMI 4.0 architecture, which facilitates predictive maintenance utilizing the FIWARE framework.

Keywords: AI, Computerized Physical System, Industry 4.0, Machine learning, Predictive Maintenance.

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INTRODUCTION

Optimization techniques for predictive maintenance in Industry 4.0 focus on improving the efficiency and effectiveness of maintenance tasks using advanced technologies.

Machine Learning Algorithms: These algorithms analyze historical data to predict when equipment is likely to fail, allowing maintenance to be scheduled before issues arise.

IoT Sensors: Sensors collect real-time data on equipment performance, which is then analyzed to detect anomalies and predict failures.

Data Analytics: Advanced analytics processes large volumes of data to identify patterns and trends that indicate potential equipment issues.

Cloud Computing: Storing and processing data in the cloud provides scalability and accessibility, making it easier to manage and analyze data from multiple sources.

Digital Twins: Creating a digital replica of physical equipment allows for simulation and analysis, helping predict and prevent failure [1 - 3].

The introduction of cutting-edge technology like the Internet of Things (IoT), cloud computing, and big data analytics—the hallmarks of Industry 4.0—has revolutionized the way factories function. Industry 4.0's scheduled upkeep has quickly become an essential tactic for boosting equipment reliability, cutting maintenance expenses, and increasing operational effectiveness. Minimizing unplanned downtime and increasing the usable life for manufacturing assets are two goals of automated upkeep strategies. These techniques leverage data from sensors, machine learning methods, and analytics in real time to determine the ideal timing for maintenance interventions. The absence of sensors and connections in older machinery is a major obstacle to deploying predictive maintenance in brownfields or preexisting industrial settings. With the goal of integrating old systems with predictive maintenance capabilities, researchers have investigated ways to retrofit inexpensive sensors and establish an Industrial Internet of Things architecture.

AI and Deep Learning: These technologies enhance the accuracy of predictions by learning from vast amounts of data and improving over time.

Maintenance plays a crucial role in smart factories and in fulfilling operational priorities and plans. As noted, a significant chunk of a processing or manufacturing facility's operational expenses goes toward maintenance. The percentage of production expenses attributable to maintenance might range from fifteen percent to sixty percent, depending on the sector (Fig. **1**).

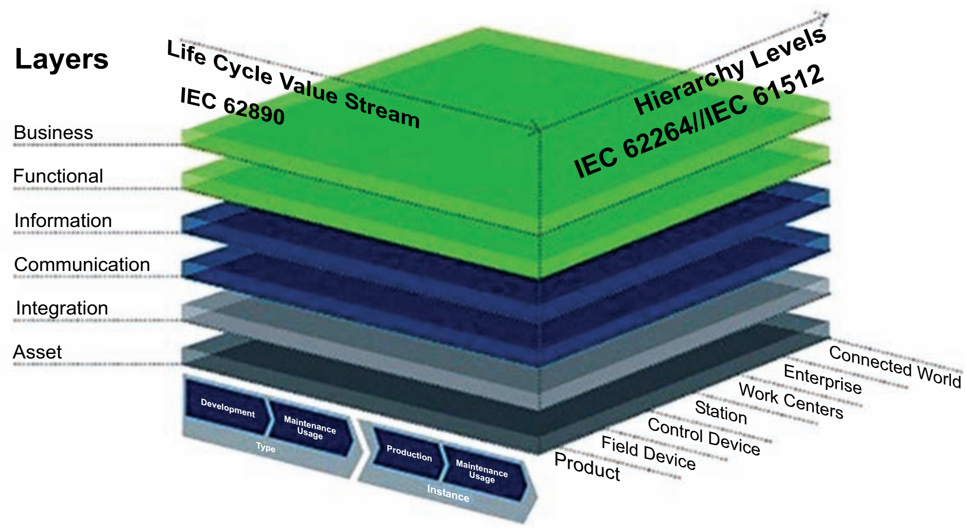

Fig. (1). Architecture layer of Industrial 4.0.

Equipment and machinery downtime may be decreased, efficiency can be increased, and production can be boosted with an effective maintenance method. It noted that to achieve environmental objectives within the framework of Industry 4.0, it is essential to choose the correct maintenance strategy due to the complexity and volatility of maintenance management and the difficulty in evaluating and cataloging the effectiveness of maintenance. The need for proper maintenance is stressed to prevent unanticipated plant and equipment failures. These failures incur various expenses for the business, such as labor, spare parts, rework, scrap, late order charges, and lost orders caused by unhappy consumers [4].

Small and Medium-sized Enterprises (SMEs) are the primary subject of this article. The hefty price tag of proprietary software and hardware solutions makes predictive maintenance a tough sell for Small and Medium-sized Enterprises (SMEs). Nonetheless, SMEs may build predictive maintenance apps using open-source tools far more affordably compared to proprietary remedies. It makes available a number of machine learning and statistical resources that are necessary for maintenance prediction. Assistance and additional helpful materials are readily available because of R's extensive ecosystem of developers and users who work together to improve the language of programming and its numerous packages.

CHAPTER 11

Enhancing Predictive Maintenance through Optimization in the Era of Industry 4.0

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Abstract: The concept of Industry 4.0 is key to predictive maintenance, as it aids in balancing asset requirement utilization maximization, reducing downtime, and lowering maintenance expenditure. In this chapter, we look closely at the various methods of predictive maintenance strategies within Industry 4.0. It includes data analysis, machine learning, fault detection, anomaly prediction, sensor placement, and repair organization, as well as close reading with IoT and cyber-physical systems. In this way, companies can increase the performance of their assets, make them more reliable, and reduce insurance costs in Industry 4.0. This chapter dives deeply into how well optimized methods can be used in predictive maintenance. The lessons learned from such approaches by examining books, real examples, and useful experiences are also discussed, along with an understanding of effective results that come while you are studying data for your machine learning ways to get information based on lots of sensor data, which is what predictive maintenance essentially relies on as a bet against failure with early fault detection in place, yet avoiding downtime before problems start. Further, the chapter includes optimization techniques on the planning and scheduling of predictive maintenance. The integration of IoT and cyber-physical systems and the optimization of condition-based maintenance, as well as demonstrating their potential for autonomous decision-making and self-optimization, are also discussed. This chapter aims to provide a vision of using predictive maintenance, optimizing asset reliability, and driving operational efficiency in the era of Industry 4.0.

Keywords: Industry 4.0, IoT, Optimizing techniques, Predictive decision-making models, Predictive maintenance.

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INTRODUCTION

Industry 4.0, also known as the Fourth Industrial Revolution, has brought digitalization and automation into manufacturing and industrial processes. At the crux of this revolution is the convergence and integration of cutting-edge technologies like Internet-of-Things (IoT), big-data analytics, Artificial Intelligence (AI), *etc*. with traditional industrial systems. Predictive maintenance has become a key application area that has been obtained using these technologies, with benefits dwarfing existing strategies for reactive and preventive maintenance [1, 2].

A Brief Introduction to Predictive Maintenance in Industry 4.0

Predictive maintenance is a proactive strategy with the goal of forecasting when an in-service asset will fall into a state of disrepair. Predictive maintenance systems can use machine learning to continuously monitor and analyze real-time data from sensors and other data sources in order to detect patterns, trends, and early warning signs of imminent failures. This allows minimizing unplanned downtime, reduces maintenance costs, and extends assets lifespan by scheduling necessary activities at the right time [3, 4].

Predictive maintenance scales with Industry 4.0. Predictive maintenance uses information from an array of sources that are produced by all the connected industrial systems—so it can assess precisely and be trusted [5, 6]. This data can be processed using advanced analytics techniques such as machine learning and deep learning to essentially go beyond the capability of human experts to identify complex patterns and relationships that are not straightforward.

The Significance of Optimization Techniques

As beneficial as predictive maintenance can be, it is also quite cumbersome to carry out and implement, especially in large industrial setups with myriad interconnected assets under multiple constraints. Optimization is a modeling tool that might help us to develop systems and decision-making in industrial maintenance. Fig. (**1**) shows IoT-enabled predictive maintenance.

These optimization techniques can be used to identify the best possible time and order in which maintenance activities should be done, considering asset criticality, resource availability, operational constraints, and more [7]. These same techniques can help optimize the managing of spare parts inventories to have the right parts available when needed and where they are needed at a minimum cost of carrying excess inventory [8].

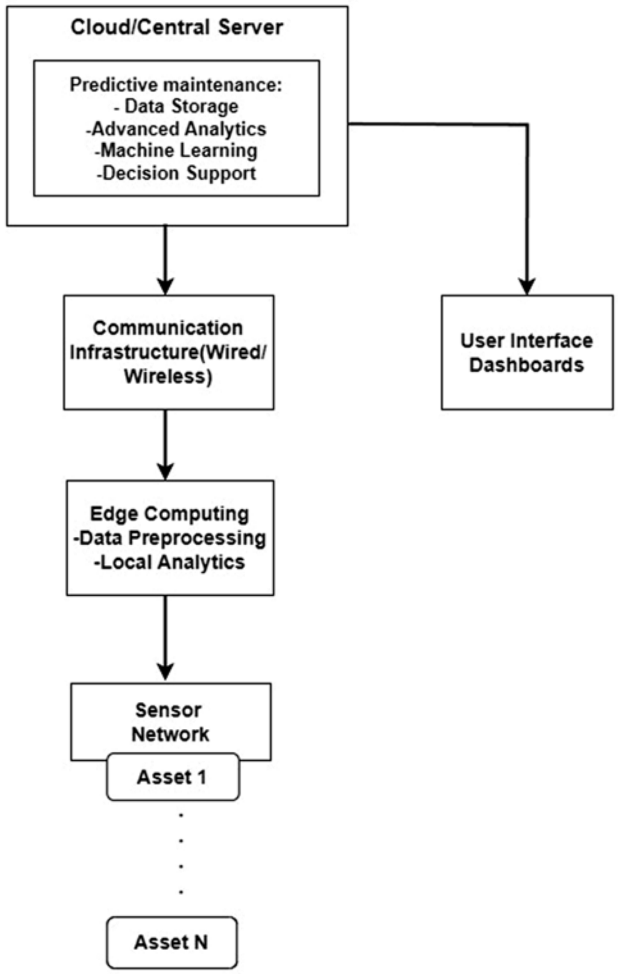

Fig. (1). IoT-enabled Predictive Maintenance.

Research Objectives and Scope

The main purpose is to investigate the performance of different predictive maintenance optimization approaches in an Industry 4.0 setting. In particular, the study tries to:

- Study the available approaches for fault diagnostics and predictive maintenance using mathematical programming, metaheuristics, machine learning-based solutions, *etc*.
- Study approaches for combining optimization methods with predictive maintenance models and frameworks in Industry 4.0 settings.

CHAPTER 12

Future Trends in Secure Healthcare Predictive Analysis: Homomorphic Encryption Perspectives

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Abstract: In the healthcare system, the application of predictive analysis is essential to the enhancement of patient benefits as well as the development of healthcare delivery systems. The digitization of health records presents an increasing threat of data leakage and breaches of patient privacy. This chapter discusses how homomorphic encryption can be applied as a solution to secure healthcare information. We discuss the state of the art of predictive analysis in healthcare organizations and realize that the issue of data security is still relevant and needs to be further investigated due to evolving healthcare regulations and rapid technological advancements. We then discuss an overview of different available encryption techniques. We particularly focus on homomorphic encryption that allows computations to be made on data without decryption while maintaining patient data privacy. After that, we discuss how predictive analysis techniques can be applied to encrypted healthcare data. Some of the issues arising when attempting to carry out predictive analysis on encrypted data are discussed, in addition to the advantages of and technical hurdles in homomorphic encryption. We examine trends and opportunities, focussing on how secure predictive analytics, as one of the potential solutions, can improve the trust and reliability of healthcare data and patients' care. Finally, we perform a case study on the use of predictive analysis techniques in encrypted heart disease data with the help of the Paillier Homomorphic encryption scheme to maintain data security.

Keywords: Case studies, Data security, Homomorphic encryption, Machine learning model, Privacy, Secure healthcare predictive analysis.

INTRODUCTION

In the context of healthcare, predictive analyses involve the application of data from the past mathematical models to estimate future outcomes. Hence, this methodology employs Electronic Health Records (EHRs), medical imaging, genetics, and patient demographic data to predict patients' future health events, treatment, and disease progression. Predictive models are useful to predict

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diseases like diabetes, heart disease, and chronic kidney disease. Healthcare providers can use these outcomes to develop preventive actions, enhance treatment programs, and improve patient care [1].

In healthcare, predictive analysis has several uses that are vital in improving patient care and productivity. One of them is the use of analytical models to identify patients with risk factors associated with specific ailments, thus enabling early diagnosis and management of a disease. Personalized care is another important domain; with the help of predictive analytics, it is possible to come up with individual or even patient-specific care plans that would correspond to the specific patient data and his or her potential response to certain therapies, which would increase the effectiveness of the procedure as well as the outcome for the patient. In the context of resource utilization, the predictive analysis assists in estimating the number of patients in a given period. It thus ensures adequate utilization of the health facilities, personnel, and other resources in anticipation of the flow of patients. In the same regard, predictive analysis helps predict the success rate of a specific treatment type by providing estimates on the possibilities of treatment success, thus assisting clinicians in choosing the most suitable treatment interventions [1].

With the advancement in technology, patient data has turned out to be a sensitive issue, particularly with the enhancement of the use of technology in the healthcare sector. More so, in the context of healthcare, the data collected is highly confidential and personal since it consists of information relating to a patient's medical history, treatment, and genetics. This data, if accessed by unauthorized persons, can cause very serious violation of people's privacy, identity theft, and loss of confidence in healthcare systems [2].

Encryption is the technology that forms the basis of protection of data that is stored and transmitted through the internet. In this context, an algorithm and encryption keys are applied to transform the readable text, also known as plaintext, into an unreadable form known as ciphertext. In contrast to plaintext, for converting ciphertext back to plaintext, only authorized parties with decryption keys shall be eligible. This helps in determining that data, even if intercepted or viewed by unauthorized personnel, remains unreadable.

Homomorphic encryption is one of the most advanced encrypting methods by which computations are made on the encrypted data without needing decryption. This special feature makes it possible to input, store, analyze, and retrieve sensitive information without compromising its security. Due to this, the use of homomorphic encryption is capable of solving many of the privacy and security issues arising from the use of predictive analysis in healthcare by allowing computations to be run on the encrypted data, thus leading to efficient and secure use of patient data [3, 4].

CURRENT STATE OF PREDICTIVE ANALYSIS IN HEALTHCARE

Healthcare predictive analytics uses computational and machine learning approaches to diagnose patients, estimate their prognosis, predict future health issues, and provide the best treatment plans. Nowadays, various predictive models, methodologies, and tools are employed to facilitate decision-making and increase the effectiveness of healthcare [5].

Different techniques employed in prediction models in healthcare practice are used to balance between accuracy and interpretability. For example, in regression models, researchers can predict both continuous and binary outcomes. The different types of neural networks include CNNs and RNNs, which are used for undertaking functions such as image recognition and analyzing language. Boosting (for example AdaBoost, XGBoost) and Bagging are examples of the ensemble methods in which many models are employed. Methods used when improving predictive models in healthcare include selecting relevant features and generating new features from the raw data, which can be derived *via* methods such as PCA and mutual information. Cross-validation is used to evaluate the models' ability to generalize by selecting different subsets of data. Said differently, hyperparameter tuning aims at the ideal adjustment of model parameters, frequently utilizing grid search or random search techniques. Based on the concept of predictive models in healthcare, we have tools like libraries and frameworks like scikit-learn, TensorFlow, Keras, and PyTorch, among others, which are key to establishing models. Hadoop and Spark are some of the biggest data management systems that need to be used in the storage and analysis of the large amounts of healthcare data that are collected. Reporting tools like Tableau and Power BI help in understanding and passing the message of the outcome of the predictive models [6, 7].

Analytics in the forecast is especially valuable in the healthcare industry with its multiple areas of application based on the prediction of patient's health, treatment impact, and disease development. For instance, in healthcare services, predictive models apply in estimating patients' vulnerability to diseases such as diabetes, hypertension, and cardiovascular diseases to allow for early intervention and preventive measures particular to the patient. This personalization even reaches treatment efficacy, where the use of predictive analysis helps doctors predict and estimate the effects of different treatments on patients, thereby identifying the best therapy to use on a patient. Also, prescriptive tools track patients' compliance with the recommended treatments, estimate the level of compliance, and provide

CHAPTER 13

Future Trends and Emerging Technologies in Predictive Maintenance Research

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Abstract: Predictive Maintenance (PdM) refers to a forward-looking approach that uses data analytics to predict equipment failures and schedule maintenance at the most optimal time. This chapter explores the future trends and emerging technologies shaping PdM, focusing on its ability to enhance operational efficiency and reduce downtime. Key developments include the integration of Artificial Intelligence (AI) and Machine Learning (ML) to improve predictive accuracy, the use of IoT and sensor technologies for real-time monitoring, and the application of cloud and edge computing for decentralized data processing. Additionally, technologies such as Augmented Reality (AR) and Virtual Reality (VR) are transforming training and diagnostics, while blockchain ensures data security. The chapter also highlights quantum computing's potential to revolutionize predictive models. Despite these advancements, challenges like data privacy concerns, interoperability issues, workforce skill gaps, and high implementation costs are discussed, alongside recommendations for overcoming these obstacles to maximize PdM's benefits.

Keywords: Artificial intelligence, Augmented reality, Blockchain, Cloud computing, Edge computing, IoT, Machine learning, Predictive maintenance, Quantum computing, Real-time monitoring.

INTRODUCTION

Predictive Maintenance (PdM) is a proactive strategy that leverages data analytics to monitor machinery health, enabling timely maintenance actions, minimizing downtime, and optimizing repair costs. Its main goal is to pre-arrange the maintenance operations by selecting the right time in advance, guarantee that malfunction can be prevented, and reduce the cost of equipment repair. Among reactive maintenance (normally post FMEA), preventive maintenance, and

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PdM(Predictive Maintenance), predictivemaintenance is the one that processes data in real time using various mathematical methods to predict failures based on information about arrays of machines problems [1].

Maintenance Operations: Fig. (**1**) illustrates all the different categories of maintenance operations [2].

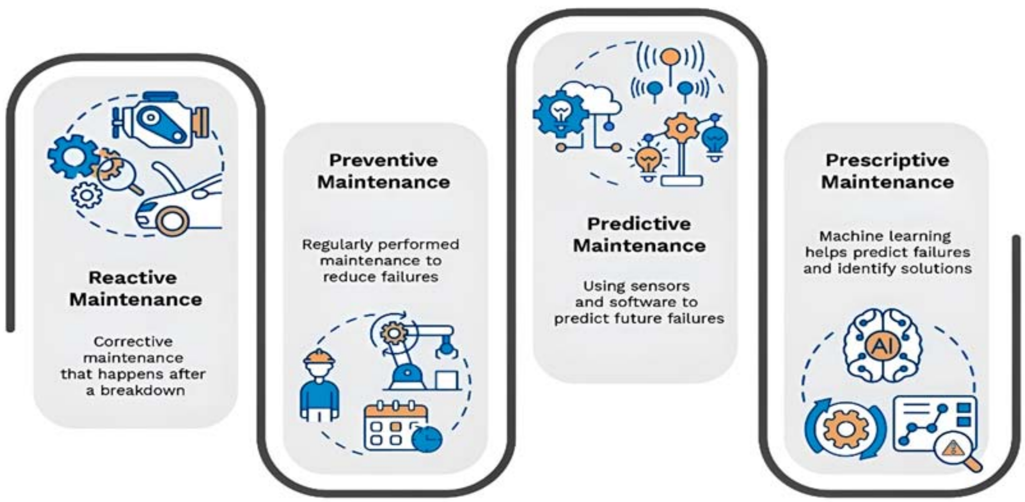

Fig. (1). Different types of maintenance activities [2].

Importance of Predictive Maintenance in Various Industries

Predictive Maintenance (PdM) is one of the powerful methodologies used across manufacturing, energy sector, transportation, and aerospace. This is further highlighted due to the fact it can add efficiency, minimize downtime, and extend the operational life of key assets. This might come in the form of unexpected downtime for manufacturing, which already leads to significant production decreases and even higher operational costs. PdM overcomes these issues by allowing maintenance to be done when it is required, which reduces unnecessary maintenance and prevents large failures [3]. The same goes for transportation vehicles where PdM keeps them running with maximal reliability and minimal sudden breakdowns. The efficiency of PdM in the aerospace industry leads to greater reliability and safety for full-size aircraft, faults occurrence on which may have catastrophic consequences [4]. Fig. (**2**) shows different benefits offered by PdM [2].

Fig. (2). Advantages offered by PdM [2].

Overview of Existing Predictive Maintenance Techniques

Throughout the years, many different Predictive Maintenance (PdM) strategies have been developed, where each presents its own advantages and use cases. They can broadly be grouped into statistical methods, machine learning methods, and model-based methods. A number of these statistical methods include regression analysis and time series analysis, which have been applied in the past for equipment failure predictions as they mine historical information. However, the introduction of PdM systems has changed the landscape by allowing the analysis of bigger and larger data sets for distinguishing patterns that other systems would not have been able to reveal. As a result, machine learning-based methods like decision trees, support vector machines, and deep learning model building have gained ground in the prediction of impending equipment failure, outpacing traditional predictive modeling techniques [5].

On the other hand, model-based frameworks concentrate their efforts on the creation of detailed mathematical models of equipment for simulating their behavior operating under various conditions. It also helps these models to predict the likeliness of component failure depending on operating conditions and degradation. PdM is a major strategy in almost all industries, bringing greater benefits, such as cost-effectiveness, safety, and dependability of the equipment. With continuous development, sophisticated condition-based monitoring using machine learning and data analytics is expected to add further value to PdM in the coming years. Fig. (**3**) depicts a survey conducted by marketsandmarkets.com, which estimates that the global PdM market is projected to increase from USD 10.6 billion in 2024 to USD 47.8 billion by 2029, at a CAGR of 35.1% during the forecast period [6].

SUBJECT INDEX

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Tanu Singh

Dr. Tanu Singh is currently working as an Assistant Professor (Senior Scale) at the School of Computer Science (SoCS), UPES, Dehradun, India. With a teaching and research career spanning over seven years, she brings a blend of academic rigor and administrative leadership. In addition to her teaching role, she holds a key position as Program Lead for the B.Tech (Big Data) and M.Tech programs offered by SoCS. She earned her Ph.D. in Computer Science and Engineering from GGSIPU, New Delhi, in 2022. Prior to that, she completed her M.Tech in CSE (2014) and B.Tech in IT (2011), both from PTU, Punjab. Her academic foundation lies in core computer science areas such as data analytics, software engineering, data warehousing, and requirements engineering. Dr. Singh has an impressive academic portfolio, with more than 25 publications, including journal and conference papers, two patents, and two edited books. Her research interests include data science, machine learning, artificial intelligence, and related emerging technologies. Her ability to translate innovative ideas into real-world applications is reflected in her multiple patents and design registrations. Committed to continuous learning and academic excellence, Dr. Singh strives to inspire students and contribute meaningfully to the advancement of knowledge.

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Dr. Vinod Patidar is a Fellow of the Executive Leadership Academy (UC Berkeley), the Institution of Engineering and Technology (UK), and the Institution of Electronics and Telecommunication Engineers (India), with 25 years of experience in teaching, research, and academic leadership. He is presently a Professor at the School of Computer Science, UPES, Dehradun, India. He has served as a Visiting Scientist at the Helmholtz Institute for Supercomputational Physics, University of Potsdam (Germany), and the International Centre for Theoretical Physics (ICTP), Trieste. He received training in university governance under the EU's ERASMUS+ LEAD2 Programme (Vrije Universiteit, Brussels). An internationally recognized expert in Nonlinear Dynamics, Chaos Theory, Chaos-based Cryptography, and Image Encryption, he has published around 100 research papers with over 4900 citations (h-index: 24, i10-index: 40). His work has received multiple accolades, including the Most Cited Paper award (Elsevier), the Editor's Pick Outstanding Article Award 2022 (FAMS), and several listings in ScienceDirect's Top 25 most downloaded articles. He has secured major research grants, including the DST Young Scientist Research Grant, SERB-MATRICS Grant, and numerous travel and research fellowships from CSIR, NBHM, CIMPA, ICTP, and ICM. He also serves on the editorial boards of several journals, including Scientific Reports, Frontiers in Applied Mathematics and Statistics (Dynamical Systems), Frontiers in Signal Processing (Image Processing), and Chaos Theory and Applications.

Arvind Panwar

Dr. Arvind Panwar is a distinguished researcher and academician with over 15 years of experience in Computer Science and Engineering. He holds a Ph.D. from Guru Gobind Singh Indraprastha University, where his thesis focused on designing a secure cloud-based blockchain framework for health record management. His expertise spans blockchain technology, information security, cybersecurity, and data analytics. Dr. Panwar is actively involved in academic publishing, having authored 9 SCI/SCOPUS-indexed journal articles, 15 conference papers, and 18 book chapters. He is currently editing three significant books for esteemed publishers: Data Analytics and Artificial Intelligence for Predictive Maintenance in Industry 4.0 for Bentham, Qubits Unveiled: Quantum Computing Solutions for Efficient Supply Logistics for Nova Publications, and Energy Efficient Internet of Things-Based Wireless Sensor Network for Wiley-Scrivener Publishing LLC. These works highlight his expertise in cutting-edge technologies and their applications in modern industry and logistics. A prolific innovator, Dr. Panwar holds 8 granted patents and 11 published patents in the domains of blockchain, AI, and IoT applications. His academic contributions include mentoring graduate students, spearheading interdisciplinary research, and engaging in global collaborations, such as his visiting professorship at South Kazakhstan Pedagogical University. Dr. Panwar's dedication to advancing technological innovation and his extensive academic achievements make him a leading figure in bridging research and industry.

Urvashi Sugandh

Dr. Urvashi Sugandh is an accomplished academician and researcher with over 12 years of teaching and research experience in Computer Science and Engineering. She holds a Ph.D. in Computer Science and Engineering from Banasthali Vidyapith, with her thesis focusing on a blockchain-based smart agriculture framework. Her expertise spans blockchain technology, cybersecurity, and IoT applications, demonstrated by 7 SCI/SCOPUS-indexed journal publications, 10 conference papers, and 11 book chapters. Dr. Sugandh is currently editing two significant books for leading publishers: Data Analytics and Artificial Intelligence for Predictive Maintenance in Industry 4.0 for Bentham, and Energy Efficient Internet of Things-Based Wireless Sensor Network for Wiley-Scrivener Publishing LLC. These works highlight her expertise in cutting-edge technologies and their applications in modern industry and logistics. A prolific innovator, she holds 6 granted patents and 11 published patents in domains such as artificial intelligence, IoT, and blockchain. As a dedicated educator, Dr. Sugandh excels in teaching courses like Data Structures, Software Engineering, and Computer Networks, while mentoring students and driving transformative research initiatives. Her work continues to bridge academia and industry, fostering interdisciplinary collaborations and delivering impactful solutions to contemporary technological challenges.