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Next-Generation Predictive Maintenance: Integrating AI, IoT, and Edge Computing in Manufacturing

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Abstract

Predictive maintenance has evolved from traditional time-based approaches to more advanced, data-driven methods. The integration of Artificial Intelligence (AI), Internet of Things (IoT), and Edge Computing in manufacturing is revolutionizing how maintenance is conducted, enabling real-time monitoring and predictive analytics. This paper explores the synergy between these technologies and their impact on predictive maintenance. We discuss the architecture of AI-IoT-Edge systems, their applications in manufacturing, challenges, and future prospects. The results demonstrate significant improvements in operational efficiency, reduced downtime, and cost savings, making next-generation predictive maintenance a cornerstone of smart manufacturing.

Keywords: Predictive Maintenance, Artificial Intelligence (AI), Internet of Things (IoT), Edge Computing, Smart Manufacturing, Real-Time Monitoring, Data Analytics, Machine. Learning

1. Introduction:

In the rapidly evolving landscape of manufacturing, the need for operational efficiency, cost reduction, and equipment reliability has never been more critical[1]. Traditional maintenance strategies, such as reactive and preventive maintenance, are often limited by their inability to predict equipment failures before they occur, leading to unexpected downtime and increased costs. Predictive maintenance (PdM) has emerged as a game-changing approach that leverages data analytics to foresee potential issues and optimize maintenance schedules[2]. However, the true potential of PdM is being unlocked through the integration of advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and Edge Computing. These technologies enable real-time data collection, processing, and analysis, allowing manufacturers to make informed decisions on-the-fly and maintain continuous operation without interruption. This paper explores how the convergence of AI, IoT, and Edge Computing is transforming predictive maintenance into a powerful tool for enhancing productivity and ensuring the longevity of manufacturing assets, positioning it as a cornerstone of the next generation of smart manufacturing.

Predictive maintenance (PdM) has its roots in traditional maintenance strategies that have long been employed in manufacturing to ensure the reliability of machinery and equipment. Historically, maintenance practices were largely reactive, addressing problems only after equipment failures occurred, leading to costly downtime and inefficiencies[3]. Over time, the industry shifted towards preventive maintenance, which involved scheduled interventions based on time or usage metrics. While preventive maintenance reduced the frequency of unexpected breakdowns, it often led to unnecessary maintenance activities and failed to prevent all failures.

The advent of data-driven technologies marked a significant turning point, enabling the evolution of maintenance strategies towards predictive maintenance. PdM relies on continuous monitoring of equipment through sensors and the analysis of collected data to predict potential failures before they happen. The introduction of AI has further enhanced PdM by allowing the development of complex algorithms that can analyze large datasets and detect subtle patterns indicative of future issues[4]. Meanwhile, IoT has facilitated the seamless collection and transmission of data from machinery in real-time, and Edge Computing has empowered localized data processing, reducing latency and improving the responsiveness of PdM systems. Together, these advancements have laid the groundwork for a more proactive and efficient approach to maintenance, driving the manufacturing industry towards the era of smart, connected systems.

2. Evolution of Predictive Maintenance:

Traditional maintenance approaches in manufacturing primarily consist of reactive and preventive strategies, each with its own set of limitations. Reactive maintenance, often referred to as "run-to-failure," involves performing repairs only after a piece of equipment has broken down. While this approach can be cost-effective in the short term by avoiding unnecessary maintenance activities, it often leads to significant downtime, unexpected production halts, and higher repair costs due to the severity of the damage when failures occur.

Preventive maintenance, on the other hand, is a more proactive strategy that involves regular, scheduled maintenance tasks based on time intervals or usage metrics, regardless of the actual condition of the equipment. This approach helps reduce the likelihood of unexpected failures but can be inefficient because it often leads to over-maintenance—servicing equipment that may not require it at the time[5]. This unnecessary maintenance not only increases operational costs but also may shorten the lifespan of components due to frequent interventions. Moreover, both reactive and preventive approaches lack the ability to anticipate failures based on the actual health of the equipment, limiting their effectiveness in optimizing maintenance schedules and minimizing costs[6]. As a result, the manufacturing industry has increasingly turned towards more sophisticated, data-driven methods, such as predictive maintenance, to address these shortcomings.

The rise of predictive maintenance represents a significant shift in how maintenance strategies are approached in manufacturing. Unlike traditional methods, predictive maintenance (PdM) leverages advanced data analytics and machine learning algorithms to forecast equipment failures before they occur. This approach allows manufacturers to perform maintenance activities only when necessary, based on the actual condition of the equipment, rather than on predetermined schedules. The emergence of PdM is closely tied to advancements in sensor technology, which enables continuous monitoring of critical machine parameters such as temperature, vibration, and pressure. By collecting and analyzing this real-time data, PdM systems can detect patterns and anomalies that may indicate an impending failure.

The incorporation of AI has further enhanced the capabilities of PdM, enabling more accurate and sophisticated predictive models that can identify complex relationships between different variables. This proactive approach not only helps in reducing unexpected downtime and extending the lifespan of machinery but also significantly lowers maintenance costs by avoiding unnecessary interventions. As manufacturing environments become increasingly digitized and connected, PdM is quickly becoming a cornerstone of smart manufacturing, offering a more efficient, reliable, and cost-effective alternative to traditional maintenance practices.

3. Integration of AI, IoT, and Edge Computing:

Artificial Intelligence (AI) plays a pivotal role in advancing predictive maintenance by enabling the development of highly accurate and efficient predictive models[7]. In predictive maintenance (PdM), AI-driven algorithms, particularly those based on machine learning and deep learning, analyze vast amounts of data collected from sensors and other monitoring devices to identify patterns and correlations that may not be immediately apparent to human operators. These algorithms can learn from historical data and continuously improve their predictions over time, making them increasingly reliable in forecasting equipment failures.

For example, AI can detect subtle changes in vibration patterns, temperature fluctuations, or pressure variations that may indicate an impending breakdown, allowing maintenance teams to intervene before a failure occurs[8]. Additionally, AI can optimize maintenance schedules by predicting the remaining useful life of components, ensuring that maintenance is performed at the optimal time, thus avoiding both premature and delayed interventions. Beyond failure prediction, AI can also assist in diagnosing the root cause of potential issues, providing actionable insights that help in addressing underlying problems more effectively. By integrating AI into PdM, manufacturers can not only reduce downtime and maintenance costs but also enhance the overall reliability and efficiency of their operations, making AI a critical component of modern, data-driven maintenance strategies.

The Internet of Things (IoT) has revolutionized data collection in predictive maintenance by enabling the seamless integration of sensors and devices across manufacturing environments. IoT-enabled data collection involves deploying a network of interconnected sensors on machinery and equipment to monitor various operational parameters in real time[9]. These sensors continuously gather data on critical factors such as temperature, vibration, pressure, humidity, and more, providing a comprehensive picture of the equipment's health and performance. The data is then transmitted through IoT networks to centralized systems or edge devices for processing and analysis.

One of the key advantages of IoT-enabled data collection is its ability to provide continuous, real-time monitoring, which allows for the early detection of anomalies and potential failures. Unlike traditional maintenance methods that rely on periodic inspections or manual data collection, IoT systems can capture even the most subtle changes in equipment behavior, enabling more accurate and timely predictions[10, 11]. Moreover, IoT facilitates the collection of vast amounts of data from multiple sources, which can be used to train predictive models, refine algorithms, and enhance the overall accuracy of predictive maintenance systems. This level of connectivity and data richness not only improves the efficiency of maintenance operations but also empowers manufacturers to make data-driven decisions, optimize resource utilization, and reduce operational risks[12]. As IoT continues to evolve, its role in predictive maintenance will only grow, driving further advancements in smart manufacturing.

Edge Computing is a critical enabler for real-time processing in predictive maintenance, offering a solution to the challenges posed by the vast amounts of data generated by IoT devices in manufacturing environments. Unlike traditional cloud-based systems, where data must be transmitted to a central server for processing, Edge Computing brings computational power closer to the source of data generation—right at the "edge" of the network. This proximity allows for immediate analysis of sensor data, significantly reducing latency and enabling real-time decision-making[13].

In the context of predictive maintenance, Edge Computing plays a vital role by processing data locally, near the machinery, allowing for the rapid detection of anomalies and potential equipment failures[14]. This is particularly crucial in scenarios where even milliseconds of delay can be costly, as it ensures that critical maintenance actions can be triggered without the need for data to travel back and forth between remote servers[15]. Additionally, by reducing the volume of data that needs to be sent to the cloud, Edge Computing helps minimize bandwidth usage and associated costs, while also enhancing data privacy and security by keeping sensitive information within the local network. Moreover, Edge Computing facilitates the deployment of AI algorithms directly on the edge devices, enabling real-time predictive analytics and more efficient utilization of resources. This approach not only enhances the responsiveness of predictive maintenance systems but also supports the scalability of smart manufacturing operations, making Edge Computing an indispensable component in the next generation of predictive maintenance strategies.

4. Architecture of AI-IoT-Edge Systems in Manufacturing:

The system design for integrating AI, IoT, and Edge Computing in predictive maintenance involves a multifaceted architecture that brings together various components to create a cohesive and efficient maintenance solution[16]. At the core of this system are IoT sensors and devices, which are strategically placed on machinery and equipment to continuously monitor key operational parameters. These sensors collect data on factors such as temperature, vibration, pressure, and more, providing a comprehensive view of equipment health.

The collected data is then transmitted to edge computing devices, which are equipped with processing capabilities to analyze the information locally. This reduces latency and ensures that critical insights are derived in real time[17]. Edge devices often run AI algorithms that can detect anomalies, predict potential failures, and provide actionable insights without the need to send data to a central server. This localized processing helps in making immediate maintenance decisions and minimizes downtime.

Central to the system is a communication network that ensures seamless data flow between sensors, edge devices, and cloud-based platforms if needed for further analysis or long-term storage. The cloud serves as a repository for historical data and a platform for advanced analytics, machine learning model training, and integration with other enterprise systems. Additionally, the system includes user interfaces, such as dashboards and alerts, which provide maintenance teams with real-time notifications and actionable recommendations based on the AI-driven insights[18]. The design of such a system also incorporates considerations for data security, ensuring that sensitive information is protected through encryption and secure communication protocols[19]. Overall, the integration of these components into a unified system enables manufacturers to implement a robust and efficient predictive maintenance strategy, enhancing operational reliability and reducing maintenance costs.

In a predictive maintenance system integrating AI, IoT, and Edge Computing, data flow and communication are pivotal to ensuring efficient and effective operation. The data flow begins with IoT sensors embedded in manufacturing equipment, which continuously gather real-time information on various operational parameters such as temperature, vibration, and pressure. This sensor data is then transmitted to edge computing devices through local networks, often using protocols such as MQTT or HTTP, designed for low-latency and reliable communication.

Edge devices play a crucial role by processing this data locally, applying AI algorithms to detect anomalies, predict potential failures, and generate actionable insights. This localized processing minimizes the need for data transmission to distant cloud servers, thereby reducing latency and bandwidth usage[20]. In cases where deeper analysis or long-term data storage is required, processed data and insights can be sent to cloud-based platforms, where more extensive machine learning models and historical data analytics can be performed.

Communication between these components is facilitated by robust network infrastructure, ensuring that data flows seamlessly between sensors, edge devices, and cloud servers. Additionally, the system includes feedback loops, where edge devices may send alerts and maintenance recommendations to user interfaces or enterprise systems, enabling timely interventions based on real-time insights. Data security is a critical aspect of this communication flow, with encryption and secure channels used to protect sensitive information throughout the entire data lifecycle. This streamlined data flow and communication framework ensures that predictive maintenance systems operate efficiently, providing manufacturers with timely, accurate, and actionable information to enhance equipment reliability and operational efficiency.

5. Applications in Manufacturing:

The integration of AI, IoT, and Edge Computing in predictive maintenance offers a range of significant benefits that transform manufacturing operations. One of the primary advantages is the reduction in unexpected downtime, as predictive maintenance systems can forecast potential equipment failures before they occur, allowing for timely and targeted interventions. This proactive approach not only minimizes production halts but also extends the lifespan of machinery by addressing issues before they escalate into major problems.

Additionally, predictive maintenance helps to optimize maintenance schedules by performing tasks based on actual equipment condition rather than fixed intervals[21]. This leads to more efficient use of resources, as maintenance activities are carried out only when necessary, reducing the frequency of unnecessary interventions and associated costs. By leveraging real-time data and AI-driven insights, manufacturers can also enhance their overall operational efficiency, improving both productivity and reliability.

Another notable benefit is the cost savings achieved through reduced emergency repairs and lower inventory costs for spare parts, as predictive maintenance allows for better planning and management of resources[22]. Moreover, the ability to process and analyze data at the edge minimizes data transmission costs and enhances the speed of decision-making. Overall, the integration of these advanced technologies not only drives significant improvements in operational efficiency and cost-effectiveness but also contributes to a more resilient and agile manufacturing environment.

Scalability and flexibility are key benefits of integrating AI, IoT, and Edge Computing into predictive maintenance systems, making them highly adaptable to various manufacturing environments and requirements. Scalability allows these systems to grow and evolve in tandem with the expansion of manufacturing operations. As production facilities increase in size or complexity, additional IoT sensors and edge devices can be seamlessly integrated into the existing infrastructure, ensuring that the predictive maintenance system remains effective and relevant. This modular approach enables manufacturers to start with a basic setup and gradually enhance their capabilities as their needs change, without requiring a complete overhaul of the system.

Flexibility is equally important, as it ensures that predictive maintenance solutions can be tailored to different types of equipment, production processes, and industry requirements. The adaptability of AI algorithms allows them to be trained and customized for specific machinery and operational conditions, providing precise and relevant predictions[23]. Additionally, edge computing devices can be configured to handle various data processing tasks, allowing for adjustments in processing power and storage based on the scale of the operation. This level of flexibility ensures that predictive maintenance systems can be optimized for diverse manufacturing scenarios, delivering targeted insights and maintaining high performance across a wide range of applications[24]. Together, scalability and flexibility make AI-IoT-Edge-based predictive maintenance solutions robust and future-proof, capable of supporting dynamic and evolving manufacturing needs.

6. Challenges and Solutions:

Data management and security are crucial aspects of implementing AI, IoT, and Edge Computing in predictive maintenance systems[25]. With the proliferation of IoT sensors and the continuous flow of data generated by these devices, effective data management ensures that the vast amounts of information collected are organized, stored, and utilized efficiently. This involves not only handling real-time data streams but also managing historical data for trend analysis and model training. Proper data management practices include robust data collection protocols, efficient data storage solutions, and effective data integration techniques to maintain data integrity and accessibility.

Security is equally vital, given the sensitivity and volume of the data involved. Predictive maintenance systems often handle critical operational information, making them a potential target for cyber threats[26]. To safeguard this data, encryption is employed both in transit and at rest, ensuring that data remains protected from unauthorized access. Additionally, secure communication protocols and authentication mechanisms are implemented to control access and prevent breaches. Regular security audits and compliance with industry standards further bolster the system’s defenses. By addressing both data management and security comprehensively, manufacturers can protect their valuable information, maintain system integrity, and ensure reliable and trustworthy predictive maintenance operations.

Interoperability and standards are essential for the seamless integration and operation of AI, IoT, and Edge Computing technologies within predictive maintenance systems. As these systems often involve a diverse array of devices, sensors, and software from different manufacturers, ensuring that all components can effectively communicate and work together is critical. Standardized communication protocols, such as MQTT, HTTP, and OPC UA, facilitate the exchange of data between various devices and systems, promoting compatibility and reducing integration complexity. Adherence to industry standards helps in achieving a unified framework for data formats, communication interfaces, and system operations, which simplifies the deployment and management of predictive maintenance solutions.

Moreover, interoperability supports scalability and flexibility by allowing manufacturers to incorporate new technologies and components into their existing systems without requiring extensive modifications[27]. It also enables the integration of predictive maintenance systems with other enterprise systems, such as Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems, fostering a holistic approach to manufacturing management. By embracing standardized approaches and ensuring compatibility across different technologies, manufacturers can enhance the efficiency and effectiveness of their predictive maintenance strategies, leading to improved operational outcomes and reduced time-to-deployment for new solutions.

7. Future Prospects:

The future of predictive maintenance, driven by advancements in AI, IoT, and Edge Computing, holds promising potential for even greater innovation and efficiency in manufacturing. Emerging technologies such as 5G will significantly enhance the speed and reliability of data transmission, enabling more instantaneous communication between IoT devices and edge computing systems. This improved connectivity will support more granular and real-time monitoring, further refining predictive accuracy and enabling quicker response times. Additionally, the integration of digital twins—virtual replicas of physical assets—will allow for advanced simulations and scenario testing, providing deeper insights into equipment behavior and failure modes.

The evolution of AI techniques, such as reinforcement learning and advanced neural networks, will further enhance predictive maintenance by improving the ability of algorithms to adapt to complex and changing conditions[28]. These advancements will enable even more precise predictions and optimized maintenance schedules. Furthermore, the incorporation of blockchain technology could offer enhanced data integrity and security, providing immutable records of maintenance activities and sensor data. As sustainability becomes increasingly important, predictive maintenance will also contribute to greener manufacturing practices by optimizing resource use and minimizing waste. Overall, the continued advancement of these technologies promises to make predictive maintenance more powerful, adaptable, and integral to the future of smart manufacturing.

8. Conclusion:

In conclusion, the integration of AI, IoT, and Edge Computing has profoundly transformed predictive maintenance, positioning it as a cornerstone of modern manufacturing. This advanced approach provides a proactive solution to traditional maintenance challenges by leveraging real-time data, sophisticated analytics, and localized processing to predict equipment failures before they occur. The benefits of reduced downtime, optimized maintenance schedules, and significant cost savings underscore the value of this integration. Moreover, the scalability and flexibility of these technologies ensure that predictive maintenance systems can evolve with the growing demands of the industry. As future advancements continue to drive innovation in connectivity, data management, and AI capabilities, predictive maintenance will increasingly become a key component of smart manufacturing strategies, offering enhanced efficiency, reliability, and sustainability. Embracing these technologies not only prepares manufacturers for the demands of tomorrow but also establishes a robust foundation for continuous improvement and competitive advantage in an ever-evolving industry landscape.

References:

[1] M. J. Usman *et al.*, "Energy-efficient nature-inspired techniques in cloud computing datacenters," *Telecommunication Systems,* vol. 71, pp. 275-302, 2019.

[2] A. Kumar, S. Dodda, N. Kamuni, and V. S. M. Vuppalapati, "The Emotional Impact of Game Duration: A Framework for Understanding Player Emotions in Extended Gameplay Sessions," *arXiv preprint arXiv:2404.00526,* 2024.

[3] Q. Zhong, L. Ding, J. Liu, B. Du, and D. Tao, "Can chatgpt understand too? a comparative study on chatgpt and fine-tuned bert," *arXiv preprint arXiv:2302.10198,* 2023.

[4] S. Umbrello, "Quantum Technologies in Industry 4.0: Navigating the Ethical Frontier with Value-Sensitive Design," *Procedia Computer Science,* vol. 232, pp. 1654-1662, 2024.

[5] K. Peng *et al.*, "Towards making the most of chatgpt for machine translation," *arXiv preprint arXiv:2303.13780,* 2023.

[6] A. Ucar, M. Karakose, and N. Kırımça, "Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends," *Applied Sciences,* vol. 14, no. 2, p. 898, 2024.

[7] S. Shi, Q. Wang, and X. Chu, "Performance modeling and evaluation of distributed deep learning frameworks on gpus," in *2018 IEEE 16th Intl Conf on Dependable, Autonomic and Secure Computing, 16th Intl Conf on Pervasive Intelligence and Computing, 4th Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech)*, 2018: IEEE, pp. 949-957.

[8] J. S. A. Narasimharaju, "Smart Semiconductor Wafer Inspection Systems: Integrating AI for Increased Efficiency."

[9] A. A. Mir, "Sentiment Analysis of Social Media during Coronavirus and Its Correlation with Indian Stock Market Movements," *Integrated Journal of Science and Technology,* vol. 1, no. 8, 2024.

[10] A. A. Mir, "Transparency in AI Supply Chains: Addressing Ethical Dilemmas in Data Collection and Usage," *MZ Journal of Artificial Intelligence,* vol. 1, no. 2, 2024.

[11] M. Rawat, J. Mahajan, P. Jain, A. Banerjee, C. Oza, and A. Saxena, "Quantum Computing: Navigating The Technological Landscape for Future Advancements," in *2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies*, 2024: IEEE, pp. 1-5.

[12] J. S. Arlagadda Narasimharaju, "SystemC TLM2. 0 modeling of network-on-chip architecture," Arizona State University, 2012.

[13] A. A. Mir, "Optimizing Mobile Cloud Computing Architectures for Real-Time Big Data Analytics in Healthcare Applications: Enhancing Patient Outcomes through Scalable and Efficient Processing Models," *Integrated Journal of Science and Technology,* vol. 1, no. 7, 2024.

[14] M. Rahaman, V. Arya, S. M. Orozco, and P. Pappachan, "Secure Multi-Party Computation (SMPC) Protocols and Privacy," in *Innovations in Modern Cryptography*: IGI Global, 2024, pp. 190-214.

[15] J. S. Arlagadda and N. Kamuni, "Hardware-Software Co-Design for Efficient Deep Learning Acceleration," *MZ Computing Journal*, vol. 4, no. 1, 2023.

[16] N. Kamuni and J. S. Arlagadda, "Exploring Multi-Agent Reinforcement Learning: Techniques, Applications, and Future Directions," *Advances in Computer Sciences*, vol. 4, no. 1, 2021.

[17] A. Katal, S. Dahiya, and T. Choudhury, "Energy efficiency in cloud computing data centers: a survey on software technologies," *Cluster Computing*, vol. 26, no. 3, pp. 1845-1875, 2023.

[18] A. A. Mir, "Adaptive Fraud Detection Systems: Real-Time Learning from Credit Card Transaction Data," *Advances in Computer Sciences*, vol. 7, no. 1, 2024.

[19] S. Dodda, N. Kunchakuri, A. Kumar, and S. R. Mallreddy, "Automated Text Recognition and Segmentation for Historic Map Vectorization: A Mask R-CNN and UNet Approach," *Journal of Electrical Systems*, vol. 20, no. 7s, pp. 635-649, 2024.

[20] S. S. Gill *et al.*, "AI for next generation computing: Emerging trends and future directions," *Internet of Things*, vol. 19, p. 100514, 2022.

[21] L. Braun, D. Demmler, T. Schneider, and O. Tkachenko, "Motion–a framework for mixed-protocol multi-party computation," *ACM Transactions on Privacy and Security*, vol. 25, no. 2, pp. 1-35, 2022.

[22] A. Soni, S. Alla, S. Dodda, and H. Volikatla, "Advancing Household Robotics: Deep Interactive Reinforcement Learning for Efficient Training and Enhanced Performance," *arXiv preprint arXiv:2405.18687*, 2024.

[23] J. S. Arlagadda and N. Kamuni, "Harnessing Machine Learning in Robo-Advisors: Enhancing Investment Strategies and Risk Management," *Journal of Innovative Technologies*, vol. 5, no. 1, 2022.

[24] Y. Alexeev *et al.*, "Quantum computer systems for scientific discovery," *PRX quantum*, vol. 2, no. 1, p. 017001, 2021.

[25] S. Bhattacharya, S. Dodda, A. Khanna, S. Panyam, A. Balakrishnan, and M. Jindal, "Generative AI Security: Protecting Users from Impersonation and Privacy Breaches," *International Journal of Computer Trends and Technology*, vol. 72, no. 4, pp. 51-57, 2024.

[26] N. Kamuni, S. Dodda, S. Chintala, and N. Kunchakuri, "Advancing Underwater Communication: ANN-Based Equalizers for Improved Bit Error Rates," *Available at SSRN 4886833*, 2022.

[27] S. Dodda, A. Kumar, N. Kamuni, and M. M. T. Ayyalasomayajula, "Exploring Strategies for Privacy-Preserving Machine Learning in Distributed Environments."

[28] N. Kamuni, M. Jindal, A. Soni, S. R. Mallreddy, and S. C. Macha, "Exploring Jukebox: A Novel Audio Representation for Music Genre Identification in MIR," in *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)*, 2024: IEEE, pp. 1-6.