Quantum Machine Learning for Predictive Maintenance and

Anomaly Detection in Smart Manufacturing and Industrial IoT Networks

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***Abstract*—The rapid digitalization of manufacturing systems has led to the widespread adoption of Industrial Internet of Things (IIoT) networks, enabling real-time monitoring, data-driven optimization, and intelligent automation. A critical application within this paradigm is predictive maintenance, which aims to anticipate equipment failures before they occur, thereby reducing downtime, operational costs, and safety risks. However, traditional machine learning approaches for predictive maintenance and anomaly detection often struggle with high-dimensional sensor data, complex nonlinear relationships, and scalability constraints in large industrial environments. This paper explores the emerging role of Quantum Machine Learning (QML) as a novel computational framework for enhancing predictive maintenance and anomaly detection in smart manufacturing systems. By leveraging quantum principles such as superposition and quantum-enhanced feature spaces, QML algorithms offer new possibilities for processing complex industrial data more efficiently and accurately. The study examines hybrid quantum–classical models for fault prediction, early anomaly detection, and pattern recognition in IIoT networks, highlighting their potential advantages over classical methods. Challenges related to hardware limitations, data encoding, and industrial deployment are also discussed, providing a balanced perspective on the feasibility and future impact of quantum-enhanced intelligence in smart manufacturing.**

The evolution of manufacturing toward smart and connected production systems has fundamentally transformed how industrial processes are monitored, controlled, and optimized [6]. Under the framework of Industry 4.0, Industrial Internet of Things (IIoT) networks integrate sensors, machines, and control systems to generate continuous streams of operational data. These data-driven environments enable advanced analytics and artificial intelligence techniques to support decision-making across the production lifecycle [8]. Among the most impactful applications of this transformation is predictive maintenance, which seeks to identify early signs of equipment degradation and failure before disruptions occur.

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Conventional maintenance strategies—such as reactive maintenance, performed after a failure, or preventive maintenance, based on fixed schedules—are often inefficient and costly [4]. Predictive maintenance addresses these limitations by using machine learning models trained on historical and real-time sensor data to forecast failures and optimize maintenance schedules [7]. Despite significant progress, classical machine learning techniques face persistent challenges when applied to industrial settings. High-dimensional sensor data, non-stationary operating conditions,

