AI-Driven Predictive Maintenance for Intelligent Tires: A Real-Time Digital Twin Framework

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Abstract. The current trend in the technology of intelligent tire is revolutionizing vehicle performance and safety by integrating advanced sensing methodologies, Digital Twin, and Artificial intelligence. This paper introduces an approach of Predictive Maintenance framework that combines machine learning, sensor fusion, and cloud-based analytics enabling a real-time tire health monitoring, performing a self-repair if needed to maintain an optimized state of the tire. An AI driven diagnostic, Digital Twin virtual simulation integrated an advanced physical system is implemented. The model proposed in this research is detecting early faults, reducing maintenance costs and enhancing road safety. The framework goes beyond traditional tire monitoring systems by integrating adaptive algorithms and cutting-edge data processing techniques, enabling a continuous and dynamic condition assessment of the tire. This approach represents A key step towards a robust, scalable tire management system aligning with the trend of Industry 4.0 standards and the future of autonomous driving and mobility.

Keywords: Intelligent Tires, Digital Twin, Predictive Maintenance, Industry 4.0, Artificial Intelligence, Reinforcement Learning.Page layout

1 Introduction

The rapid progress of autonomous driving technology has provided a route to significant advancements in tire monitoring and maintenance. As Traditional tire maintenance relies on periodic inspections and reactive strategies, which often result in un-expected failures and increased operational costs, the emergence of Industry 4.0, Artificial Intelligence (AI), and Digital Twins has revolutionized predictive maintenance, offering real-time insights into vehicle health and tire conditions. Multiple Studies [1,2] bring more attention to the role of connected cyber-physical systems in predictive maintenance and manufacturing optimization.

Tire Pressure Monitoring Systems (TPMS) have played a critical role in vehicle safety feature, fuel efficiency, and maintain vehicle handling. However, traditional TPMS solutions

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often provide delayed or limited insights into tire conditions. Research has demonstrated the benefits of sensor-based solutions for tire diagnostics [3]. Further-more, [4] explores how RF transceivers can enhance tire localization, reducing false alerts and improving diagnostic accuracy.

Early research highlights the importance of multi-scale modeling to understand tire-road interactions under real-world driving conditions. [5] introduces a computational approach for modeling tire behavior under various road conditions. Additionally, [6] provides insights into how aerodynamic forces affect tire performance, energy consumption, and vehicle efficiency. In the Industry 4.0 landscape, AI-driven predictive maintenance models have demonstrated the effectiveness in various industrial applications, that has been introduced in several research. Studies such as [7] and [8] draw attention to the im-portance of data-driven diagnostics in reducing downtime and maintenance costs. Meanwhile,[9] explores AI-based optimization techniques for predictive maintenance, enhancing overall manufacturing efficiency.

Digital Twins integrated with AI has further enhanced predictive maintenance capabilities. proposes A real-time monitoring approach leveraging machine learning and sensor fusion to predict tire failures is presented by [10]. Moreover, [11] provides a comprehensive analysis of how AI-powered digital twins can optimize maintenance strategies and reduce failure rates.

Studies such as [12,13] confirm the effectiveness of AI-driven predictive maintenance applications across various industrial domains. Meanwhile, [14] introduces an AI-powered framework that enhances fault detection accuracy and interpretability.

This paper explores a real-time predictive maintenance framework integrating AI, Digital Twins, and cloud-based analytics for enhanced tire health monitoring. adaptive machine learning algorithms has been selected, enabling an automated model diagnostic, early fault detection, and optimized maintenance scheduling. Further-more, [15] demonstrates how AI-driven solutions have significantly improved tire safety and performance in modern applications.

The framework aligns with modern industrial practices, leveraging advancements in railcar diagnostics, manufacturing, and predictive maintenance strategies to improve operational efficiency [5].

The remainder of this paper is organized as follows: Section II reviews related work on AI-driven predictive maintenance and digital twin applications. Section III details the proposed AI-enhanced framework for real-time tire health monitoring. Section IV presents the framework's key components, theoretical modeling, and expected out-comes based on existing literature. Section V concludes the paper and discusses future research directions.

2 Related works on ai-driven predictive maintenance and digital twin applications

The evolution of Predictive maintenance in Industry 4.0 is a result of the integration of advanced AI techniques and digital twin technologies. Throughout this section, we highlight the most widely adopted approaches, supported by high-quality literature, and outline their key features and limitations.

2.1 A. AI-Driven Predictive Maintenance Techniques

AI is revolutionizing maintenance strategies by phasing out rigid, rule-based systems that often falter in dynamic environments. Traditional approaches may perform adequately under controlled conditions but fall short in the adaptability required for real-time decision-making.

On the other hand, machine learning (ML) models provide advanced predictive capabilities by analyzing intricate data patterns to foresee failures before they happen.

Take, for instance, the comparison of prediction models using single source versus multisource data. Multisource approaches can significantly reduce the Mean Square Deviation (MSE) from 0.1823 to 0.1504 [7], showcasing improved prediction accuracy. This is vividly illustrated in Fig. 1 a) clearly highlights the benefits of incorporating diverse sensor inputs.

In the realm of anomaly detection, performance metrics reveal that advanced deep learning models, such as the 2D-CNN-AE, achieve an F1 score of 0.99, compared to 0.92 for the Null Space method [14]. Fig. 1 b) underscores the superior capability of deep learning approaches to detect even the smallest variations in failure signals.

Additionally, sequence modeling techniques for predicting tire endurance damage have been evaluated using Mean Absolute Percentage Error (MAPE) [10]. Fig. 1 c) shows that the TFT model achieved a MAPE of 29.5%, outperforming traditional methods like LSTM (36.23%), RNN (37.85%), GRU (38.61%), and Transformer En-coder (35.40%). These findings emphasize that state-of-the-art AI models consistently offer higher accuracy and adaptability for predictive maintenance.

Collectively, these performance metrics illustrate that advanced deep learning models (e.g., LSTM, CNN, and 2D-CNN-AE) substantially outperform traditional methods in processing complex, real-time sensor data. This not only enhances predictive accuracy but also facilitates proactive maintenance strategies—an essential advancement for Industry 4.0 applications in automotive and other tire-reliant industries.

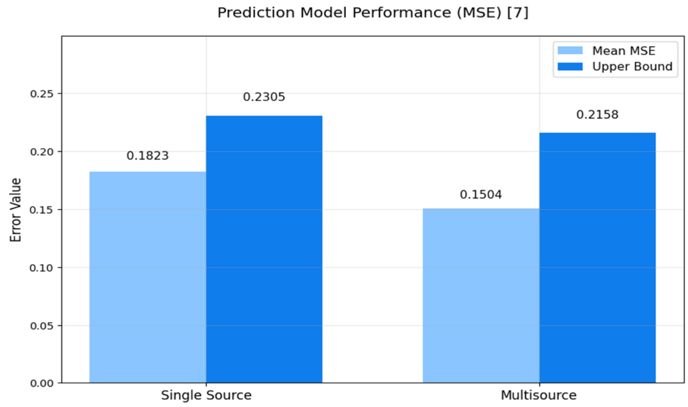
2.2 Digital Twin Integration in Predictive Maintenance

Digital twin technology presents a virtual replica of physical assets, enabling continuous simulation and real-time monitoring of equipment conditions. This innovative approach enhances predictive maintenance by integrating real-time sensor data with AI-driven analytics.

A study [10] showcases how digital twins optimize maintenance schedules and enhance fault detection accuracy by simulating tire behavior under diverse conditions. Furthermore, [11] underscores how digital twins streamline tire health assessments by merging sensor data with ML models.

From sensor data acquisition and cloud/edge computing to AI model analysis and maintenance decision-making, digital twin integration provides real-time feedback. These schematic (see Fig. 2) underscores the layered approach required for effective predictive maintenance. Additionally, Fig. 3 offers a visual comparison of different methods. It shows that while traditional approaches are simpler and require less data, they lack the adaptability and precision achieved by ML-based and digital twin-enabled methods. Fig 3 highlights that digital twin-enabled predictive maintenance, although more complex and data-intensive, delivers the highest performance and real-time capability.

a)



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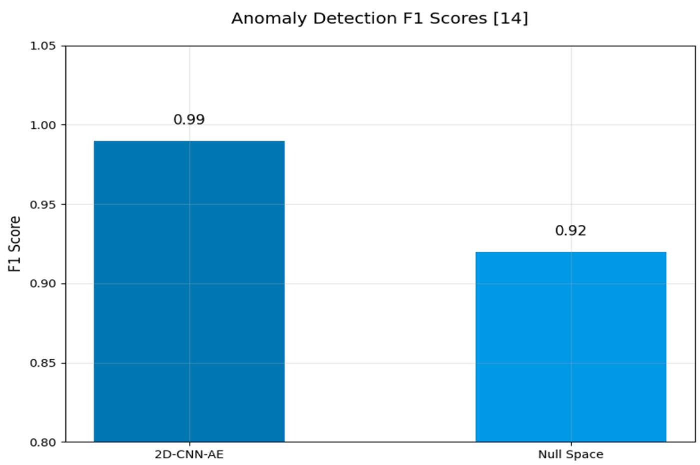

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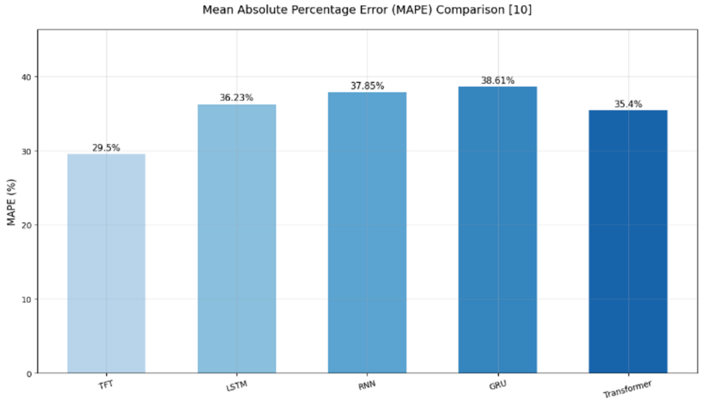

Fig. 1. Performance of AI Models for Predictive Maintenance

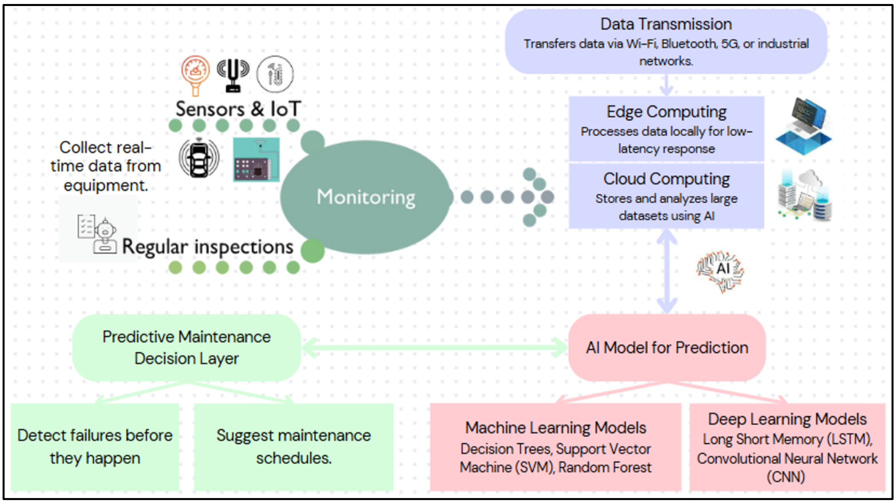

Fig. 2. Architecture of AI-Driven Predictive Maintenance

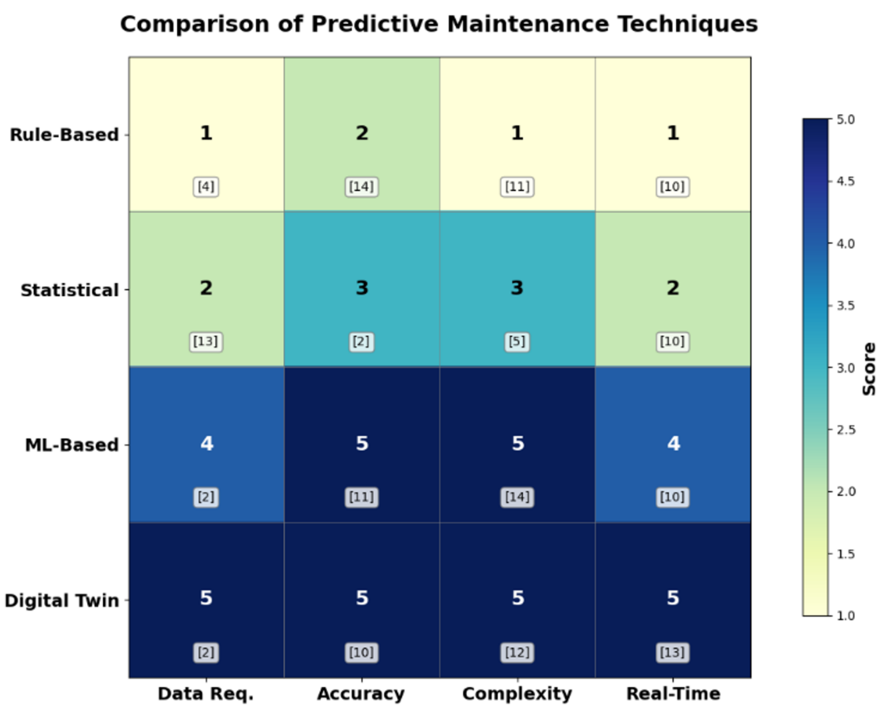

Fig. 3. Comparison of Predictive Maintenance Techniques

In the following section, we shift gears from this broad overview to a more focused discussion on our proposed methodology. This approach specifically applies the insights gained to develop a comprehensive, real-time predictive maintenance framework for intelligent tire systems. This case study serves as a prime example of how the advanced techniques discussed can be effectively tailored to meet the unique challenges of tire monitoring and maintenance in the automotive industry.

3 AI-enhanced framework for real-time tire health monitoring

In this section, we present an AI-driven framework that takes a leap forward in real-time tire health monitoring. By leveraging predictive maintenance strategies and digital twin technology, this approach aims to revolutionize the way we monitor and maintain intelligent tire systems.

3.1 A. System Architecture and Data Flow

Our framework is built on a multi-layered architecture that seamlessly integrates data acquisition, processing, and decision-making. Tire-mounted sensors (measuring pressure, temperature, and vibration) continuously collect data and transmit it via IoT networks to edge and cloud computing nodes. Here, the raw data is preprocessed—cleaned, normalized, and feature-extracted—to ensure high-quality inputs for the AI models.

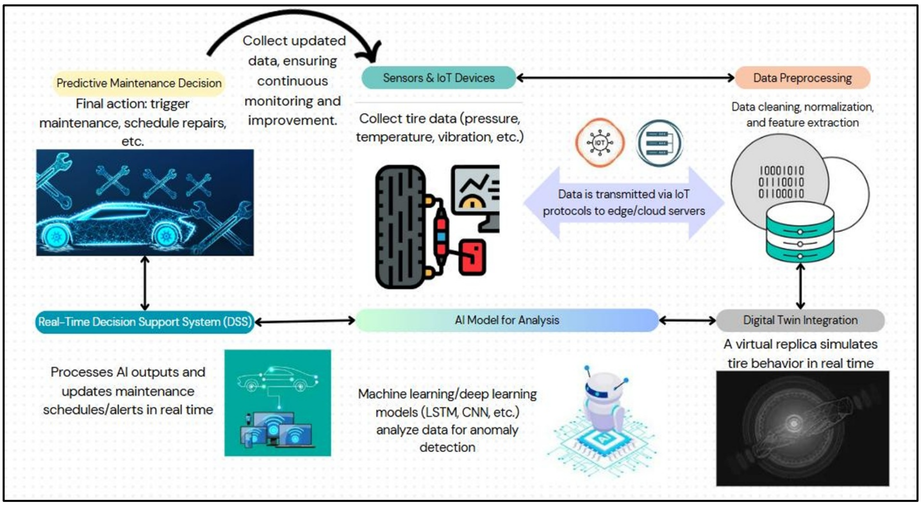

Fig. 4. System Architecture and Data Flow

The schematic presented in Fig. 4 includes an explicit real-time decision-making layer. The updated flow is as follows:

- Sensors & IoT Devices: Collect tire data in real time [3].
- Edge/Cloud Computing: Preprocess and store data for immediate analysis [7].
- AI Model: Applies machine learning algorithms (e.g., LSTM, CNN) to predict tire degradation [2].
- Real-Time Decision Support: Continuously updates maintenance schedules and triggers alerts, leveraging Digital Twin simulations to validate predictions [2].

Adding the decision-making layer emphasizes the framework's real-time capabilities and highlights its innovative contribution, ensuring proactive maintenance interven-tions rather than delayed, reactive responses.

3.2 Real-Time Decision Support and AI Model Integrat

A recall of the comparative analysis of various approaches—traditional, ML-based, and Digital Twin-enabled predictive maintenance. Key observations include (see Fig. 3):

- Traditional Techniques: Low adaptability and accuracy, as they rely on fixed schedules [8].
- ML-Based Methods: Higher accuracy (e.g., SVM, Random Forest) but require significant data [14].
- Digital Twin-Enabled Methods: Offer real-time, simulation-driven insights with the highest performance, albeit with increased complexity [12].

Considering the results observed in Fig. 3, it is evident that while traditional methods are simpler, the integration of Digital Twins with AI significantly enhances predictive accuracy and real-time responsiveness. These improvements are crucial for applications such as intelligent tire monitoring, where precision and timely decision-making are paramount.

3.3 Expected Outcomes, Performance Evaluation, and Future Directions

The proposed framework is anticipated to significantly enhance tire health monitoring by leveraging multisource sensor data, digital twin simulation, and advanced AI models, as evidenced by performance metrics extracted from previous studies. For instance, a reduction in Mean Square Deviation from 0.1823 to 0.1504 ([7]) and an F1 score improvement from 0.92 to 0.99 ([14]) serve as benchmarks indicating the potential for higher predictive accuracy. In addition, framework's integration of cloud-edge computing and reinforcement learning is expected to enable real-time, adaptive maintenance decisions, thereby reducing downtime and maintenance costs while extending tire lifespan.

Future research will focus on validating these improvements in real-world deployments, refining computational efficiency, and enhancing model interpretability to facilitate broader industrial adoption, ultimately contributing to safer, more efficient, and sustainable mobility solutions.

4 Proposed framework and expected outcomes

Traditional TPMS (Tire Pressure Monitoring Systems) typically rely on basic pressure sensors and static alerts, which can leave vehicles exposed to unexpected tire failures. In contrast, our AI-enhanced framework integrates a fusion of advanced sensors—capturing pressure, temperature, stress, and vibration via MEMS accelerometers and RF transceivers—to provide a comprehensive, real-time view of tire health. Sensor data is transmitted through IoT networks to edge and cloud computing nodes for robust preprocessing, ensuring high-quality inputs for subsequent analysis. A digital twin continuously simulates tire behavior under various operational conditions, enabling proactive fault prediction and maintenance planning [1].

The framework's hybrid AI approach combines deep learning models (CNN-RNN Hybrid and 2D-CNN-AE) for accurate anomaly detection with reinforcement learning for adaptive decision-making, thus forecasting wear trends well in advance and autonomously adjusting maintenance schedules [10,9]. With Edge AI integration, the system minimizes latency, enabling immediate maintenance actions—such as dynamic tire pressure adjustments, emergency alerts, or fine-tuning maintenance interventions based on real-time road conditions, driving behavior, and weather data. This innovative closed-loop system not only improves predictive accuracy but also delivers substantial benefits in terms of enhanced safety, reduced downtime, and cost-effective maintenance for the automotive industry and other tire-reliant sectors like aerospace (See Fig. 5).

4.1 Expected Outcomes & Added Value

1. Enhanced Accuracy and Reliability: by integrating multisource sensor data and digital twin models with advanced AI techniques, the framework substantially improves the precision of predictive maintenance. This leads to earlier detection of anomalies and fewer false positives, ultimately enhancing overall system reliability ([7,10,14]).

2. Real-Time Decision-Making for Auto-Maintenance: the inclusion of edge computing and reinforcement learning enables the system to continuously update maintenance schedules in real time. This dynamic, automated decision-making process minimizes downtime and reduces unnecessary maintenance interventions, ensuring proactive and efficient responses to emerging tire issues [9,16].

3. Sustainable and Cost-Effective Maintenance: optimized maintenance planning, driven by improved predictive analytics, contributes to significant re-ductions in maintenance costs and extends tire lifespan. This results in a more sustainable operational model for automotive and other tire-reliant industries ([10], [9]).

This framework is able to create a balance between cost-effectiveness and human well-being.

To highlight the added value of this framework, TABLE 1 presents a comparison of the proposed system with traditional maintenance techniques.

Table 1. Comparison of the proposed system with traditional maintenance techniques

Feature	Predictive maintenance method	Font size and style
	Traditional Predictive Maintenance	Proposed Real-Time AI-Driven Framework
Real-Time Processing	✕	☑
Digital Twin Integration	✕	☑
Adaptive AI Model	✕	☑
Automated Decision-Making	✕	☑
Reduced Maintenance Cost	⚠ Partial	☑ Optimized

But is this just for cars? Absolutely not. This framework is revolutionary for the automotive industry, yes, but it also holds immense value for aerospace, heavy machinery, logistics, and even motorsports. In these fields, tire integrity is paramount for safety, efficiency, and reducing operational costs. By blending physics-informed AI, real-time monitoring, and adaptive self-learning, this system sets a new standard for intelligent, autonomous, and predictive tire management. It makes vehicles and fleets not just safer, but also more efficient and cost-effective across various industries [10].

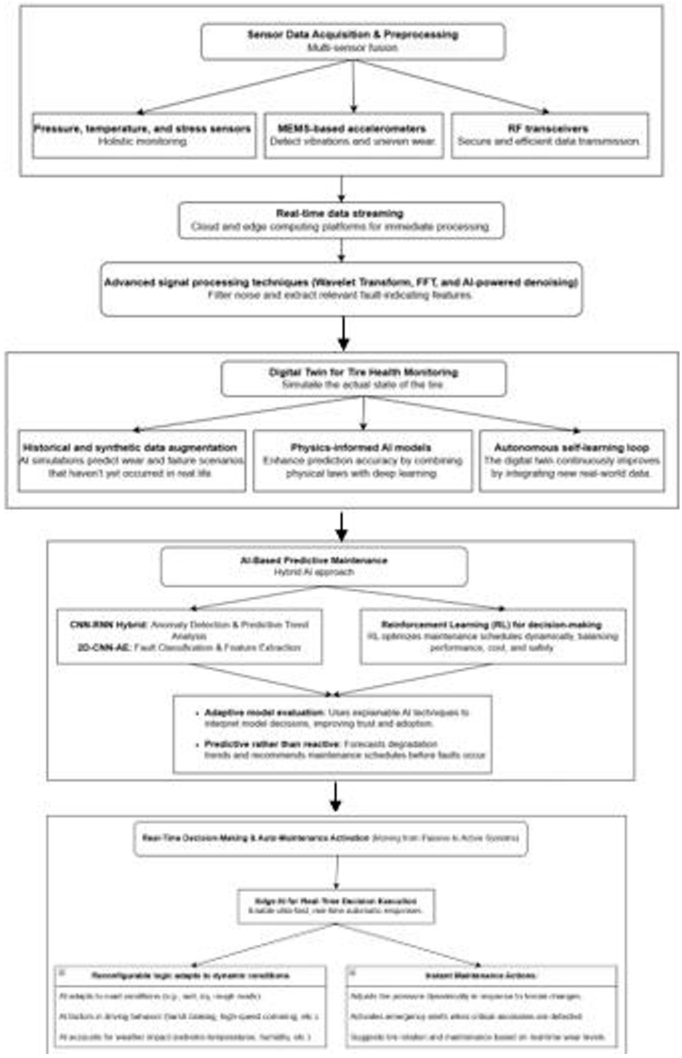

Fig. 5. System Architecture for Real-Time AI-Driven Predictive Maintenance

5 Conclusion and future directions

The research contributes to the field of AI-driven tire health monitoring by integrating predictive maintenance strategies with digital twin technology, leveraging real-time sensor data, cloud computing, and advanced AI models. Our work aligns with the principles of Industry 4.0 by promoting data-driven decision-making for proactive maintenance, thereby reducing unexpected failures and optimizing tire performance [1].

The proposed framework incorporates big data analytics and AI-based anomaly detection, ensuring robust predictive insights for tire health monitoring. This builds upon research in digital twins and smart manufacturing, which emphasize highly integrated and real-time simulation models for predictive maintenance [2]. The implementation of machine learning-enhanced tire monitoring systems further enhances real-time diagnostics and fault detection [10].

Moreover, the study reinforces the importance of reinforcement learning in adaptive maintenance scheduling, improving efficiency in predictive frameworks [9]. The integration of deep learning-based anomaly detection contributes to enhanced reliability in industrial maintenance [14].

Looking ahead, future research will focus on validating the framework in large-scale deployments, enhancing computational efficiency, and improving model interpretability to ensure broader industry adoption [8]. These advancements will contribute to the evolution of intelligent, AI-powered tire management systems, ensuring safer, more cost-efficient, and sustainable mobility solutions [15].

By continuously refining this framework, this study aims to support the next generation of intelligent transportation systems, fostering resilient, high-performance solutions for modern automotive applications.

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