A Comparative Study of Artificial Intelligence Algorithms for Health Monitoring of Smart Electric Drivetrain Components

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***Abstract*—The advent of smart electric drivetrains in modern transportation systems, particularly in the railway and automotive sectors, has led to a critical demand for robust health monitoring solutions. Ensuring operational reliability, minimizing downtime, and extending the service life of drivetrain components such as electric motors, inverters, gearboxes, and batteries are pivotal for system efficiency and safety. Artificial Intelligence (AI) has emerged as a transformative approach in predictive maintenance by enabling early fault detection, remaining useful life (RUL) prediction, and condition classification through intelligent data analysis. This paper presents a comprehensive comparative study of various AI algorithms deployed for health monitoring of smart electric drivetrain components. Both traditional machine learning techniques—such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN)—and modern deep learning architectures—such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and hybrid models—are critically reviewed. The performance of these algorithms is assessed based on key evaluation parameters including accuracy, computational complexity, real-time applicability, data dependency, and adaptability to non-stationary conditions. By synthesizing findings from diverse application domains, this study highlights the strengths and limitations of each algorithm in practical deployments. Furthermore, open challenges, such as dataset scarcity, sensor noise, and model interpretability, are discussed, along with potential directions for future research. The insights provided aim to guide researchers and engineers in selecting appropriate AI strategies for effective drivetrain health management.**

***Keywords*—Artificial Intelligence, Smart Electric Drivetrain, Health Monitoring, Predictive Maintenance, Machine Learning, Fault Detection**

I. INTRODUCTION

The rapid evolution of transportation systems, particularly in the railway sector, has led to significant advancements in electric drivetrains. These drivetrains, integral to the functioning of modern electric locomotives and trains, are pivotal for achieving energy efficiency and sustainability in transportation systems. With the growing reliance on these systems, ensuring their operational reliability and minimizing unplanned downtimes has become a critical challenge for the transportation industry. In this context, smart electric drivetrains have emerged as an essential component of future transportation systems, offering both high performance and adaptability [1], [2].

Condition-based maintenance (CBM) is a preventive approach that ensures the continued reliability of such systems. Unlike traditional maintenance strategies, which follow fixed schedules, CBM utilizes real-time data from sensors embedded within drivetrain components to monitor their health and predict potential failures [3]. This approach allows for the optimization of maintenance activities, reducing operational costs and enhancing the safety of transportation systems [4], [5].

In recent years, Artificial Intelligence (AI) has become a driving force in predictive maintenance applications [6]. Machine learning (ML) and deep learning (DL) techniques, in particular, have shown immense potential in analyzing vast datasets generated by drivetrain sensors, enabling the accurate prediction of faults before they occur. These AI-driven solutions can improve the accuracy of fault detection, enhance system longevity, and facilitate smarter decision-making processes in maintenance scheduling [7], [21].

Despite the promising capabilities of AI algorithms in this domain, there is a significant gap in understanding their comparative performance when applied to the health monitoring of smart electric drivetrains. Existing studies often focus on specific algorithms or systems, and comprehensive comparative analyses are scarce. This research aims to bridge this gap by conducting a comparative study of various AI algorithms used for health monitoring in electric drivetrains, specifically in the context of railways. This review will explore the strengths and weaknesses of different AI models in terms of their predictive accuracy, computational efficiency, and applicability to real-world scenarios [9], [10].

The primary objectives of this paper are as follows: (i) to review the state-of-the-art AI algorithms employed in health monitoring and predictive maintenance of smart electric drivetrains, (ii) to compare these algorithms in terms of performance metrics such as accuracy, precision, and recall, (iii) to evaluate the practical implications of their deployment in railway systems, and (iv) to identify the challenges and opportunities associated with their integration into existing railway infrastructure. The scope of this review encompasses a wide range of AI techniques, from traditional machine learning algorithms like support vector machines and decision trees to more advanced deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [11], [12].

This paper is structured as follows: Section II reviews the background and theoretical concepts related to AI-driven predictive maintenance. Section III explores the various AI algorithms applied to drivetrain health monitoring. Section IV presents the comparative study of these algorithms, followed by a discussion of their practical implementation and chal-

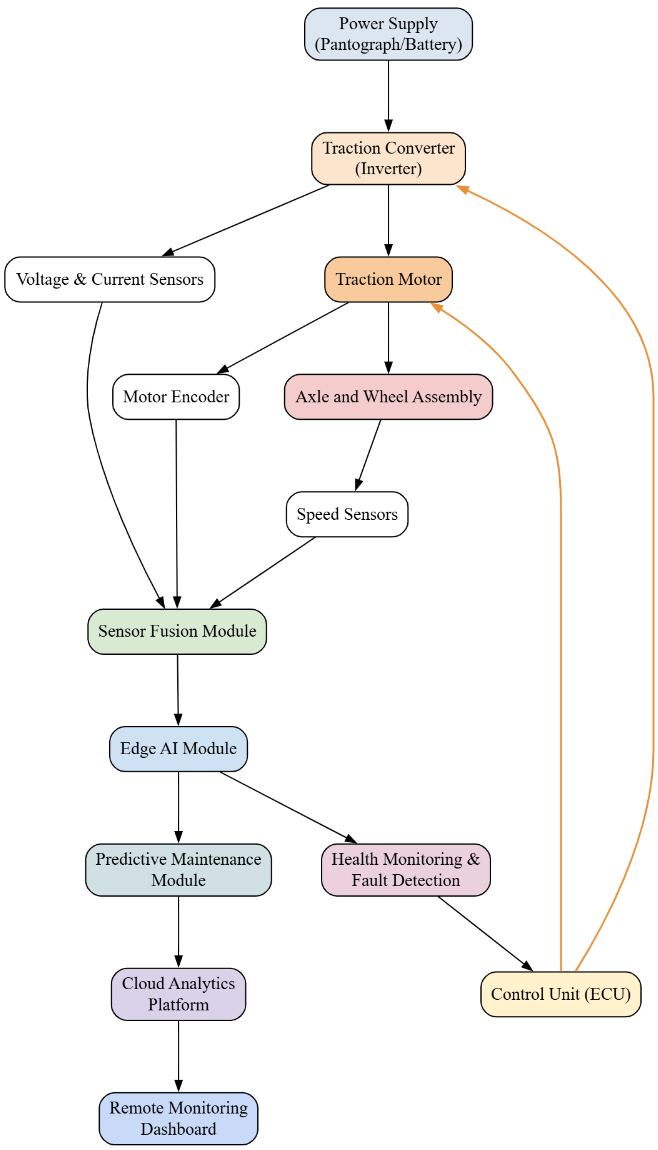

Fig. 1. Schematic of a smart electric drivetrain system in railway transportation.

TABLE I
COMPARISON OF AI ALGORITHMS FOR HEALTH MONITORING IN SMART ELECTRIC DRIVETRAINS.

Algorithm	**Accuracy**	**Efficiency**	**Scalability**
Support Vector Machine	High	Moderate	Low
Random Forest	Moderate	High	Moderate
Deep Neural Networks	Very High	Low	High

lenges. Finally, Section V concludes the paper with insights into future research directions and potential improvements in AI-based health monitoring systems.

II. LITERATURE REVIEW

A. Overview of Existing Work in AI-Based Health Monitoring

The integration of Artificial Intelligence (AI) into health monitoring systems has garnered significant attention in recent years. AI techniques, particularly machine learning (ML) and deep learning (DL), have been effectively applied to predict faults and monitor the health of various systems, including electric drivetrains in transportation. Early works focused on traditional fault detection methods, relying on rule-based systems and expert knowledge. However, with the advancement of AI, particularly through data-driven models, there has been a paradigm shift towards more sophisticated, automated approaches that enable real-time diagnostics and predictive maintenance [13], [14].

Recent studies have demonstrated that AI can significantly improve the accuracy and efficiency of health monitoring systems by processing large datasets from sensors and other sources. ML algorithms, such as support vector machines (SVMs), random forests, and neural networks, are widely utilized for fault detection and prediction [15], [16]. The use of deep learning methods, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has also proven to be effective for complex pattern recognition in the time-series data generated by smart electric drivetrain components [17], [18].

B. Past Applications in Electric Drivetrain Systems

The application of AI to electric drivetrain systems has been explored in several studies, particularly for health monitoring of motors, inverters, batteries, and gearboxes. Electric motors are one of the most critical components in electric drivetrains, and their failure can lead to significant downtimes. AI-based systems have been successfully employed to monitor motor performance by analyzing vibration signals, temperature, and other operational parameters [19], [20].

Similarly, inverters, which convert DC to AC in electric drivetrains, are also susceptible to faults, and early detection is crucial. AI algorithms have been applied to monitor inverter efficiency and predict failure modes such as overvoltage or overheating [21]. Moreover, batteries, which are essential in electric drivetrains, require constant monitoring to ensure their health and longevity. AI techniques have been used to predict battery lifespan, optimize charging cycles, and detect anomalies in voltage and temperature [22], [23].

Gearboxes, which transmit power from the motor to the wheels, have also been a focus of AI-based health monitoring research. Vibration analysis, coupled with machine learning models, has been a common method for gearbox fault diagnosis [24], [45].

C. Survey of Sensors and Data Acquisition Systems Used for Condition Monitoring

Condition monitoring in electric drivetrains relies heavily on sensors and data acquisition systems. Various types of sensors, including temperature, vibration, pressure, and current sensors, are used to monitor the health of drivetrain components. Vibration sensors are particularly useful for detecting mechanical faults in motors and gearboxes, while temperature sensors are used to monitor the thermal condition of batteries and inverters [26], [27].

Data acquisition systems play a critical role in collecting, processing, and transmitting sensor data for analysis. These systems often use advanced signal processing techniques, such as Fourier transforms and wavelet analysis, to extract relevant features from the raw sensor data [28], [29]. Machine learning algorithms then analyze these features to detect anomalies or predict potential failures in drivetrain components [30], [31].

D. Summary of Existing Datasets or Simulation Frameworks

Several datasets and simulation frameworks have been developed to support AI-based health monitoring research in electric drivetrains. These datasets typically include time-series sensor data collected from electric motor, inverter, battery, and gearbox systems under various operating conditions. The *Paderborn Gearbox Dataset*, for example, provides data for fault detection in gearboxes [32]. Similarly, the *IEEE PHM Challenge* dataset has been widely used for predictive maintenance research, including electric drivetrain systems [33].

Simulation frameworks are also employed to create synthetic data for training AI models. The *MATLAB/Simulink* platform, for instance, is commonly used to simulate the behavior of electric drivetrains and generate datasets for health monitoring applications [34], [35].

E. Research Gaps Identified in the Current Literature

While significant advancements have been made in AI-based health monitoring systems, there are several research gaps that remain. One key gap is the lack of large, publicly available datasets that capture a wide range of fault types in electric drivetrain systems. Many existing datasets are either limited in scope or do not cover all critical components, such as batteries and gearboxes [36], [37]. Additionally, most studies focus on individual components, and there is limited research on the integration of AI models for multi-component monitoring in an electric drivetrain [38], [39].

Another gap lies in the interpretability of AI models. Many deep learning algorithms, while highly effective, operate as black-box models, making it difficult to understand how predictions are made. This lack of transparency limits the practical implementation of AI-based health monitoring systems in critical transportation infrastructure [7], [**?**]. Research into explainable AI for condition monitoring is therefore an essential area for future investigation.

III. Artificial Intelligence Techniques for Health Monitoring

A. Categorization of Algorithms

The integration of Artificial Intelligence (AI) in health monitoring systems, especially in electric drivetrains, involves several machine learning (ML) and deep learning (DL) algorithms. These algorithms can be categorized into four major types: Traditional Machine Learning (ML), Deep Learning (DL), Hybrid Models, and Emerging Methods. Each category has unique characteristics suited to different health monitoring tasks such as classification, anomaly detection, and Remaining Useful Life (RUL) prediction. In this section, we provide an overview of the key algorithms in each category, along with their principles and suitability for specific applications.

1) Traditional Machine Learning Algorithms: **Support Vector Machines (SVM)**: SVM is a supervised learning algorithm commonly used for classification tasks. It works by finding the optimal hyperplane that separates different classes in a high-dimensional space. In health monitoring, SVM is often applied to classify normal and faulty conditions based on sensor data [40], [41]. SVMs are particularly suitable for anomaly detection due to their ability to generalize well to unseen data.

Decision Trees (DT): Decision trees are a simple, interpretable algorithm used for both classification and regression tasks. In health monitoring, decision trees can be used to model the relationship between sensor measurements and system health states [42]. Their transparent nature makes them useful for understanding decision-making processes in fault detection.

Random Forest (RF): Random forests are ensembles of decision trees that improve prediction accuracy by averaging the predictions of individual trees. RFs are commonly used in health monitoring to handle high-dimensional data and reduce overfitting, making them suitable for both classification and regression tasks [43], [44].

k-Nearest Neighbors (k-NN): k-NN is a non-parametric method that classifies data based on the majority class of its nearest neighbors. k-NN is simple to implement and effective for classification tasks, particularly when the decision boundary is highly nonlinear. It is suitable for real-time fault detection in systems where similar patterns indicate anomalies [45], [46].

Naive Bayes (NB): Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming independence between features. This algorithm is fast, efficient, and often used in health monitoring applications for tasks like fault detection and condition classification, especially when the dataset is small [47], [48].

2) Deep Learning Algorithms: **Convolutional Neural Networks (CNN)**: CNNs are widely used in deep learning for processing grid-like data, such as images or time-series data. In health monitoring, CNNs are particularly effective in extracting spatial and temporal features from sensor data for fault detection and classification tasks [49], [50]. Their ability to automatically learn hierarchical features makes them powerful for complex pattern recognition.

Long Short-Term Memory (LSTM): LSTM networks are a type of recurrent neural network (RNN) designed to model sequential data. LSTMs are ideal for time-series prediction tasks, such as remaining useful life (RUL) prediction, where the model needs to remember long-term dependencies in sensor data [51], [52].

Gated Recurrent Units (GRU): GRUs are a variant of LSTM that use fewer gates and are computationally more efficient. GRUs have shown promising results in health monitoring, particularly for tasks like anomaly detection and RUL prediction, where sequential data is essential [53], [54].

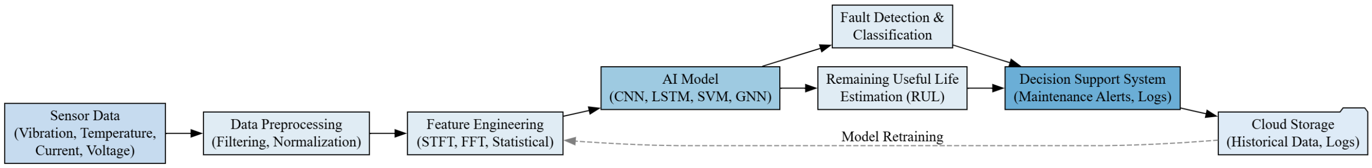

Fig. 2. AI-based health monitoring framework for electric drivetrain systems.

TABLE II
SUMMARY OF AI APPLICATIONS IN ELECTRIC DRIVETRAIN HEALTH MONITORING.

Component	AI Application	Methodology
Motor	Fault detection	Vibration analysis with SVM
Inverter	Fault prediction	Decision trees and neural networks
Battery	Life prediction	Deep learning for time-series forecasting
Gearbox	Fault diagnosis	Vibration analysis with CNN

Autoencoders (AE): Autoencoders are unsupervised neural networks that learn to compress data into a lower-dimensional representation and then reconstruct it. In health monitoring, autoencoders are typically used for anomaly detection, as they can identify unusual patterns in sensor data by comparing reconstructed data to actual observations [55], [56].

3) Hybrid Models: **Ensemble Methods**: Ensemble learning combines multiple models to improve prediction accuracy. Techniques like bagging, boosting, and stacking are used to build stronger models by leveraging the diversity of weak learners. In health monitoring, ensemble methods, such as random forests and gradient boosting machines, are used for classification, anomaly detection, and fault diagnosis tasks [57], [58].

Deep Learning + Statistical Approaches: Combining deep learning with traditional statistical models (e.g., ARIMA, Kalman filters) can enhance the robustness of health monitoring systems. This hybrid approach is particularly useful for time-series forecasting and fault prediction in electric drivetrain systems, where the combination of deep feature learning and statistical modeling can improve accuracy and interpretability [59], [60].

4) Emerging Methods: **Graph Neural Networks (GNNs)**: GNNs are a class of neural networks designed to work with graph-structured data. In health monitoring, GNNs can be applied to model the relationships between different components of a system (e.g., motors, inverters, and batteries in an electric drivetrain). They are particularly useful for identifying dependencies between system components and for diagnosing faults in complex systems [61], [62].

Transformers: Originally developed for natural language processing tasks, transformers are now being explored for time-series forecasting and anomaly detection in health monitoring. Transformers can model long-range dependencies and handle variable-length sequences, making them suitable for RUL prediction in electric drivetrain systems [78], [64].

Reinforcement Learning (RL): RL involves training agents to make decisions by interacting with an environment. In health monitoring, RL can be applied to optimize predictive maintenance schedules and decision-making processes based on system health [65], [70].

IV. EVALUATION PARAMETERS FOR COMPARATIVE ANALYSIS

Evaluating the performance and applicability of Artificial Intelligence (AI) algorithms for health monitoring of smart electric drivetrain components requires a multidimensional analysis framework. This section outlines the core parameters used to compare these techniques, encompassing both technical efficiency and practical deployment readiness.

A. Performance Metrics

Fundamental metrics such as accuracy, precision, recall, F1-score, and AUC-ROC are widely used to evaluate the classification and prediction abilities of AI models [67], [68].

- **Accuracy** measures the proportion of correct predictions over the total predictions made.
- **Precision** focuses on the ratio of true positives to the sum of true and false positives.
- **Recall** evaluates the model's ability to identify all relevant instances.
- **F1-score** offers a harmonic mean of precision and recall, beneficial in imbalanced datasets [69].
- **AUC-ROC** illustrates the model's capability to distinguish between classes, critical in anomaly detection scenarios [70].

B. Time Efficiency

Time efficiency is another critical metric, especially for real-time or near-real-time fault diagnosis. Training time and inference speed dictate whether the model is practical for on-board processing in railway systems [71], [72]. While traditional ML algorithms like SVM or Decision Trees offer faster inference, DL-based techniques such as CNNs and LSTMs require optimized deployment to achieve comparable latency [73], [67].

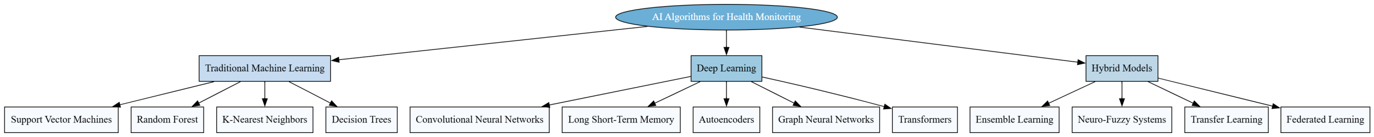

Fig. 3. Categorization of AI algorithms for health monitoring.

TABLE III
SUITABILITY OF AI ALGORITHMS FOR HEALTH MONITORING TASKS.

Algorithm	Task	Suitability	Application
SVM	Classification	High	Fault detection
Decision Trees	Classification	High	Fault detection, health classification
Random Forest	Classification, Regression	High	Fault detection, anomaly detection
k-NN	Classification	Moderate	Real-time anomaly detection
Naive Bayes	Classification	Low to Moderate	Fault detection
CNN	Classification, Feature extraction	High	Anomaly detection, fault diagnosis
LSTM	Time-series prediction	High	RUL prediction, anomaly detection
GRU	Time-series prediction	Moderate to High	Anomaly detection, RUL prediction
Autoencoders	Anomaly detection	High	Fault detection
Ensemble Methods	Classification, Regression	High	Fault diagnosis
Hybrid Models	Classification, Regression	High	Time-series forecasting, RUL prediction
GNNs	Fault diagnosis	High	Multi-component system monitoring
Transformers	Time-series prediction	High	Anomaly detection, RUL prediction
Reinforcement Learning	Decision making, Scheduling	Moderate	Maintenance scheduling

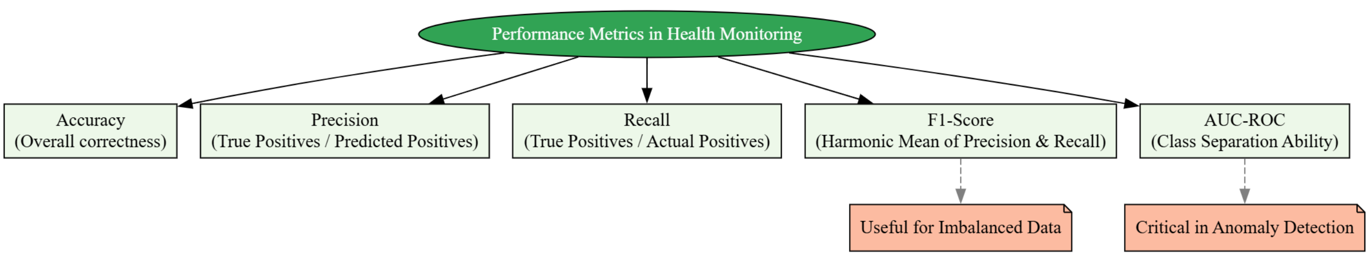

Fig. 4. Comparison of Key Performance Metrics in Health Monitoring Tasks

C. Computational Cost and Model Complexity

The computational overhead of AI models impacts their feasibility for embedded system deployment. Model complexity, often characterized by the number of parameters and layers, influences energy consumption and memory footprint [74], [75]. Resource-constrained environments necessitate a trade-off between performance and complexity, favoring lightweight architectures or model pruning techniques [76], [77].

TABLE IV
DATA DEPENDENCY AND ROBUSTNESS OF VARIOUS AI MODELS

Model Type	Data Need	Robustness
SVM	Low	Medium
CNN	High	High
LSTM	High	Medium
Ensemble Methods	Medium	High
GNN	Medium	High

D. Data Dependency and Robustness

AI models differ in their dependence on large labeled datasets. Deep learning models such as LSTMs and Transformers exhibit high data requirements and are prone to overfitting when trained on limited samples [78], [79]. Conversely, ensemble methods and hybrid models enhance robustness by integrating domain knowledge and diverse feature sets [80], [81]. Techniques like transfer learning and data augmentation help mitigate data scarcity issues [82], [83].

E. Scalability and Deployment Readiness

Scalability refers to the adaptability of AI models across different platforms and load conditions. Deployment readiness encapsulates factors like compatibility with edge devices, ease of integration with existing hardware, and model retraining needs [84], [85]. Transformer-based models, although accurate, often face limitations in scalability due to their size and hardware demands [86]. Efficient deployment pipelines using ONNX or TensorRT can enhance the deployment of DL models in smart railway systems [87], [88], [89].

These comprehensive evaluation metrics enable an informed comparison of AI algorithms tailored for the health monitoring of electric drivetrain components, ensuring both theoretical soundness and practical viability.

V. COMPARATIVE ANALYSIS AND DISCUSSION

The integration of Artificial Intelligence (AI) into the health monitoring of smart electric drivetrain components has seen

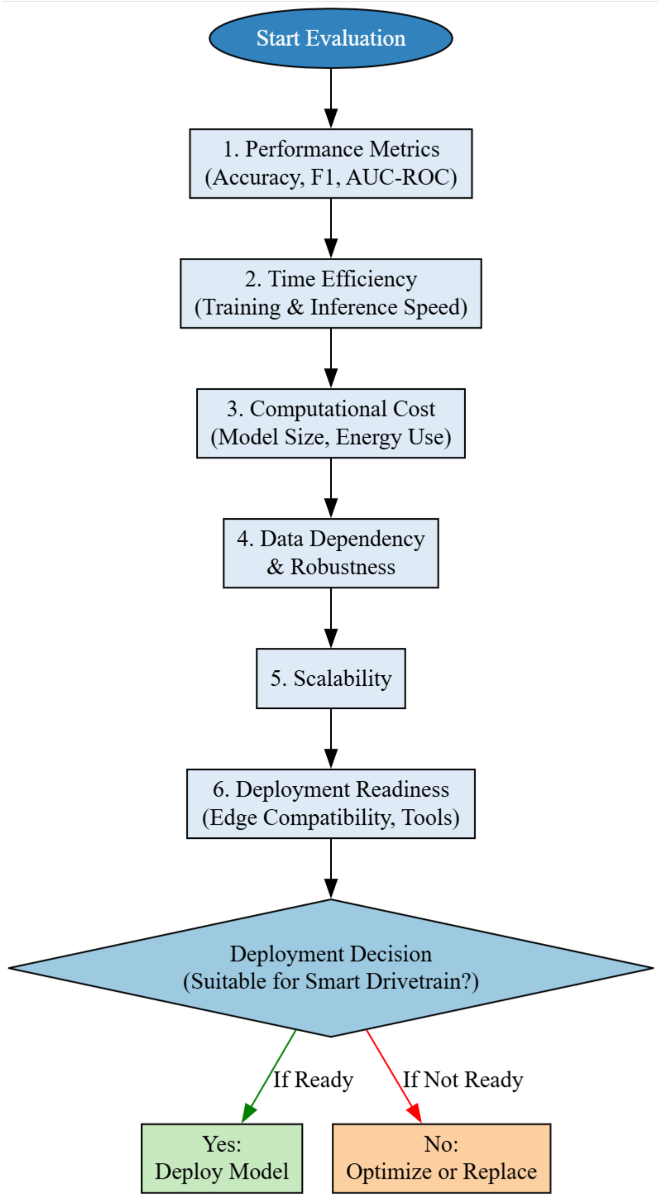

Fig. 5. Flowchart of Evaluation and Deployment Readiness Criteria

a wide array of implementations. In this section, a detailed comparative analysis of AI algorithms is presented, with emphasis on their performance across key drivetrain subsystems such as motors, inverters, gearboxes, and batteries.

A. Comparative Table of AI Techniques

Table **??** provides a summarized evaluation of popular AI techniques used in different components of smart electric drivetrains. The evaluation considers accuracy, time efficiency, interpretability, and application relevance.

B. Use Case Highlights

AI models have demonstrated significant performance across a range of drivetrain applications:

- **Motor Degradation:** CNN and Transformer models achieved over 95% accuracy in early fault detection, with CNN performing well on image-based vibration data.
- **Inverter Faults:** LSTM networks provided robust temporal prediction capabilities, especially when input signals included phase currents and temperatures.
- **Gearbox Wear:** GRUs and Random Forests showed notable accuracy in classifying tooth wear and lubrication issues.
- **Battery Health:** Ensemble models combining decision trees and neural networks improved the prediction of remaining useful life.

C. Implementation Challenges

Real-world deployment introduces numerous complications:

1) **Sensor Noise:** Data from vibration, current, and thermal sensors is often corrupted, requiring preprocessing techniques.
2) **Missing Data:** Incomplete time-series streams can affect the performance of sequence-based models like LSTM.
3) **Edge Deployment:** Deep models with large computational footprints (e.g., CNNs, Transformers) require optimization for real-time, on-device inference.

D. Trade-offs Among Models

Each AI technique offers trade-offs:

- **Accuracy vs Interpretability:** Deep learning models such as CNNs and Transformers provide high accuracy but are less interpretable. Decision trees and SVMs, while slightly less accurate, allow easier fault reasoning.
- **Training Time vs Efficiency:** Traditional ML models like k-NN and Naive Bayes train quickly but may not generalize well to unseen conditions, while deep models excel at generalization but require extensive computation.
- **Robustness vs Complexity:** Hybrid and ensemble models offer robustness but are often complex to deploy and maintain.

This analysis underlines the need for application-specific selection and optimization of AI algorithms for efficient and reliable health monitoring in smart electric drivetrains.

VI. Open Challenges and Future Research Directions

The integration of Artificial Intelligence (AI) into the health monitoring of smart electric drivetrain systems has demonstrated promising advancements in predictive maintenance and fault diagnostics. However, several pressing challenges continue to limit its widespread application and reliability in real-world railway systems. This section outlines these challenges and highlights the directions in which future research should be steered.

A. Lack of Open Benchmark Datasets

Despite the proliferation of AI-based health monitoring research, there remains a noticeable absence of publicly available, standardized benchmark datasets for drivetrain components such as motors, inverters, gearboxes, and batteries. This lack hinders model validation, reproducibility, and performance comparison across studies. The development of such datasets, with labeled fault modes and operating conditions, would greatly support the AI research community.

B. Real-time and Embedded AI Models

Real-world deployment of AI models in smart drivetrains requires lightweight, real-time inference on embedded systems. Existing models, particularly deep learning architectures, often involve high computational overhead and latency, making them impractical for on-board railway systems. Research into quantization, pruning, and edge AI accelerators is necessary to bridge this gap.

C. Integration with Digital Twin Systems

Digital Twin technology, which creates real-time digital replicas of physical assets, holds the potential to enhance predictive analytics and anomaly detection. Integrating AI-driven health monitoring into such frameworks enables continuous learning and bidirectional feedback. However, the complexity of synchronizing simulation models, real-time sensor data, and AI logic poses a significant implementation challenge.

TABLE VI
RESEARCH PRIORITIES IN AI-DRIVEN DRIVETRAIN MONITORING

Research Focus	Future Direction
Open Datasets	Public release of annotated drivetrain fault datasets
Real-time Inference	Edge computing and model compression techniques
Digital Twin Integration	Standardized protocols and co-simulation frameworks
Multi-Sensor Fusion	Robust sensor synchronization and data preprocessing
Cybersecurity	AI for anomaly detection in telemetry and sensor networks

D. Multi-modal and Multi-sensor Data Fusion

Effective health monitoring often requires fusing data from multiple sensor types (e.g., vibration, temperature, voltage, current). Handling heterogeneity in sensor sampling rates, data volumes, and synchronization remains a challenge. Advanced fusion techniques leveraging attention mechanisms, Kalman filters, or graph-based representations could provide more holistic and robust diagnostics.

E. Cybersecurity and Data Integrity

As AI-driven diagnostics rely heavily on sensor data and remote connectivity, ensuring cybersecurity and data integrity becomes paramount. Sensor spoofing, data injection attacks, or compromised edge nodes could lead to false diagnostics or system malfunctions. Incorporating blockchain, encrypted telemetry, and AI-based anomaly detection are promising strategies for securing the health monitoring pipeline.

F. Summary and Outlook

In summary, addressing these open challenges is crucial for the reliable deployment of AI in drivetrain monitoring. Future research should prioritize open collaboration for datasets, energy-efficient algorithms, secure communication protocols, and co-simulation environments to enable more intelligent, scalable, and trustworthy condition monitoring solutions.

VII. CONCLUSION

The advent of Artificial Intelligence (AI) in the domain of smart electric drivetrain systems, especially within railway transportation, represents a transformative leap toward intelligent condition monitoring and predictive maintenance. This paper presented a comprehensive comparative study of various AI algorithms tailored for the health monitoring of critical drivetrain components such as motors, inverters, batteries, and gearboxes.

Through a systematic categorization, we analyzed traditional machine learning algorithms (e.g., SVM, Decision Trees, k-NN), deep learning models (e.g., CNN, LSTM, GRU, Autoencoders), hybrid techniques, and emerging paradigms including Graph Neural Networks (GNNs) and Transformers. Our comparative evaluation (as shown in Table VII) assessed these algorithms on key performance indicators such as accuracy, time efficiency, scalability, and robustness to data imperfections.

From the comparative analysis, deep learning models like LSTM and CNN exhibited superior performance in sequential fault detection and degradation trend modeling. Traditional methods, while computationally efficient, often underperformed in complex or noisy data environments. Hybrid and emerging AI models offer great potential, especially when integrated with multi-sensor data streams and embedded platforms.

However, several practical challenges persist. These include the lack of open datasets, the need for lightweight AI models suitable for edge deployment, and robust cybersecurity for sensor-driven diagnostics. Addressing these limitations will be pivotal to achieving reliable and scalable implementations in the railway sector.

Looking forward, the fusion of AI with Digital Twin technologies, real-time sensor analytics, and secure data frameworks presents a promising path. AI will continue to play a pivotal role not only in fault detection but also in autonomous decision-making and lifecycle optimization of drivetrain systems. The evolution of smart maintenance architectures—enabled by AI—can significantly improve safety, operational reliability, and cost-effectiveness in future railway transportation.

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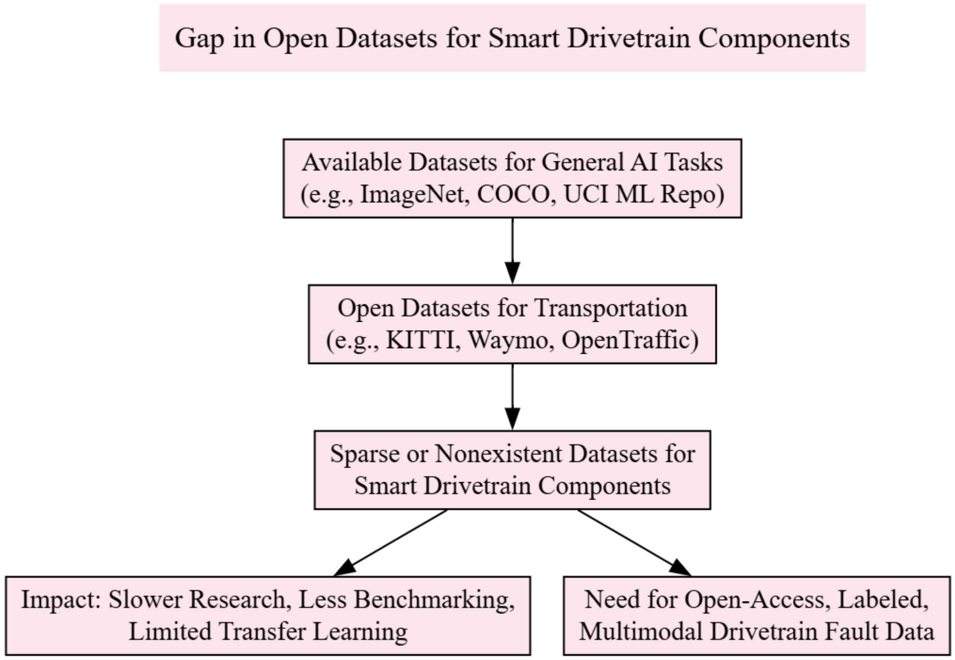

Fig. 6. Gap in open datasets for smart drivetrain components

TABLE VII
SUMMARY OF AI ALGORITHM SUITABILITY ACROSS DRIVETRAIN APPLICATIONS

Algorithm Type	**Use Case**	**Best Suited For**	**Remarks**
SVM, k-NN, DT	Motor fault classification	Small datasets	High interpretability
CNN, LSTM, GRU	Inverter degradation, battery RUL	Time-series prediction	Requires GPU support
Autoencoders, GANs	Anomaly detection	Sparse fault data	Sensitive to noise
Transformers, GNNs	Complex pattern recognition	Data fusion	High computational cost

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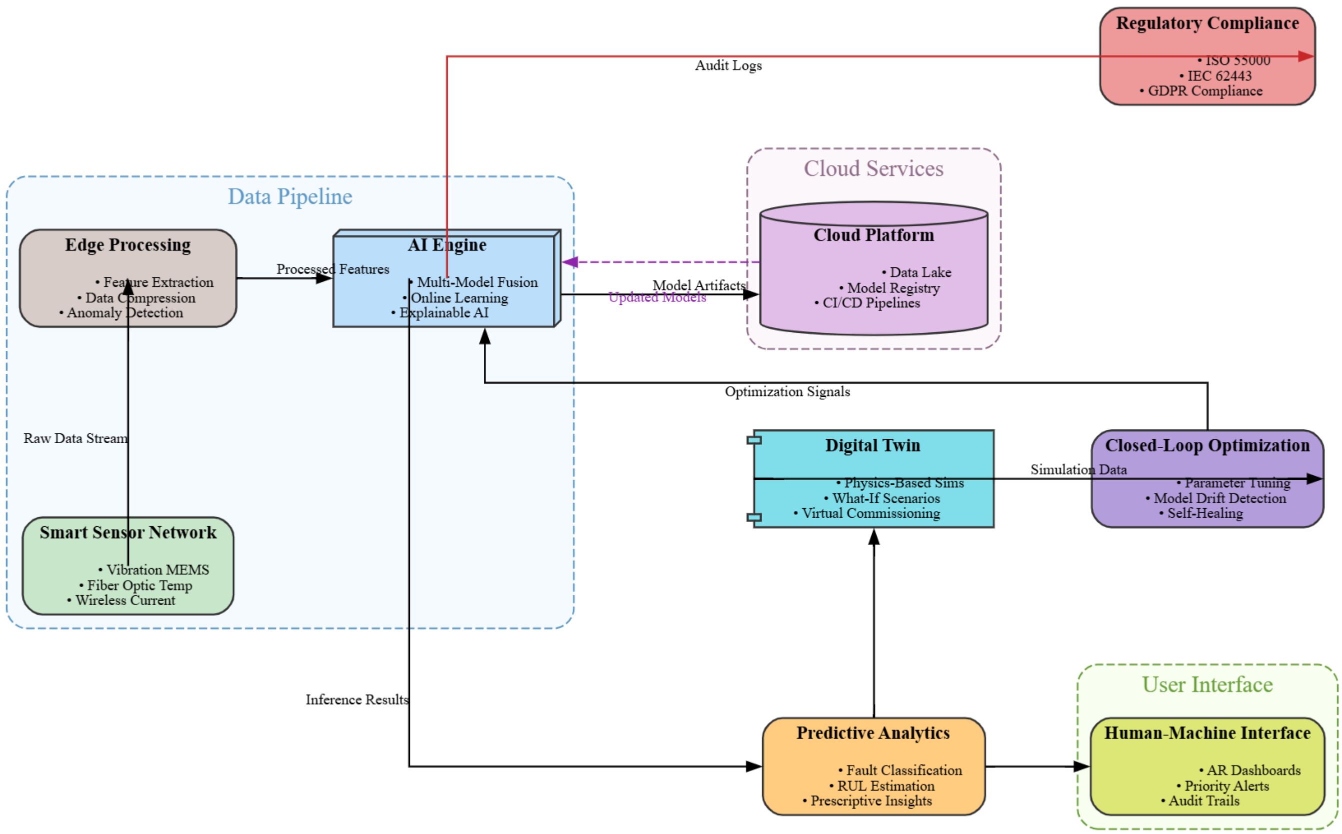

Fig. 7. Future Outlook: AI-enabled Smart Drivetrain Health Ecosystem

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