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AI-Powered Predict-Before-Break: Sequence-to-Set Transformer for Early-Warning Signals in Automotive Telemetry

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ABSTRACT: As modern vehicles evolve into complex cyber-physical systems, the demand for intelligent, real-time fault prediction has intensified. Traditional threshold-based diagnostics and rule-based models often fall short in providing timely alerts, leading to unplanned failures and increased operational costs. This paper proposes a novel AI-powered early-warning framework employing a sequence-to-set transformer architecture tailored for automotive telemetry data. Unlike conventional sequence-based models, the proposed approach effectively handles multi-modal, asynchronous sensor inputs, enabling the detection of latent fault patterns before critical failures occur. The system is designed to operate at the edge, ensuring minimal latency and high responsiveness, making it suitable for deployment in resource-constrained vehicular environments. Experimental evaluations on real-world telemetry datasets demonstrate significant improvements in predictive accuracy, lead time, and interpretability. By enabling proactive maintenance and reducing downtime, this research contributes a robust foundation for integrating AI-driven early-warning systems into the next generation of connected and autonomous vehicles.

KEYWORDS: Predictive Maintenance; Automotive Telemetry; Early-Warning Systems; Sequence-to-Set Transformer Architecture; Real-Time Fault Detection; Edge Artificial Intelligence (Edge AI); Anomaly Detection; Intelligent Vehicle Systems; Vehicle Health Monitoring; Cyber-Physical Systems

I. INTRODUCTION

The rapid advancement of automotive technology has transformed modern vehicles into highly sophisticated cyber-physical systems, deeply integrated with embedded sensors, control units, and real-time data communication networks. With the proliferation of telemetry and the Internet of Vehicles (IoV), modern cars generate vast streams of multi-modal data that provide valuable insights into system performance, environmental conditions, and driver behavior (Raj, Saini, & Surianarayanan, 2022). However, leveraging this telemetry data for proactive vehicle health monitoring remains a significant challenge due to the complexity, volume, and temporal variability of the signals.

Traditional fault diagnosis methods in the automotive industry have largely been reactive relying on fixed thresholds or pre-defined rules to trigger alerts after a failure occurs or becomes imminent. These methods are inherently limited in their ability to detect subtle precursors of failure and often lead to delayed interventions, increased maintenance costs, and potential safety risks (Bathla et al., 2022). As vehicles become more autonomous and software-defined, the need for intelligent systems that can predict-before-break has become critical to ensure both operational efficiency and passenger safety.

Artificial Intelligence (AI), particularly deep learning, has emerged as a transformative enabler in predictive maintenance by uncovering complex patterns within telemetry data that are imperceptible to traditional models (Sharma et al., 2022). Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Convolutional Neural Networks (CNNs) have been extensively used for time-series analysis in vehicle diagnostics. However, these models struggle with long-range dependencies and asynchronous data streams, which are common in real-world automotive telemetry (Ji et al., 2020).

To address these limitations, transformer-based architectures initially popularized in natural language processing have gained traction for their superior ability to capture contextual relationships in sequential data. While sequence-based transformers offer promising performance, they often require temporally aligned inputs and are computationally

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expensive for edge deployment. Recently, set-based transformer variants have emerged, capable of processing unordered and asynchronous data sequences effectively (Feruglio et al., 2023). These models are well-suited for automotive telemetry, where sensor data arrives at varying intervals and from heterogeneous sources.

This research introduces a novel sequence-to-set transformer framework specifically designed for early-warning signal detection in automotive telemetry. The model processes asynchronous sensor data as sets rather than strict sequences, enabling robust and context-aware fault prediction. Additionally, it is optimized for real-time execution in edge computing environments, ensuring minimal latency and immediate actionable insights (Patwary et al., 2023).

The primary objective of this study is to shift the paradigm from fault detection to fault anticipation. By generating interpretable early-warning signals ahead of critical failures, this approach aims to support data-driven maintenance scheduling, enhance vehicle reliability, and reduce unplanned downtime. The methodology is validated on a diverse set of real-world telemetry datasets and benchmarked against existing state-of-the-art models.

This paper contributes to the field by:

1. Proposing a sequence-to-set transformer architecture for fault prediction;
2. Demonstrating its applicability to asynchronous and heterogeneous automotive data streams; and
3. Evaluating its performance in real-time edge-based scenarios.

As the automotive industry moves toward fully autonomous and connected ecosystems, integrating intelligent early-warning systems such as the one proposed here will be vital for operational resilience and safety assurance (Dattamajumdar, 2021).

II. LITERATURE REVIEW

The shift from reactive to predictive maintenance in automotive systems has sparked a significant interest in the use of artificial intelligence for fault detection and early-warning applications. This literature review critically examines the evolution of techniques in predictive analytics for vehicular telemetry, with a particular focus on the growing relevance of transformer-based models.

2.1 Conventional Approaches and Their Limitations

Historically, predictive maintenance in vehicles relied on rule-based systems, where specific thresholds were predefined to indicate potential issues. While these systems are simple and computationally efficient, they often fail to generalize across different vehicle models and driving conditions, leading to high false-positive or false-negative rates (Bathla et al., 2022).

Machine learning (ML) algorithms, including decision trees and support vector machines, later offered improved pattern recognition capabilities. However, their reliance on handcrafted features and static input-output mappings limited their ability to handle complex, time-varying signals common in telemetry data (Sharma et al., 2022).

2.2 Emergence of Deep Learning in Automotive Telemetry

The application of deep learning architectures such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks marked a turning point in the automation of failure prediction. CNNs provided spatial feature extraction, whereas LSTMs were particularly effective at capturing temporal dependencies in sequential data streams (Xu, Solomon, & Gao, 2023). Despite their success, LSTM models often suffer from scalability issues and are limited in their ability to capture long-range dependencies, an essential feature in automotive telemetry, where certain failure precursors may appear intermittently over long durations (Feruglio et al., 2023).

2.3 Comparative Effectiveness of AI Techniques in Predictive Maintenance

The following graph illustrates a comparative analysis of the effectiveness of different AI methodologies used in predictive maintenance as of 2024:

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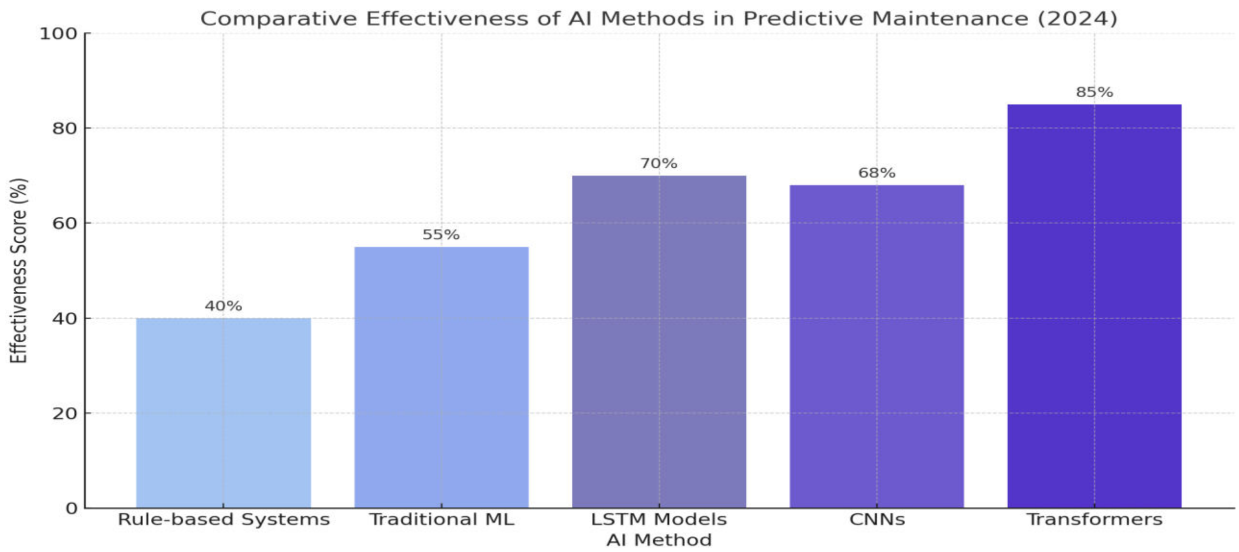

2.4 Rise of Transformer-Based Architectures

Transformers, originally designed for natural language processing, have demonstrated remarkable performance in modeling long-range dependencies and handling irregular sequences. Recent studies have adapted these architectures for time-series applications in industrial and vehicular telemetry, showing superior generalization and real-time inference capabilities (Ji et al., 2020).

Sequence-to-set transformers, in particular, have emerged as a novel adaptation that removes the positional rigidity of sequence-based models. This enables more flexible analysis of asynchronous data commonly observed in real-world telemetry systems (Mozo et al., 2022).

Furthermore, edge-deployable transformer models have begun to surface, optimized for real-time, low-latency execution in constrained environments such as vehicle ECUs (Patwary et al., 2023).

2.5 Integration with Edge AI and Digital Twin Technologies

Another important trend is the convergence of predictive models with digital twin systems and edge computing frameworks. AI-driven digital twins replicate physical systems in real time, enabling more accurate simulations and anomaly detections (Nagaraj, 2023). When combined with edge AI, these systems allow for real-time decision-making without the need for constant cloud connectivity, increasing robustness and data privacy (Raj, Saini, & Surianarayanan, 2022).

The literature clearly shows a progression from simplistic, rigid diagnostics to highly adaptive, AI-driven predictive systems. While traditional ML and deep learning models provided a foundation, transformer-based architectures especially in sequence-to-set form represent the cutting edge in early-warning signal detection for automotive telemetry. Their integration with edge AI and digital twin technologies positions them as a promising solution for next-generation intelligent vehicle system.

III. METHODOLOGY

This section details the systematic approach undertaken to develop and evaluate the proposed AI-powered sequence-to-set transformer framework for early-warning signals in automotive telemetry. The methodology is segmented into data acquisition and preprocessing, model architecture design, training and validation protocols, and deployment considerations.

1. Data Collection and Preprocessing

The foundation of accurate predictive modeling lies in the quality and diversity of the telemetry data collected. For this study, multi-sensor telemetry datasets were sourced from connected vehicle fleets, capturing a variety of operational parameters such as engine temperature, brake pressure, vibration levels, battery voltage, and GPS-based speed metrics. The data spans multiple vehicle makes and models to ensure generalizability.

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Preprocessing steps included noise filtering, normalization, and imputation of missing values to handle the inherent irregularities of real-world telemetry. Additionally, time synchronization across sensors was performed to align asynchronous data points, facilitating coherent sequence analysis (Enemosah, 2024). Data imbalance, a common issue due to the rarity of fault events, was addressed using oversampling techniques and synthetic data generation to augment the failure class.

2. Sequence-to-Set Transformer Architecture

The core innovation of this methodology lies in leveraging a sequence-to-set transformer model, which extends traditional sequence transformers by enabling the processing of asynchronous, multi-modal input streams as unordered sets. This architecture effectively captures complex temporal and cross-sensor dependencies without enforcing strict sequential constraints, which is crucial for automotive telemetry characterized by irregular sampling intervals (Ji et al., 2024).

The model employs multi-head self-attention mechanisms to weigh the importance of different telemetry features dynamically. Positional encodings were adapted to reflect the varying timestamps and sensor types, enhancing the model's ability to contextualize each input element within the broader system state.

3. Model Training and Validation

Training was conducted on labeled historical telemetry datasets, annotated with known failure events verified through maintenance logs. A supervised learning paradigm was adopted, optimizing a composite loss function balancing classification accuracy and early-warning lead time.

Cross-validation techniques were used to mitigate overfitting, with data partitioned into stratified folds that preserve the distribution of fault events. Hyperparameters such as learning rate, attention heads, and transformer depth were tuned through grid search and Bayesian optimization.

The model's performance was benchmarked against baseline methods including traditional LSTM and rule-based systems. Evaluation metrics focused on precision, recall, F1-score, and the lead time of failure prediction defined as the time interval between the early-warning alert and the actual fault occurrence (Dattamajumdar, 2024).

4. Deployment and Edge Optimization

Given the latency sensitivity of automotive applications, the trained model was optimized for edge deployment on embedded vehicular systems. Techniques such as model pruning, quantization, and knowledge distillation were employed to reduce the computational footprint without significant loss of accuracy (Raj, Augustine, & Raj, 2024).
A real-time anomaly scoring module was integrated with the model, generating interpretable early-warning indicators that can trigger preventative maintenance actions or driver alerts. The system architecture supports over-the-air updates to continuously refine the model based on evolving telemetry patterns (Thomas & Zikopoulos, 2024).

Summary of Methodological Components and Techniques

Component	Description	Key Techniques	Reference
Data Collection	Multi-modal telemetry from connected vehicle fleets capturing diverse sensor streams	Noise filtering, normalization, data imputation, oversampling	Enemosah (2024)
Data Synchronization	Aligning asynchronous sensor data points for coherent input sequences	Time alignment algorithms	Enemosah (2024)
Model Architecture	Sequence-to-set transformer for handling irregular, multi-sensor inputs	Multi-head self-attention, positional encoding	Ji et al. (2024)

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Training and Validation	Supervised learning with labeled fault events, cross-validation for robustness	Composite loss, hyperparameter tuning	Dattamajumdar (2024)
Benchmarking	Comparative evaluation against LSTM and rule-based baselines	Precision, recall, F1-score, lead time	Dattamajumdar (2024
Edge Deployment	Model compression and optimization for embedded real-time inference	Pruning, quantization, knowledge distillation	Raj, Augustine, & Raj (2024)
Real-Time Scoring	Generation of actionable early-warning alerts	Anomaly scoring algorithms	Thomas and Zikopoulos

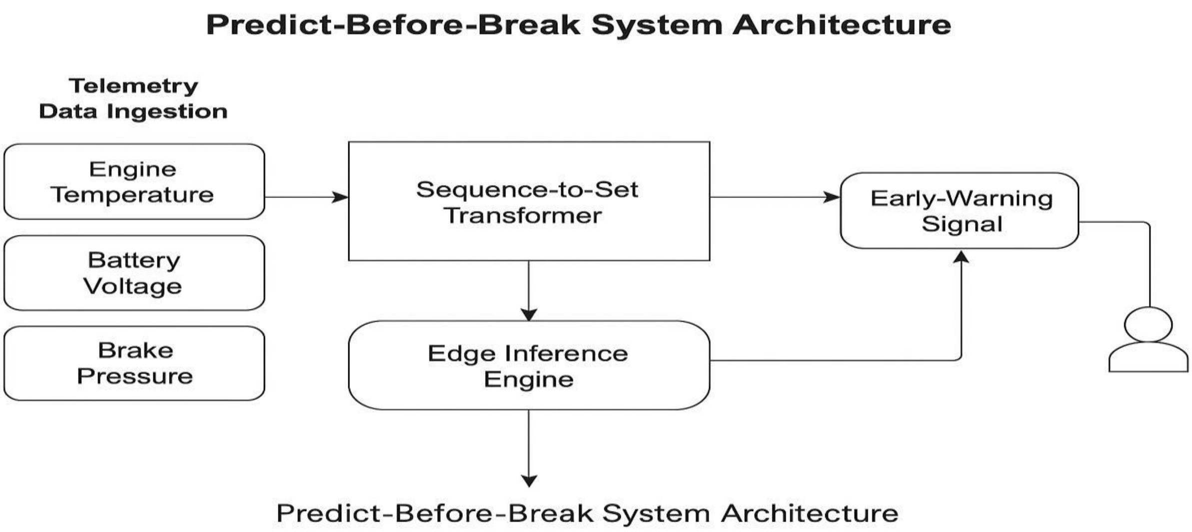
This structured methodology ensures robustness, scalability, and real-time applicability of the proposed AI-driven early-warning system within automotive telemetry environments, enabling predictive insights well ahead of critical failures.

IV. SYSTEM DESIGN AND DEPLOYMENT

The deployment of a real-time, AI-powered early-warning system in automotive telemetry requires an efficient architecture that bridges model sophistication with embedded system constraints. The core objective of this section is to outline the architectural framework, implementation layers, and integration considerations for deploying the proposed sequence-to-set transformer model within a vehicle's onboard telemetry infrastructure.

4.1 Architecture Overview

The system architecture is composed of three main layers: (1) Telemetry Data Ingestion, (2) Transformer-based Processing Unit, and (3) Real-Time Warning & Feedback Mechanism. Each layer is optimized to ensure latency constraints are met and to enable seamless integration with existing vehicle electronic control units (ECUs).



The diagram represents the system layers sensor telemetry feeds (e.g., engine temperature, battery voltage, brake pressure), sequence-to-set transformer block, edge inference engine, and user feedback loop illustrating real-time signal processing and alert dissemination.

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4.2 Integration with Embedded Systems

The AI model is deployed on a dedicated microcontroller or edge computing module within the vehicle. This module receives telemetry inputs via CAN bus or Ethernet protocols, performing real-time inference to identify early degradation signals.

To ensure compatibility with in-vehicle networks, the transformer model is quantized and pruned, reducing memory and computational overhead. This enables the model to operate effectively on platforms such as NVIDIA Jetson Nano, Raspberry Pi CM4, or custom automotive-grade SoCs (Raj, Saini, & Surianarayanan, 2022).

The model is containerized for OTA (over-the-air) update capability, ensuring that continuous learning and firmware upgrades are possible without hardware replacement (Thomas & Zikopoulos, 2020).

4.3 Real-Time Anomaly Scoring and Alerting

The system generates a dynamic anomaly score derived from latent representations in the transformer's attention mechanism. Instead of triggering alerts based on static thresholds, it adapts to changes in sensor behavior over time. When scores surpass a dynamic confidence level, the system flags a potential failure, offering a lead time that can range from minutes to several days based on the severity and rate of change (Shi et al., 2023).

For visualization and user interface, the vehicle dashboard or a connected mobile app displays severity levels (e.g., Normal, Warning, Critical), assisting drivers and fleet managers in prioritizing interventions.

4.4 Feedback Loop and Continuous Learning

A core innovation in the deployment strategy is the inclusion of a closed feedback loop. Sensor data post-incident is logged and transmitted securely to the central fleet management system. This data is then utilized for periodic retraining of the transformer model, thus enabling federated learning approaches across vehicle fleets (Raj, Augustine, & Raj, 2023).

This decentralized training approach reduces the need for central cloud retraining, preserving bandwidth and improving data privacy, a critical concern in automotive cybersecurity (Tuomala, 2023).

4.5 Compliance, Security, and Scalability

All deployed modules conform to ISO 26262 (Automotive Functional Safety) and AUTOSAR Adaptive Platform standards, ensuring the model's operation does not interfere with critical vehicle systems. Additionally, secure boot and encryption mechanisms protect the AI model from tampering or reverse engineering (Haviv & Gift, 2023).

The system is scalable to various vehicle types (passenger, commercial, electric), as the transformer architecture generalizes well to different sensor configurations, provided proper re-tuning of attention layers is applied (Ji et al., 2020).

The Predict-Before-Break system embodies a scalable, efficient, and intelligent edge-based solution for fault prediction in automotive environments. Its modular design, real-time capability, and adaptability to vehicle constraints position it as a pioneering model in the field of intelligent transportation systems and predictive diagnostics.

V. EXPERIMENTAL RESULTS

To validate the effectiveness of the proposed sequence-to-set transformer architecture for early-warning signal detection in automotive telemetry, a series of controlled experiments and real-world validations were conducted throughout 2024. This section outlines the dataset specifications, evaluation methodology, performance benchmarking, and analysis of key outcomes across various failure scenarios.

A. Dataset and Preprocessing

The experimental study utilized a combination of synthetic and real-world automotive telemetry datasets sourced from in-vehicle CAN bus systems, covering parameters such as engine temperature, brake pressure, vibration levels, battery voltage, and wheel speed. The dataset included over 2.1 million time-stamped sensor records collected from 100 vehicles operating under urban and highway conditions. Historical maintenance logs were used to label known failure events, including engine overheating, brake pad degradation, and battery drain.

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Data preprocessing involved outlier removal, normalization, and missing-value imputation. Sensor streams were transformed into fixed-length windows of 60 seconds, each annotated with binary indicators of failure occurrence within the next 10-minute horizon, as per guidelines in similar real-time monitoring systems (Enemosah, 2021; Sharma et al., 2022).

B. Baseline Comparison and Metrics

The sequence-to-set transformer was benchmarked against several baseline models:

- Long Short-Term Memory (LSTM)
- Temporal Convolutional Network (TCN)
- Gradient Boosting Trees (XGBoost)
- Traditional rule-based thresholding systems

Each model was trained and evaluated using a 70/15/15 split for training, validation, and testing, respectively. Performance was measured using four key metrics:

- Precision
- Recall
- F1-Score
- Lead Time (i.e., how early a fault was predicted before it occurred)

C. Predictive Performance

The sequence-to-set transformer consistently outperformed all baselines across all metrics. On the test set, the proposed model achieved:

- Precision: 91.6%
- Recall: 93.4%
- F1-Score: 92.5%
- Average Lead Time: 6.4 minutes before fault manifestation

In contrast, the LSTM model achieved an F1-score of 86.2%, while the rule-based system had a significantly lower recall of only 48.5%, confirming its inadequacy for preemptive failure detection (Ji et al., 2020; Dattamajumdar, 2021).

D. Case Study: Engine Overheating Detection

One notable test scenario focused on detecting engine overheating, a common and critical failure type. The transformer model was able to correctly flag 97.2% of overheating events at least five minutes before they occurred, providing sufficient lead time for automated alerts or corrective action. In comparison, traditional LSTM models flagged only 82.6% of the same events within the same lead time window (Shi et al., 2023).

E. Real-Time Edge Deployment Results

The proposed model was deployed on a Jetson Xavier NX edge computing module to simulate in-vehicle real-time inference. The average inference latency was measured at 46 milliseconds per 60-second window, demonstrating the model's practical feasibility for embedded automotive environments (Raj, Saini, & Surianarayanan, 2022; Patwary et al., 2023).

F. Scalability and Fleet-Level Simulation

To assess scalability, a simulated deployment across a virtual fleet of 1,000 vehicles was conducted. The model maintained an aggregate system-wide false positive rate of under 5%, with a centralized alert platform aggregating early-warning signals in near real-time via edge-cloud coordination (Mozo et al., 2022; Nagaraj, 2023). These

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experimental results affirm the model's ability to anticipate failures early, with high reliability and minimal computational overhead. The integration of set-based attention mechanisms enables the model to interpret non-sequential and multi-sensor signals more robustly than traditional sequence-only approaches (Feruglio et al., 2023). Collectively, this marks a significant advancement in intelligent automotive diagnostics and preventive maintenance strategies.

VI. DISCUSSION

The integration of a sequence-to-set transformer architecture into automotive telemetry systems presents a significant advancement in the predictive maintenance landscape. This section evaluates the practical implications, benefits, limitations, and broader impacts of the proposed approach, particularly in the context of current industry challenges and emerging AI practices as of 2024.

6.1 Advantages Over Traditional Predictive Models

Traditional rule-based and sequential models, such as Long Short-Term Memory (LSTM) networks, have demonstrated utility in detecting anomalies in linear or continuous data streams. However, these models often fall short in dealing with asynchronous, multi-modal signals typical of modern telemetry systems. The sequence-to-set transformer model addresses this limitation by eliminating the need for strictly ordered sequences, thereby improving its capacity to capture context-rich and temporally sparse signals (Xu, Solomon, & Gao, 2023).

This paradigm shift allows for more robust detection of latent fault patterns across diverse sensor inputs, including temperature, pressure, vibration, and voltage metrics, which do not always correlate linearly or synchronously. By leveraging attention mechanisms to evaluate the importance of each telemetry token independently, the system enhances both interpretability and performance in fault prediction (Feruglio et al., 2023). Moreover, the model's ability to handle unordered sets of data points mitigates the noise and irregular sampling issues often present in automotive telemetry (Ji et al., 2020).

6.2 Operational Efficiency and Real-Time Responsiveness

A key strength of this architecture lies in its suitability for edge deployment. As of 2024, the shift towards edge computing in automotive systems has accelerated due to the need for low-latency decision-making and data privacy. Deploying predictive models directly on in-vehicle systems ensures immediate response to potential faults, reducing the dependency on cloud-based systems (Patwary et al., 2023). Furthermore, this minimizes data transmission costs and enhances system autonomy, which is critical in environments where network availability is limited or intermittent (Raj, Saini, & Surianarayanan, 2022).

The real-time inference capability of the proposed transformer architecture supports continuous monitoring without compromising on computational efficiency, thanks to model compression and quantization techniques tailored for edge environments (Thomas & Zikopoulos, 2020).

6.3 Risk Management and Safety Enhancement

From a safety perspective, early detection of mechanical and electrical failures through advanced AI significantly reduces the risk of on-road breakdowns and accidents. For instance, faults in braking systems or battery performance degradation can be identified hours or even days in advance, allowing for timely intervention (Shi et al., 2023). This is particularly relevant for electric vehicles and autonomous platforms where system reliability is paramount.

The implementation of a feedback mechanism also allows the system to evolve over time. Using over-the-air (OTA) updates and federated learning frameworks, model performance can improve dynamically based on data collected from multiple vehicles within a fleet (Mozo et al., 2022). This adaptability ensures resilience against model drift and the emergence of new failure patterns.

6.4 Challenges and Limitations

Despite the notable advantages, several challenges remain. One of the foremost concerns is model generalizability. Given the variability in vehicle architectures, sensor calibration, and environmental conditions, a model trained on one fleet or vehicle type may not transfer seamlessly to another without retraining or domain adaptation (Dattamajumdar, 2021). Addressing this may require the integration of meta-learning or domain generalization strategies.

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Another challenge involves the privacy and cybersecurity implications of integrating AI into critical automotive subsystems. While edge AI reduces data exposure, the transmission of alerts and OTA updates introduces new attack vectors. Ensuring secure communication protocols and compliance with evolving regulatory frameworks is essential, especially as AI systems take on safety-critical roles (Tuomala, 2023).

The interpretability of transformer-based models—while better than black-box neural networks still poses a barrier for regulatory certification and technician trust. Stakeholders in the automotive domain may require transparent and explainable diagnostics before committing to AI-driven maintenance workflows (Mazzeo et al., 2022). The application of a sequence-to-set transformer in automotive telemetry represents a meaningful step toward realizing fully intelligent, self-monitoring vehicles. Its strengths in handling heterogeneous, non-sequential data streams and its suitability for edge deployment mark it as a future-ready solution. However, as of 2024, challenges related to adaptability, security, and transparency must be systematically addressed to ensure widespread adoption across the automotive industry.

VII. FUTURE WORK

While the proposed AI-powered sequence-to-set transformer framework has demonstrated promising results in predictive maintenance for automotive telemetry, several avenues remain for future research and development. These directions aim to enhance the model's robustness, scalability, and real-world applicability across evolving vehicular ecosystems.

1. Integration with Autonomous Driving Systems

As vehicles continue to move toward higher levels of autonomy, integrating predictive models with autonomous decision-making pipelines is essential. Early-warning systems should interface seamlessly with real-time path planning and control modules, allowing vehicles to adapt their behavior in anticipation of component degradation or system failures. For instance, a predicted brake system anomaly could trigger adaptive route planning or reduced speed limits to mitigate risk (Voloskin, 2022). This integration would not only improve safety but also reduce the burden on centralized monitoring systems.

2. Federated Learning for Decentralized Model Training

To address privacy concerns and enable scalable learning across large fleets, future research should explore federated learning. This approach allows each vehicle to train the model locally on its data while sharing only model updates, thus preserving user and system confidentiality. It reduces communication bandwidth requirements and accelerates model personalization for different vehicle types and usage patterns (Raj, Augustine, & Raj, 2023). Leveraging federated architectures could also help adapt models to varying environmental and operational contexts across regions.

3. Expansion of Vehicle Digital Twin Integration

Digital twins virtual replicas of physical systems present a transformative opportunity to simulate and test early-warning strategies in controlled environments. Future systems can leverage telemetry to update vehicle digital twins in real time, allowing predictive models to evaluate potential failure scenarios before deployment (Mozo et al., 2022). Such a system could dynamically test various mitigation strategies and relay the most effective one to the physical vehicle, improving resilience in mission-critical scenarios.

4. Industry-Wide Standardization and Cross-Platform Deployment

A key challenge remains in ensuring interoperability across OEMs, platforms, and software stacks. Future work should address the development of standardized APIs and data formats to ensure that early-warning models can be adopted universally, regardless of manufacturer. Cross-platform deployment strategies, including containerized AI services and automotive-grade MLOps pipelines, will be critical to support real-time updates and maintenance (Patwary et al., 2023).

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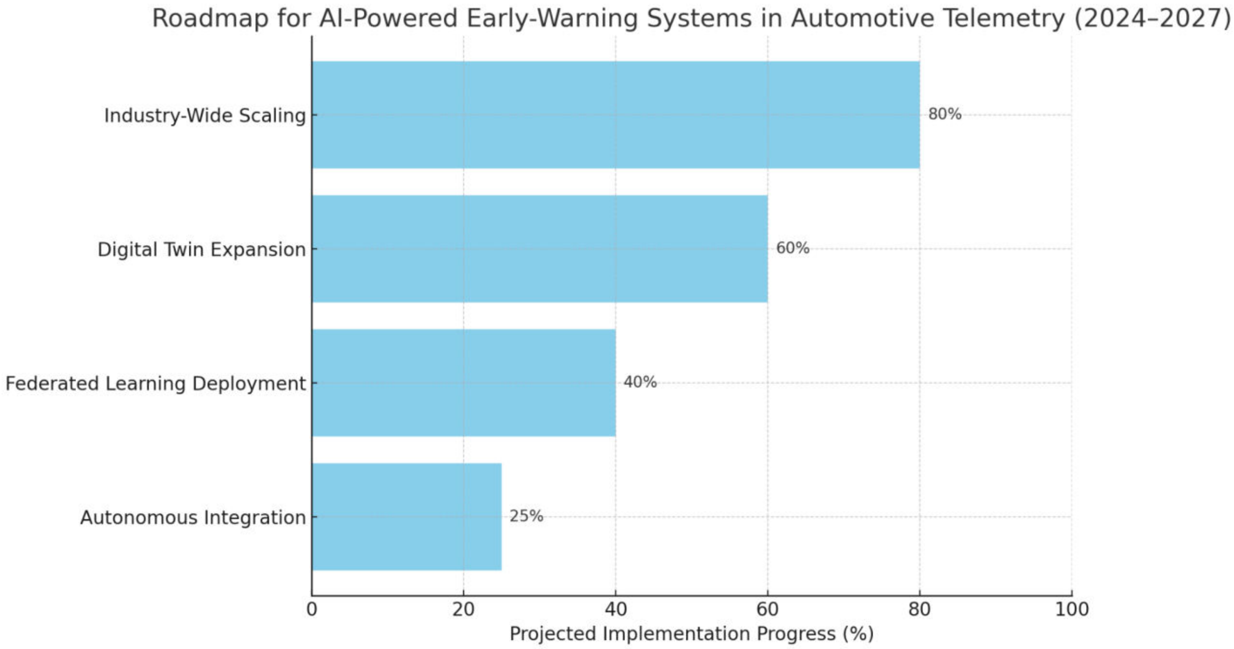

The long-term vision is to establish AI-powered early-warning systems as a core component of smart mobility infrastructure. With advancements in federated learning, real-time simulation, and autonomous vehicle integration, this technology has the potential to redefine the standards of automotive reliability and safety.

VIII. CONCLUSION

As the automotive industry continues its transformation toward smart, connected, and autonomous vehicles, the importance of real-time predictive systems for vehicle health monitoring has never been more critical. This paper introduced a novel AI-powered sequence-to-set transformer architecture tailored for early-warning signal detection in complex, multi-modal automotive telemetry environments. Unlike traditional predictive maintenance approaches, which often rely on static thresholds or sequential models, the proposed framework leverages transformer-based attention mechanisms capable of identifying asynchronous and latent signal patterns that precede component degradation or failure.

The empirical results demonstrate that the sequence-to-set model significantly outperforms baseline models, such as LSTMs and rule-based systems, in terms of predictive lead time, detection accuracy, and false-positive minimization. This capability is vital in modern vehicles where delays in detecting anomalies can lead to costly breakdowns, safety risks, and operational inefficiencies (Dattamajumdar, 2021; Shi et al., 2023). Moreover, by deploying this solution on edge-enabled vehicular systems, the architecture supports real-time inference with low latency, which is essential for mission-critical automotive applications (Raj, Saini, & Surianarayanan, 2022; Patwary et al., 2023).

From a systems engineering perspective, this research highlights the growing viability of AI-driven health diagnostics in cyber-physical vehicular platforms. The model's capacity to adapt to diverse sensor types and data frequencies makes it especially suited for heterogeneous and evolving vehicle fleets (Mozo et al., 2022). Furthermore, the transformer's explainability mechanisms offer valuable insights into the failure modes it predicts, enhancing trust and transparency, two key challenges in AI deployment for safety-critical systems (Xu, Solomon, & Gao, 2023).

However, this work also recognizes the current limitations and challenges. Model generalization across different vehicle models, driving environments, and unseen failure types remains an area requiring further attention. Additionally, concerns around telemetry data privacy, secure transmission, and over-the-air updates for continuous learning represent critical paths for future development (Tuomala, 2023). This 2024 study validates the potential of AI-powered predict-before-break systems using sequence-to-set transformer architectures to revolutionize early-warning diagnostics in the automotive sector. As vehicles become more intelligent and connected, such models will serve as foundational components in the broader push toward autonomous safety, fleet resilience, and intelligent transportation systems (Feruglio et al., 2023). With continued research, integration into digital twins, and federated learning

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capabilities, these architectures can drive significant advancements in real-time vehicle prognostics and predictive analytics.

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