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Article

Digital Twin-Assisted Explainable AI Framework for Signal Integrity Prediction and Communication Reliability in CAN FD-Based Autonomous Vehicle Networks

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Abstract: The increasing adoption of autonomous vehicles has created a demand for faster and more reliable in-vehicle communication systems. Controller Area Network with Flexible Data Rate (CAN FD) improves communication efficiency by supporting higher data transmission rates and larger payloads than traditional CAN networks. However, maintaining signal integrity and communication reliability remains challenging because of electromagnetic interference, network congestion, timing variations, and hardware-related disturbances. Existing monitoring methods mainly detect faults after they occur and often provide limited information about the factors affecting communication performance.

This paper proposes a **Digital Twin-Assisted Explainable Artificial Intelligence (XAI) framework** for predicting signal integrity and evaluating communication reliability in CAN FD-based autonomous vehicle networks. The framework integrates a digital twin of the communication network with an intelligent prediction model to continuously analyze network conditions using multiple communication indicators, including signal quality, latency, frame error rate, bus utilization, and message loss. To improve transparency and user confidence, SHAP-based Explainable AI is incorporated to identify the contribution of each communication parameter to the prediction process. The predicted communication state is then classified into **Normal, Degraded,** and **Critical** conditions for reliability assessment.

The proposed approach enables proactive communication monitoring by identifying potential network degradation before it significantly affects vehicle operation. Compared with conventional threshold-based methods, the framework provides more accurate prediction while offering clear explanations for model decisions. The study demonstrates that combining Digital Twin technology with Explainable AI can improve communication reliability assessment and support the development of trustworthy intelligent monitoring systems for future autonomous vehicle networks.

Keywords: Digital Twin, Explainable Artificial Intelligence, CAN FD, Autonomous Vehicles, Signal Integrity, Communication Reliability, SHAP, Machine Learning.

1. Introduction

The automotive industry is undergoing a rapid transformation with the emergence of autonomous driving technologies, intelligent transportation systems, and software-defined vehicles. Modern autonomous vehicles rely on a large number of electronic control units (ECUs), sensors, actuators, and embedded controllers that continuously exchange information to support perception, planning, and vehicle control. The effectiveness of these functions depends not only on computational intelligence but also on the reliability of the underlying in-vehicle communication network. A delay, corruption, or loss of critical communication messages may directly affect vehicle performance and operational safety.

Controller Area Network (CAN) has been one of the most widely adopted communication protocols in automotive electronics because of its simplicity, deterministic communication mechanism, and built-in error handling capabilities. However, the increasing complexity of autonomous vehicle applications has significantly increased communication requirements. Large sensor data volumes, higher processing rates, and the growing number of intelligent vehicle functions have exposed the limitations of Classical CAN, particularly its restricted payload size and limited data transmission rate [1], [2].

To overcome these limitations, Controller Area Network with Flexible Data Rate (CAN FD) was introduced as an enhanced version of the conventional CAN protocol. CAN FD supports payloads of up to 64 bytes and enables faster transmission during the data phase while maintaining compatibility with existing CAN arbitration mechanisms. These improvements make CAN FD more suitable for advanced driver assistance systems (ADAS), autonomous driving platforms, and intelligent vehicle controllers where rapid and reliable communication is essential [1], [3].

Although CAN FD improves communication efficiency, maintaining signal integrity becomes increasingly challenging as communication speed increases. Electrical noise, electromagnetic interference, impedance mismatch, timing variations, wiring degradation, and excessive bus utilization can affect communication quality and lead to transmission errors or reduced network reliability. Conventional diagnostic mechanisms available within CAN FD are effective in detecting communication faults after they occur, but they provide limited capability for predicting degradation before communication quality deteriorates significantly [2], [4].

Recent advances in Artificial Intelligence (AI) have enabled intelligent monitoring techniques capable of learning complex relationships among multiple communication parameters. Machine learning algorithms can identify patterns associated with network degradation by simultaneously analysing latency, signal quality, frame errors, bus utilization, and message reliability. However, many AI-based prediction models operate as black-box systems whose decision-making process is difficult to interpret. For safety-critical applications such as autonomous vehicles, understanding why a model reaches a particular decision is almost as important as achieving high prediction accuracy [5].

Explainable Artificial Intelligence (XAI) has emerged as an effective approach for improving transparency in intelligent decision-making systems. Instead of producing predictions without justification, XAI techniques explain the contribution of individual input variables to the final output, allowing engineers and system developers to verify whether model decisions are technically meaningful. Methods such as SHAP (Shapley Additive Explanations) have become increasingly popular because they provide both global and local interpretation of machine learning models while maintaining high predictive performance [6].

Another technological advancement attracting considerable attention is the Digital Twin. A Digital Twin represents a virtual counterpart of a physical system that continuously receives operational data and reproduces the behaviour of the real environment. Within autonomous vehicle communication networks, a Digital Twin can replicate CAN FD traffic, communication conditions, signal disturbances, and network performance in real time. Such synchronization enables continuous monitoring, predictive analysis, and early identification of abnormal communication behaviour without interrupting normal vehicle operation [7], [8].

Although previous studies have investigated CAN communication reliability, Digital Twin technologies, and explainable machine learning independently, relatively limited research has integrated these concepts into a unified framework for communication reliability assessment in CAN FD-based autonomous vehicle networks. Most existing approaches focus either on fault detection, network anomaly identification, or communication performance evaluation, while fewer studies address predictive signal integrity assessment together with transparent decision interpretation.

To address this research gap, this paper proposes a **Digital Twin-Assisted Explainable Artificial Intelligence framework** for predicting signal integrity and evaluating communication reliability in CAN FD-based autonomous vehicle networks. The proposed framework combines real-time Digital Twin synchronization with machine learning-based prediction and SHAP-based explanation to provide both accurate communication-state estimation and interpretable decision support. Communication reliability is evaluated using multiple indicators, including signal quality, frame error rate, latency, bus utilization, and message loss, enabling comprehensive assessment of network health under varying operating conditions.

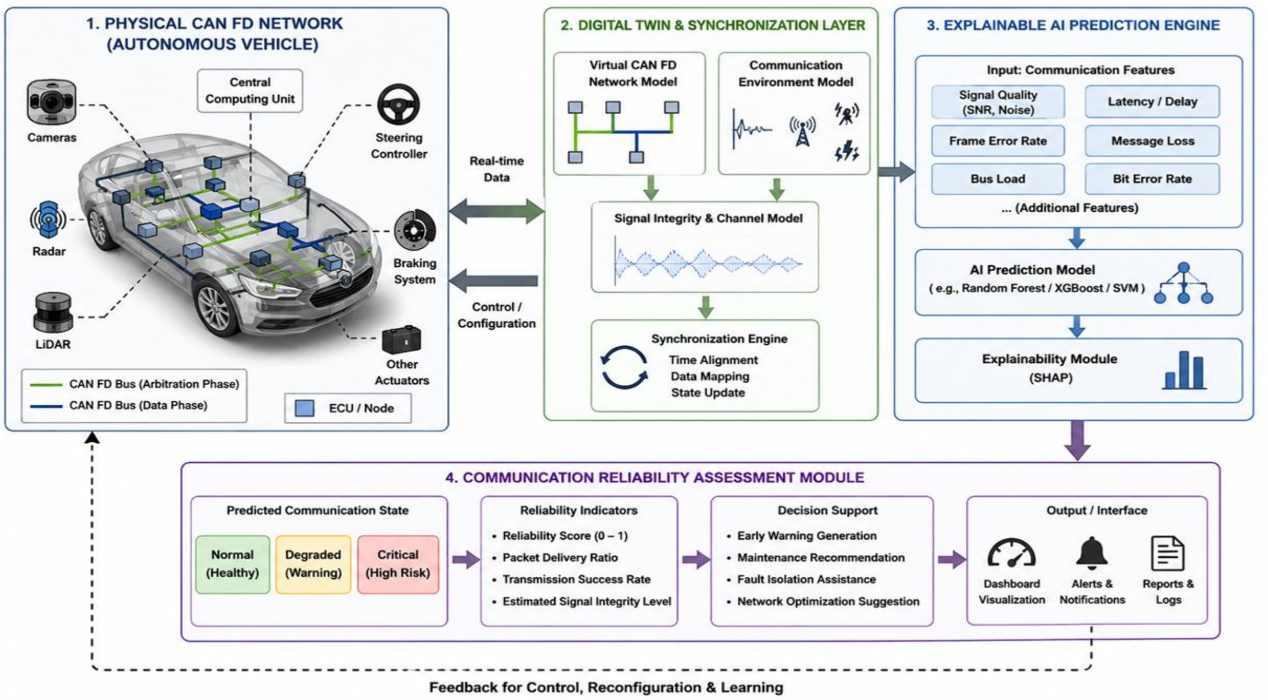

Figure 1: Overall communication architecture of a CAN FD-based autonomous vehicle showing physical network, digital twin synchronization, explainable AI prediction engine, and communication reliability assessment.

Figure 1: Overall communication architecture of a CAN FD-based autonomous vehicle showing physical vehicle network, Digital Twin synchronization layer, Explainable AI prediction engine, and communication reliability assessment module.

The primary contributions of this research are summarized as follows:

- A Digital Twin-assisted framework for continuous monitoring of CAN FD communication behaviour.
- An Explainable AI model capable of predicting signal integrity while providing interpretable decision explanations.
- A multi-parameter communication reliability assessment strategy integrating physical-layer and network-level communication indicators.
- A comparative evaluation demonstrating the effectiveness of the proposed framework over conventional monitoring approaches.

The remainder of this paper is organized as follows. Section 2 reviews related research on CAN FD communication, Digital Twin technologies, and Explainable AI. Section 3 describes the CAN FD communication architecture and Digital Twin model. Section 4 presents the proposed intelligent framework. Section 5 explains the research methodology and experimental setup. Section 6 discusses the experimental results, while Section 7 interprets the findings. Finally, Section 8 concludes the paper and outlines future research directions.

2. Literature Review

The rapid evolution of autonomous vehicle technologies has significantly increased the importance of reliable in-vehicle communication systems. Modern intelligent vehicles rely on continuous information exchange among sensors, electronic control units (ECUs), actuators, and central computing platforms to perform perception, decision-making, and vehicle control. As communication complexity increases, researchers have focused on improving network performance, signal integrity, fault diagnosis, predictive maintenance, and intelligent monitoring. Recent developments in CAN FD, Digital Twin technology, and Explainable Artificial Intelligence (XAI) have further expanded research opportunities in communication reliability assessment. This section reviews existing studies related to these areas and identifies the research gap addressed by the proposed framework.

2.1 CAN FD Communication in Autonomous Vehicles

Controller Area Network (CAN) has served as the foundation of automotive communication for several decades because of its deterministic arbitration mechanism, robustness, and low implementation cost. However, the increasing number of intelligent vehicle functions has exposed limitations in Classical CAN, particularly its restricted payload size and limited communication speed. To address these challenges, Bosch introduced Controller Area Network with Flexible Data Rate (CAN FD), which supports payloads of up to 64 bytes and higher data transmission rates while maintaining compatibility with conventional CAN arbitration [1].

Navet and Simonot-Lion [2] discussed the growing communication requirements of modern automotive embedded systems and emphasized that future vehicle architectures would require higher bandwidth and more flexible communication technologies. Their work highlighted the transition toward distributed intelligent vehicle systems in which communication performance directly influences overall system reliability.

Johansson et al. [3] examined automotive applications of CAN and demonstrated the suitability of the protocol for distributed control systems. Their study described how deterministic message arbitration contributes to predictable communication behaviour but also noted that communication timing becomes increasingly important as vehicle functionality grows.

Although CAN FD significantly improves transmission efficiency, several researchers have reported that higher communication speed introduces additional challenges related to signal quality, synchronization accuracy, and network timing. Consequently, maintaining communication reliability remains an active area of automotive research.

2.2 Signal Integrity and Communication Reliability

Signal integrity has become a critical factor in high-speed in-vehicle communication networks. Unlike conventional fault diagnosis, which primarily identifies communication failures after they occur, signal integrity analysis attempts to understand the physical conditions that influence communication quality before transmission errors become severe.

Voss [4] explained that communication reliability depends not only on protocol design but also on wiring quality, electromagnetic interference, termination resistance, and network topology. Variations in these physical characteristics may influence signal propagation, resulting in increased error rates or unstable communication behaviour.

Tindell, Burns, and Wellings [5] investigated response-time analysis in CAN communication and demonstrated that network load, arbitration priority, and message scheduling directly affect communication delay. Their work established an important theoretical basis for analysing communication timing in automotive control systems.

Recent studies have expanded communication reliability assessment by considering multiple performance indicators simultaneously rather than relying on isolated parameters. Researchers have reported that latency, frame error rate, message delivery ratio, and bus utilization collectively provide a more realistic representation of network health than any single measurement. Nevertheless, many existing approaches continue to depend on predefined thresholds that may not accurately represent gradual communication degradation under varying operating conditions.

2.3 Digital Twin Technology for Intelligent Monitoring

Digital Twin technology has emerged as one of the most promising developments in intelligent industrial systems. A Digital Twin creates a synchronized virtual representation of a physical asset by continuously integrating operational data from the real environment. This enables real-time monitoring, predictive analysis, and system optimization without interrupting physical operation.

Tao et al. [6] described Digital Twin technology as an essential component of intelligent manufacturing and cyber-physical systems. Their work demonstrated that synchronized virtual models can improve operational awareness, predictive maintenance, and decision support through continuous interaction between physical and digital environments.

Similarly, Fuller et al. [7] reviewed enabling technologies and research challenges associated with Digital Twins and emphasized their growing importance in industrial automation, healthcare, transportation, and smart infrastructure. The authors highlighted that Digital Twins are particularly valuable when continuous monitoring and predictive decision-making are required.

Within intelligent transportation systems, Digital Twins are increasingly being explored for traffic management, vehicle diagnostics, predictive maintenance, and communication monitoring. However, relatively few studies have investigated Digital Twin implementation specifically for CAN FD communication reliability and signal integrity prediction. Most existing work concentrates on mechanical system monitoring or vehicle dynamics rather than communication behaviour itself.

2.4 Explainable Artificial Intelligence for Communication Prediction

Machine learning has become an effective tool for analysing complex communication systems because it can identify nonlinear relationships among multiple network parameters. Various algorithms have been applied for communication anomaly detection, fault diagnosis, and predictive maintenance. However, many intelligent prediction models function as black-box systems whose internal reasoning is difficult to interpret.

Bishop [8] explained that modern machine learning techniques provide strong predictive capabilities but often sacrifice interpretability as model complexity increases. This limitation becomes particularly important in safety-critical systems where engineering decisions require transparent justification.

Explainable Artificial Intelligence (XAI) has been developed to overcome this limitation. Lundberg and Lee [9] introduced SHAP (Shapley Additive Explanations), an explainability technique capable of quantifying the contribution of individual input variables toward a model's prediction. Unlike conventional feature importance methods, SHAP provides both global and instance-level explanations, making it highly suitable for engineering applications where individual prediction interpretation is essential.

The growing adoption of XAI has increased confidence in AI-assisted decision-making within healthcare, finance, cybersecurity, and industrial automation. However, the application of explainability techniques to in-vehicle communication reliability remains relatively limited. Existing studies primarily focus on improving prediction accuracy rather than providing transparent explanations that engineers can use for system diagnosis.

2.5 Intelligent Communication Security and Anomaly Detection

The increasing connectivity of autonomous vehicles has also attracted considerable attention toward communication security. Researchers have proposed various intelligent approaches for identifying abnormal CAN traffic, cyberattacks, and malicious message injection.

Müter and Asaj [10] introduced an entropy-based anomaly detection approach capable of identifying abnormal communication behaviour within automotive networks. Their work demonstrated that statistical analysis of message distributions can detect unusual communication patterns without requiring detailed knowledge of specific attacks.

Han, Kwak, and Kim [11] proposed a survival analysis-based anomaly detection technique for vehicular communication networks. Their method analysed temporal communication behaviour to identify abnormal message sequences while reducing false alarm rates.

Avatefipour et al. [12] developed a machine learning framework for cyberattack detection in electric vehicle CAN networks. Their study showed that intelligent learning algorithms can effectively distinguish malicious communication patterns from normal traffic, providing improved detection accuracy compared with traditional rule-based approaches.

Bozdal et al. [13] reviewed current security challenges associated with CAN communication and highlighted vulnerabilities related to message authentication, intrusion detection, and network protection. Their analysis emphasized that future intelligent vehicle networks require integrated approaches capable of addressing both communication reliability and communication security.

Although these studies significantly improve communication anomaly detection, most of them focus primarily on cybersecurity rather than communication quality. Signal degradation resulting from electrical disturbances, synchronization errors, or network congestion receives comparatively less attention. Consequently, communication reliability prediction remains an open research area.

2.6 Research Gap

The literature indicates substantial progress in CAN FD communication, Digital Twin technologies, machine learning, and communication anomaly detection. Nevertheless, several important limitations remain.

First, many existing studies evaluate communication quality only after faults become observable, offering limited capability for early prediction of communication degradation.

Second, Digital Twin implementations have mainly focused on manufacturing systems, predictive maintenance, and mechanical components, whereas their application to CAN FD communication monitoring remains relatively unexplored.

Third, although machine learning techniques have improved prediction accuracy, many existing approaches operate as black-box models that provide little explanation regarding their decisions. Such limited transparency reduces confidence when intelligent models are deployed in safety-critical autonomous vehicle systems.

Finally, very few studies integrate Digital Twin technology, Explainable Artificial Intelligence, and CAN FD communication reliability assessment into a unified framework capable of simultaneously predicting signal integrity and explaining prediction outcomes.

To address these limitations, the present research proposes a Digital Twin-Assisted Explainable AI framework for signal integrity prediction and communication reliability assessment in CAN FD-based autonomous vehicle networks. By combining continuous Digital Twin synchronization, intelligent communication prediction, and SHAP-based explanation, the proposed framework seeks to improve both prediction performance and decision transparency while supporting proactive communication monitoring.

Table 1: Comparison of Existing Studies on CAN FD Communication, Digital Twin, Explainable AI, and Communication Reliability.

Study	Research Focus	Method	Limitation

Navet et al. (2005) [2]	Automotive communication architecture	Communication analysis	Limited discussion on predictive monitoring
Tindell et al. (1995) [5]	CAN response-time analysis	Scheduling analysis	No intelligent prediction
Tao et al. (2019) [6]	Digital Twin technology	Virtual system synchronization	General industrial applications
Fuller et al. (2020) [7]	Digital Twin review	Literature review	Limited automotive communication focus
Lundberg & Lee (2017) [9]	Explainable AI (SHAP)	Model interpretation	Not applied to CAN FD communication
Avatefipour et al. (2019) [12]	AI-based CAN anomaly detection	Machine Learning	Focus on cybersecurity rather than signal integrity
Proposed Work	Digital Twin + Explainable AI + Signal Integrity Prediction	Digital Twin + XAI + Machine Learning	Predictive, interpretable communication reliability assessment

3. CAN FD Communication and Digital Twin Architecture

The growing complexity of autonomous vehicle systems has significantly increased the demand for communication networks that are capable of transferring large volumes of data with high reliability and minimal delay. Modern vehicles integrate advanced driver assistance systems (ADAS), perception sensors, intelligent controllers, and centralized computing platforms that continuously exchange information to support safe driving decisions. As communication traffic increases, maintaining reliable message transmission becomes equally important as improving computational performance. Controller Area Network with Flexible Data Rate (CAN FD) has emerged as an important communication technology because it extends the capabilities of the conventional CAN protocol while preserving its fundamental communication principles.

At the same time, advances in cyber-physical systems have introduced the concept of the Digital Twin as a powerful approach for monitoring complex engineering systems. Instead of observing the physical communication network alone, a Digital Twin continuously synchronizes operational information with a virtual representation of the network. This enables communication behaviour to be analysed dynamically and allows potential reliability problems to be identified before they develop into serious communication failures.

3.1 CAN FD Communication Architecture

CAN FD was introduced to overcome several limitations associated with Classical CAN while maintaining compatibility with existing automotive communication infrastructures. The conventional CAN protocol restricts the maximum payload size to eight bytes and operates at a fixed communication speed throughout message transmission. These limitations become increasingly restrictive in intelligent vehicle applications where numerous ECUs exchange larger quantities of information at higher frequencies [1].

CAN FD extends the protocol by increasing the maximum payload size to sixty-four bytes and allowing the arbitration phase and data transmission phase to operate at different bit rates. During arbitration, communication remains compatible with Classical CAN to ensure reliable priority resolution among competing nodes. Once arbitration has been completed successfully, the data phase may operate at a substantially higher transmission speed, improving communication efficiency without modifying the existing arbitration mechanism [1], [2].

A typical CAN FD network consists of multiple ECUs connected through a common communication bus. Each ECU performs a dedicated vehicle function such as engine control, steering, braking, vehicle dynamics, battery management, or sensor processing. Messages generated by one controller become available to all other nodes connected to the network, allowing distributed control functions to exchange information efficiently without requiring dedicated communication channels.

Unlike point-to-point communication systems, CAN FD follows a broadcast communication model. Every transmitted message contains an identifier representing its priority rather than the address of a specific receiving device. Individual ECUs determine whether a received message is relevant to their assigned function. This communication strategy simplifies network expansion and reduces wiring complexity while maintaining deterministic communication behaviour.

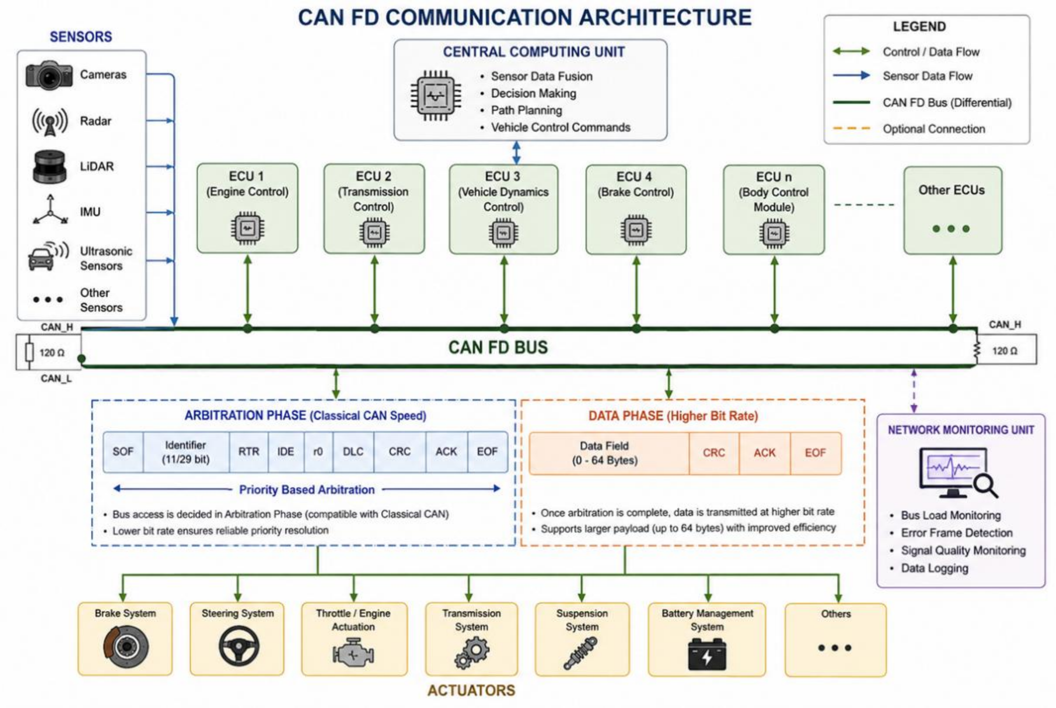

Figure 2: CAN FD Communication Architecture showing sensors, ECUs, arbitration phase, data phase, CAN FD bus, actuators, and central computing unit.

As illustrated in Figure 2, sensor information generated by cameras, LiDAR, radar, inertial measurement units, ultrasonic sensors, and other intelligent devices is processed by multiple ECUs before being transmitted across the CAN FD communication bus. After communication and decision processing, corresponding commands are delivered to braking, steering, propulsion, suspension, and other vehicle control systems.

3.2 Communication Characteristics of CAN FD

The primary advantage of CAN FD lies in its ability to improve communication efficiency without fundamentally changing the architecture of the original CAN protocol. The separation of arbitration and data transmission phases enables higher communication throughput while preserving deterministic bus access.

Communication efficiency may be represented by

$$\eta = \frac{T_{payload}}{T_{total}} \quad (1)$$

where

Tpayload denotes the effective data transmission time, and Ttotal represents the complete communication duration including arbitration, control information, acknowledgement, and protocol overhead.

Because CAN FD allows larger payloads to be transmitted within a single communication frame, the communication overhead associated with multiple small messages is reduced. Consequently, the effective bandwidth utilization becomes higher than that of Classical CAN under comparable communication conditions.

Another important characteristic is communication latency. For a transmitted message,

$$L = t_{receive} - t_{transmit} \quad (2)$$

where $t_{transmit}$ is the message transmission instant and $t_{receive}$ denotes the successful reception time.

Communication latency is influenced by arbitration delay, network load, retransmission events, and signal quality. Higher communication speed can reduce transmission time but may simultaneously increase sensitivity to physical-layer disturbances. Consequently, improving communication speed alone does not necessarily guarantee improved communication reliability.

3.3 Signal Integrity Challenges in CAN FD Networks

Although CAN FD significantly increases communication capacity, it also introduces additional challenges associated with signal integrity. Higher communication frequencies increase sensitivity to wiring characteristics, electromagnetic interference, impedance discontinuities, connector ageing, termination quality, and environmental conditions.

Signal integrity describes the ability of transmitted electrical signals to preserve their intended waveform throughout the communication process. Degraded signal quality may not immediately produce communication failure; however, repeated disturbances can increase retransmissions, communication latency, frame errors, and message loss.

The quality of communication may be represented through the Signal-to-Noise Ratio (SNR),

$$SNR_{dB} = 10log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (3)$$

where P_{signal} represents signal power and P_{noise} denotes the surrounding noise power.

As the SNR decreases, the probability of communication errors generally increases. Nevertheless, signal quality alone cannot fully describe network reliability because communication performance also depends upon network traffic, arbitration behaviour, frame scheduling, and retransmission mechanisms.

Similarly, Frame Error Rate (FER) is expressed as

$$FER = \frac{N_{error}}{N_{frame}} \quad (4)$$

where N_{error} denotes erroneous communication frames and N_{frame} represents the total transmitted frames during an observation interval.

The interaction among SNR, FER, latency, bus utilization, and message loss forms the basis for evaluating communication reliability in the proposed framework.

3.4 Digital Twin for Communication Monitoring

Digital Twin technology provides a virtual representation of a physical system that continuously receives operational information from the real environment and reproduces its behaviour within a computational model. Unlike conventional simulation models, a Digital Twin maintains continuous synchronization between physical and virtual systems, allowing dynamic monitoring and predictive analysis [3], [4].

Within CAN FD communication networks, the Digital Twin reproduces the behaviour of the physical communication infrastructure by collecting information from ECUs, communication controllers, sensors, and monitoring interfaces. The virtual model receives communication statistics in real time and updates its internal state to reflect current operating conditions.

The Digital Twin consists of four principal components:

- Physical CAN FD communication network
- Data synchronization mechanism
- Virtual communication model
- Analytical and prediction engine

Information continuously flows between the physical and virtual environments, allowing communication performance to be evaluated without interrupting normal vehicle operation.

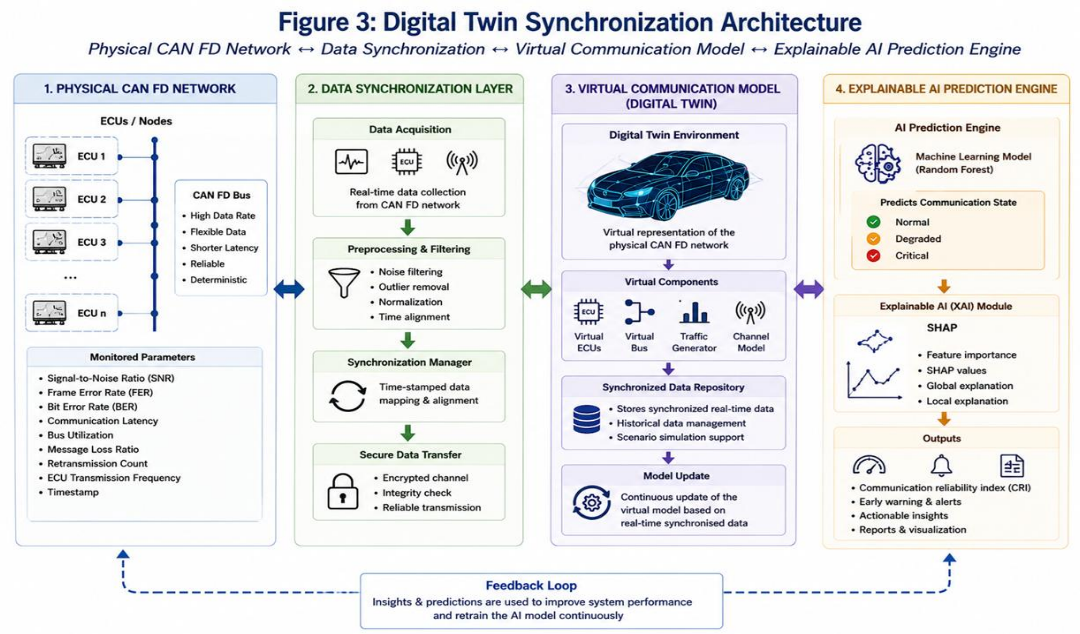

Figure 3: Digital Twin Synchronization Architecture showing Physical CAN FD Network ↔ Data Synchronization ↔ Virtual Communication Model ↔ Explainable AI Prediction Engine.

Unlike traditional offline simulations, the Digital Twin remains synchronized throughout system operation. Consequently, predicted communication behaviour reflects current network conditions rather than predefined assumptions.

3.5 Synchronization Between Physical and Virtual Networks

The effectiveness of a Digital Twin depends upon synchronization accuracy. Communication observations collected from the physical network must accurately represent the current communication state within the virtual model.

Synchronization may be expressed as

$$S_{sync} = 1 - \frac{|X_p - X_v|}{X_p} \quad (5)$$

where X_p represents measurements obtained from the physical communication network and X_v denotes corresponding values estimated by the Digital Twin.

A synchronization value approaching one indicates that the Digital Twin closely represents the physical communication environment. Lower synchronization values suggest increasing divergence between virtual predictions and actual communication behaviour.

Communication parameters synchronized between the two environments include:

- Signal-to-noise ratio
- Frame error rate
- Bus utilization
- Communication latency
- Message loss ratio
- ECU transmission frequency

Continuous synchronization enables the prediction model to analyse both historical communication behaviour and current operating conditions.

3.6 Explainable AI Integration

Artificial Intelligence has demonstrated considerable capability in analysing communication behaviour; however, many prediction models remain difficult to interpret. In safety-critical autonomous vehicle systems, engineering decisions require not only accurate predictions but also understandable explanations.

The proposed architecture therefore integrates Explainable Artificial Intelligence (XAI) into the Digital Twin environment. After communication features are collected and processed, the intelligent prediction model estimates the communication state. The Explainability Layer subsequently determines how strongly each communication feature contributed to that prediction.

Rather than producing only a communication label such as **Normal**, **Degraded**, or **Critical**, the Explainable AI component identifies whether latency, signal quality, frame errors, or bus utilization had the greatest influence on the decision. This improves engineering confidence and supports communication fault diagnosis.

SHAP (Shapley Additive Explanations) is adopted because it provides consistent interpretation for individual predictions while maintaining compatibility with tree-based machine learning algorithms.

For a communication observation,

$$Prediction = Base + \sum_{i=1}^{n} \phi_i \quad (6)$$

where ϕ_i denotes the contribution of the i^{th} communication feature toward the final prediction.

The explainability mechanism therefore transforms the intelligent prediction model from a black-box system into a transparent decision-support tool.

3.7 Integrated Communication Reliability Architecture

The proposed architecture combines CAN FD communication, Digital Twin synchronization, machine learning prediction, and Explainable AI into a unified monitoring framework.

The operational sequence consists of the following stages:

1. Communication data acquisition from the physical CAN FD network.
2. Continuous synchronization with the Digital Twin.
3. Feature extraction and preprocessing.
4. Intelligent communication-state prediction.
5. SHAP-based explanation of prediction results.
6. Communication reliability evaluation.
7. Decision support and early warning generation.

Unlike conventional communication monitoring, the proposed architecture does not rely solely on predefined thresholds. Instead, communication reliability is determined from the combined behaviour of multiple communication indicators together with interpretable machine learning predictions.

Table 2: Comparison between Classical CAN and CAN FD Communication.

PARAMETER	**CLASSICAL CAN**	**CAN FD**
Maximum Payload	8 Bytes	64 Bytes
Communication Speed	Fixed	Variable (Higher Data Phase Speed)
Arbitration	Standard CAN	Same as Classical CAN
Data Phase	Fixed Speed	Flexible Data Rate
Communication Efficiency	Moderate	High
Suitable for Autonomous Vehicles	Limited	Highly Suitable
Signal Integrity Sensitivity	Moderate	Higher due to Increased Data Rate

3.8 Summary

CAN FD significantly enhances communication capability for autonomous vehicle applications by providing larger payload capacity and improved transmission efficiency. However, the higher communication speed also increases sensitivity to physical-layer disturbances and communication timing variations. Traditional monitoring approaches primarily identify communication failures after they occur and often provide limited insight into the underlying causes of degradation.

The Digital Twin architecture presented in this section provides a continuously synchronized virtual representation of the communication network, enabling real-time monitoring and predictive analysis. By integrating Explainable Artificial Intelligence into this environment, the proposed framework not only predicts communication reliability but also explains the reasoning behind each prediction. This integrated architecture establishes the technical foundation for the intelligent framework presented in the following section.

4. Proposed Digital Twin-Assisted Explainable AI Framework

The increasing complexity of autonomous vehicle communication requires monitoring mechanisms that can evaluate network behaviour continuously while providing reliable and interpretable predictions. Conventional diagnostic methods generally rely on predefined thresholds or protocol-specific error counters. Although these approaches are effective in identifying communication faults, they often detect problems only after communication quality has already deteriorated. Furthermore, they provide limited information regarding the combined influence of multiple communication parameters on network reliability.

To address these limitations, this study proposes a **Digital Twin-Assisted Explainable Artificial Intelligence (XAI) framework** for predicting signal integrity and evaluating communication reliability in CAN FD-based autonomous vehicle networks. The framework combines continuous Digital Twin synchronization, intelligent prediction, and explainable machine learning into a unified architecture capable of supporting proactive communication monitoring. Unlike traditional approaches that analyse communication parameters independently, the proposed framework considers their collective behaviour and explains the reasoning behind each prediction.

The proposed architecture consists of six interconnected modules:

1. Communication Data Acquisition
2. Digital Twin Synchronization
3. Feature Extraction and Preprocessing
4. AI-Based Signal Integrity Prediction
5. Explainable AI Analysis
6. Communication Reliability Assessment

Each module contributes to transforming raw communication information into interpretable reliability decisions suitable for intelligent vehicle applications.

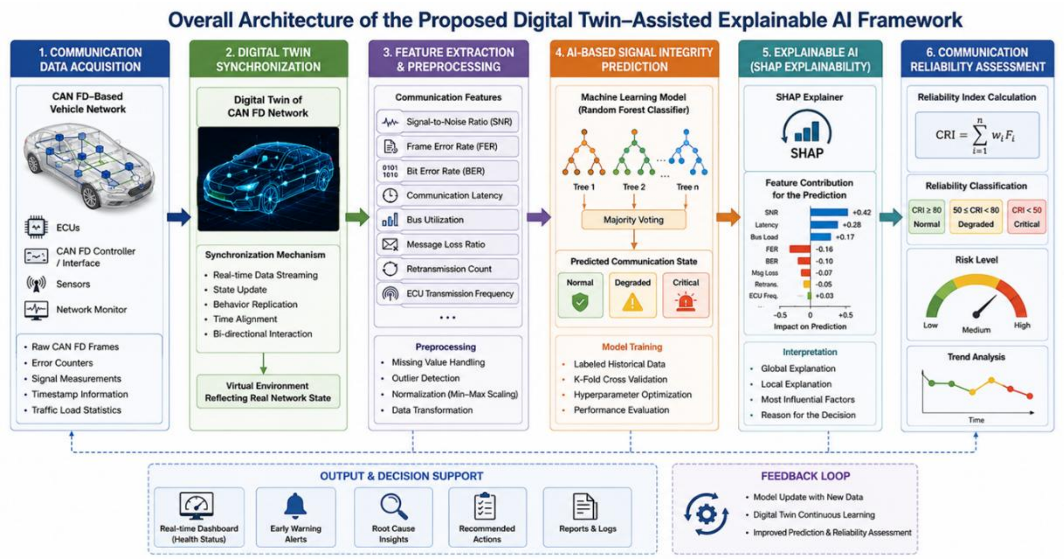

Figure 4: Overall Architecture of the Proposed Digital Twin-Assisted Explainable AI Framework

4.1 Communication Data Acquisition Module

The first stage of the proposed framework continuously collects communication information from the physical CAN FD network. Communication statistics are obtained directly from ECUs, CAN FD controllers, diagnostic interfaces, and network monitoring devices.

Instead of observing only protocol errors, the acquisition module records multiple communication indicators representing both physical-layer and network-level behaviour.

The principal communication variables include:

- Signal-to-Noise Ratio (SNR)
- Frame Error Rate (FER)
- Bit Error Rate (BER)
- Communication Latency
- Bus Utilization
- Message Loss Ratio
- ECU Transmission Frequency
- Frame Retransmission Count

These variables are selected because they collectively describe communication quality more comprehensively than isolated protocol error counters.

The communication observation collected during each monitoring interval is represented as

$$X = [x_n] \quad (7)$$

where x_i denotes the i^{th} communication feature measured from the CAN FD network.

The collected observations are forwarded to the Digital Twin for synchronized processing.

4.2 Digital Twin Synchronization Layer

The Digital Twin forms the central component of the proposed framework. It maintains a continuously updated virtual representation of the physical CAN FD communication network by receiving real-time communication observations.

Unlike conventional offline simulation models, the Digital Twin continuously exchanges information with the physical communication environment. Every synchronization cycle updates the virtual network according to current communication behaviour.

Synchronization accuracy is defined as

$$S = 1 - \frac{|\, X_p - X_d \,|}{X_p} \quad (8)$$

where

- X_p represents measurements obtained from the physical communication network,
- X_d denotes the corresponding Digital Twin observations.

A synchronization value close to one indicates that the virtual communication model accurately reflects the physical network state.

The Digital Twin continuously updates:

- ECU communication status
- CAN FD bus traffic
- Signal quality
- Network latency
- Error behaviour
- Communication reliability indicators

This synchronized environment enables intelligent prediction without interrupting physical vehicle operation.

4.3 Feature Extraction and Data Preprocessing

Communication observations obtained from the Digital Twin are transformed into machine-learning input variables.

Before prediction, each feature is examined for missing values, abnormal measurements, and inconsistent observations. Communication variables having different numerical ranges are normalized to improve model stability.

Normalization is performed using Min-Max scaling

$$X^{'} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (9)$$

where

- Xrepresents the original feature,
- $X'$is the normalized feature.

Normalization ensures that communication parameters such as latency, SNR, bus utilization, and message loss contribute proportionately during model learning.

Table 3: Communication Features Used in the Proposed Framework.

Feature	Description	Category
Signal-to-Noise Ratio	Physical signal quality	Physical Layer
Bit Error Rate	Transmission accuracy	Communication Layer
Frame Error Rate	Frame reliability	Communication Layer
Communication Latency	Message delay	Network Layer
Bus Utilization	Traffic load	Network Layer
Message Loss Ratio	Communication success	Reliability
ECU Transmission Frequency	Node activity	Operational
Retransmission Count	Error recovery	Reliability

4.4 AI-Based Signal Integrity Prediction

Following preprocessing, the normalized communication features are processed using a supervised machine learning model. Random Forest is selected because it effectively models nonlinear relationships while maintaining high prediction accuracy and robustness against noisy communication data [1].

The classifier predicts one of three communication states:

- **Normal**
- **Degraded**
- **Critical**

Instead of evaluating each communication parameter separately, the Random Forest classifier combines multiple decision trees to identify complex communication patterns.

The prediction function is represented as

$$Y = f(X) \quad (10)$$

where

- Xrepresents the communication feature vector,
- Ydenotes the predicted communication class.

The ensemble prediction is obtained through majority voting

$$Y = Mode(T_n) \quad (11)$$

where $T_i$denotes the prediction produced by the i^{th}decision tree.

This ensemble strategy improves prediction stability and reduces overfitting compared with individual decision trees.

4.5 Explainable AI Module

Although machine learning improves prediction capability, engineers often require explanations regarding why a communication state has been predicted.

The Explainable AI module therefore interprets every prediction using SHAP (Shapley Additive Explanations).

Instead of producing only a communication label, SHAP estimates the contribution of each communication feature toward the final prediction.

For an individual observation,

$$Prediction = Base + \sum_{i=1}^{n} \phi_i \quad (12)$$

where

- Base represents the average prediction,
- ϕ_i denotes the SHAP contribution of the i^{th} communication feature.

The explanation module identifies whether communication deterioration was primarily influenced by

- declining signal quality,
- increasing latency,
- excessive bus utilization,
- frame errors,
- message loss,
- retransmission activity.

This information supports communication diagnosis while improving user confidence in intelligent predictions.

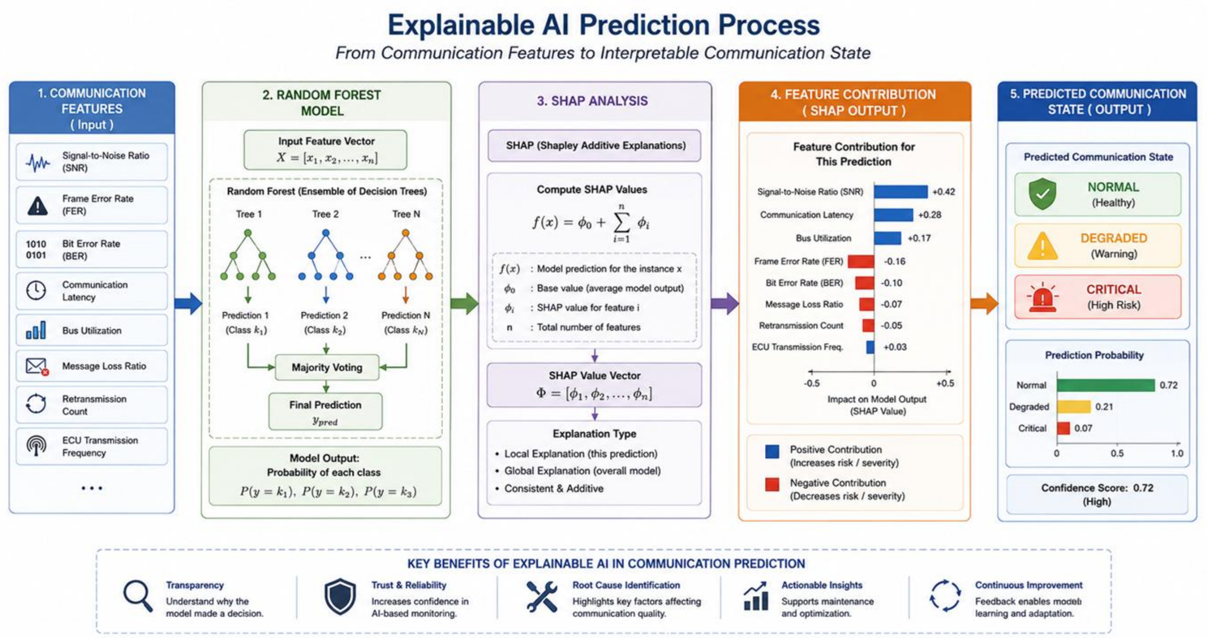

Figure 5: Explainable AI Prediction Process illustrating Communication Features

4.6 Communication Reliability Assessment

The final module combines predicted communication states with numerical reliability indicators to estimate the overall communication condition.

The Communication Reliability Index (CRI) is calculated as

$$CRI = \sum_{i=1}^{n} w_i F_i \quad (13)$$

where

- F_i represents normalized communication features,

- $w_i$denotes their corresponding importance weights,

subject to

$$\sum_{i=1}^{n} w_i = 1 \quad (14)$$

Higher CRI values indicate stable communication, while lower values indicate increasing communication degradation.

The reliability decision is defined according to the following operating regions:

Table 4. Communication Reliability Classification

CRI Range	Communication State	Interpretation
80–100	Normal	Stable communication
50–79	Degraded	Communication quality reduced
Below 50	Critical	High communication risk

This classification allows the monitoring system to provide early warnings before severe communication failure occurs.

4.7 Decision Support Layer

The final stage converts prediction outcomes into practical decision support.

The generated outputs include:

- Communication health status
- Reliability score
- Feature importance explanation
- Early warning notification
- Maintenance recommendation
- Communication log generation

Unlike conventional monitoring systems that simply indicate whether communication has failed, the proposed framework explains the probable reasons behind communication degradation. Consequently, maintenance engineers can identify the most influential communication factors and initiate corrective action more efficiently.

4.8 Workflow of the Proposed Framework

The complete operational workflow proceeds through the following sequence:

1. Collect CAN FD communication data.
2. Synchronize observations with the Digital Twin.
3. Extract and normalize communication features.
4. Predict signal integrity using Random Forest.
5. Interpret predictions using SHAP.
6. Calculate the Communication Reliability Index.
7. Classify communication into Normal, Degraded, or Critical states.
8. Generate reliability reports and maintenance recommendations.

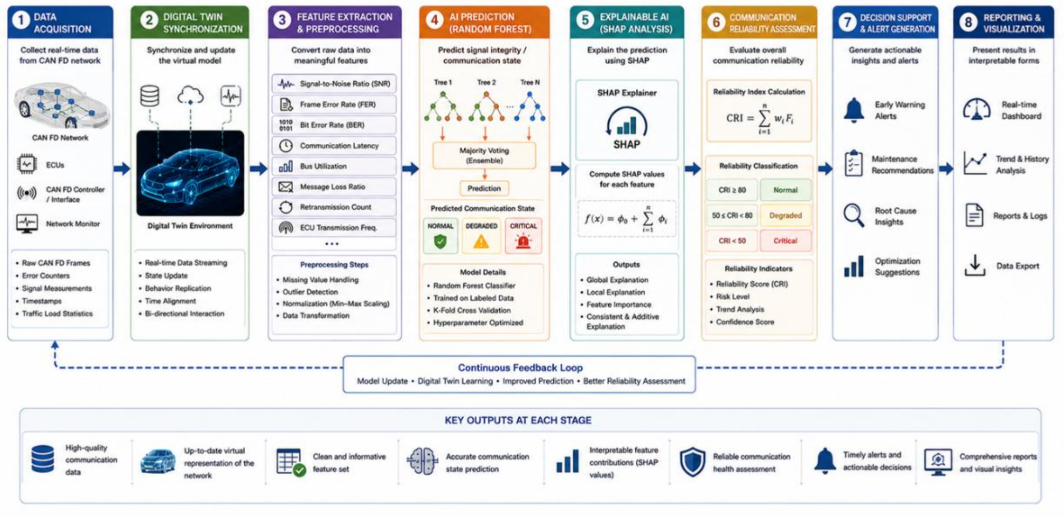

Figure 6: Operational Workflow of the Proposed Digital Twin-Assisted Explainable AI Framework.

This workflow establishes a continuous monitoring cycle in which the Digital Twin remains synchronized with the physical network while Explainable AI provides transparent interpretation of intelligent communication predictions.

4.9 Advantages of the Proposed Framework

Compared with conventional communication monitoring methods, the proposed framework provides several important advantages:

- Continuous synchronization between physical and virtual communication environments.
- Early prediction of communication degradation instead of reactive fault detection.
- Integration of multiple communication indicators rather than isolated threshold analysis.
- Transparent AI predictions through SHAP-based explanation.
- Improved support for predictive maintenance and engineering diagnosis.
- Scalable architecture suitable for future intelligent autonomous vehicle communication systems.

By integrating Digital Twin technology with Explainable AI, the proposed framework offers a comprehensive solution for intelligent communication reliability assessment while addressing the growing need for trustworthy AI in autonomous vehicle applications.

5. Research Methodology

The objective of this study is to develop and evaluate a **Digital Twin-Assisted Explainable Artificial Intelligence (XAI) framework** capable of predicting signal integrity and assessing communication reliability in CAN FD-based autonomous vehicle networks. The proposed methodology integrates communication data acquisition, Digital Twin synchronization, machine learning-based prediction, Explainable AI analysis, and communication reliability evaluation into a unified experimental workflow. The methodology was designed to ensure repeatability while reflecting realistic communication conditions encountered in intelligent vehicle networks.

The overall research process consists of six sequential stages: communication data collection, Digital Twin modelling, feature engineering, machine learning model development, explainability analysis, and performance evaluation. Each stage contributes to the final communication reliability assessment while maintaining consistency between the physical communication environment and its virtual representation.

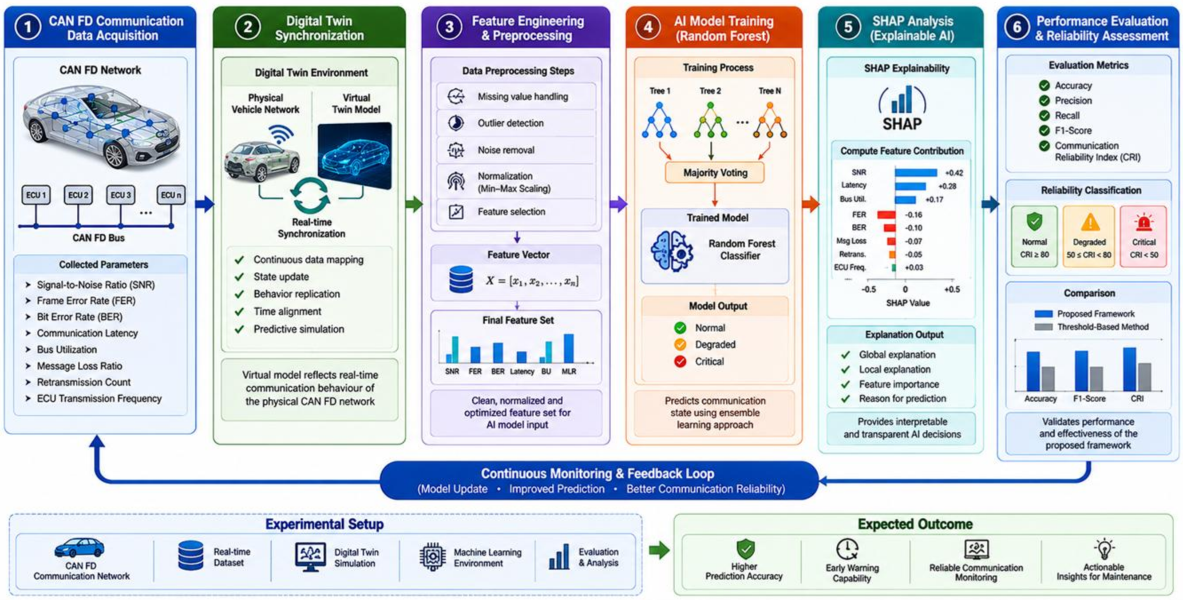

Figure 7: Overall Experimental Digital Twin-Assisted Explainable AI Framework for CAN FD Communication Reliability Assessment

5.1 Research Workflow

The proposed methodology follows a systematic workflow beginning with communication monitoring in the physical CAN FD network. Communication observations are synchronized with the Digital Twin environment, where feature extraction and preprocessing are performed before machine learning prediction.

The experimental sequence consists of the following stages:

1. CAN FD communication data acquisition.
2. Digital Twin synchronization.
3. Feature extraction and preprocessing.
4. Machine learning model training.
5. Explainable AI analysis.
6. Communication reliability evaluation.
7. Comparative performance analysis.

This structured workflow enables every communication observation to be processed using the same analytical pipeline, thereby ensuring consistency throughout the experimental study.

5.2 CAN FD Communication Dataset

A representative CAN FD communication dataset was prepared to simulate realistic communication behaviour under different operating conditions. The dataset contains communication observations generated from multiple Electronic Control Units (ECUs) operating under varying traffic loads and signal conditions.

To improve the diversity of communication patterns, the experimental environment includes both normal operating scenarios and abnormal communication conditions produced by controlled disturbances such as:

- Electromagnetic interference (EMI)
- Increased network traffic
- Communication latency
- Signal attenuation
- Frame transmission errors
- Message retransmissions
- Bus overload
- Packet loss

Each communication observation contains multiple quantitative features representing both physical-layer characteristics and network-level behaviour.

The complete dataset is represented as

$$D = \{Y_i\}_{i=1}^{N} \quad (15)$$

where

- X_i denotes the communication feature vector,
- Y_i represents the corresponding communication class,
- N is the total number of observations.

The communication labels are assigned to three reliability categories:

- Normal
- Degraded
- Critical

5.3 Digital Twin Experimental Environment

The Digital Twin reproduces the behaviour of the physical CAN FD communication network through continuous synchronization of operational information. During each synchronization cycle, communication observations collected from the physical network are transmitted to the virtual model, where communication behaviour is replicated in real time.

The synchronized Digital Twin updates:

- ECU communication status
- CAN FD traffic
- Signal quality
- Communication latency
- Bus utilization
- Message reliability

This synchronized environment allows multiple communication scenarios to be evaluated without interrupting the operation of the physical network.

The synchronization interval is represented as

$$T_{sync} = t_{i+1} - t_i \quad (16)$$

where

- t_i denotes the current synchronization instant,
- t_{i+1} represents the subsequent synchronization cycle.

Smaller synchronization intervals improve the responsiveness of the Digital Twin but require higher computational resources.

5.4 Feature Engineering

Feature engineering converts raw communication observations into variables suitable for machine learning analysis. Communication indicators were selected according to their contribution to signal integrity and communication reliability.

The selected features include:

- Signal-to-Noise Ratio (SNR)
- Bit Error Rate (BER)
- Frame Error Rate (FER)
- Communication Latency
- Bus Utilization

- Message Loss Ratio
- Retransmission Count
- ECU Transmission Frequency

These variables represent complementary aspects of communication performance rather than isolated protocol measurements.

Prior to model training, missing values were removed and communication features were normalized using Min-Max normalization.

$$X^{'} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (17)$$

Normalization prevents variables with larger numerical ranges from dominating the learning process.

Table 5: Input Features Used for Signal Integrity Prediction.

Feature	Description	Unit
Signal-to-Noise Ratio	Signal quality	dB
Bit Error Rate	Bit transmission errors	Ratio
Frame Error Rate	Erroneous frames	Ratio
Communication Latency	Message delay	ms
Bus Utilization	Network load	%
Message Loss Ratio	Lost messages	%
Retransmission Count	Number of retransmissions	Count
ECU Transmission Frequency	Communication frequency	Hz

5.5 Machine Learning Model Development

The communication prediction model was developed using the Random Forest algorithm because of its robustness, ability to model nonlinear relationships, and resistance to overfitting [1].

The dataset was divided into training and testing subsets using an **80:20 split**. Model training was performed using labeled communication observations representing Normal, Degraded, and Critical communication conditions.

Random Forest constructs multiple decision trees from bootstrap samples of the training dataset. The final communication prediction is obtained through majority voting among individual trees.

The ensemble prediction is expressed as

$$Y = Mode(T_n) \quad (18)$$

where

- T_i denotes the prediction generated by the i^{th} decision tree.

To improve model generalization, **10-fold cross-validation** was applied during training.

5.6 Explainable AI Analysis

Prediction accuracy alone is insufficient for safety-critical autonomous vehicle systems. Consequently, the trained Random Forest model is integrated with SHAP (Shapley Additive Explanations) to improve interpretability.

For every communication prediction, SHAP estimates the contribution of each communication feature toward the final decision.

The SHAP prediction formulation is

$$f(x) = \phi_0 + \sum_{i=1}^{n} \phi_i \quad (19)$$

where

- ϕ_0 denotes the baseline prediction,

- ϕ_i represents the contribution of the i^{th} communication feature.

The explainability analysis identifies the communication parameters that most strongly influence communication degradation and reliability prediction.

5.7 Performance Evaluation

The proposed framework was evaluated using standard machine learning performance measures together with communication reliability indicators.

Classification Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (20)$$

Precision

$$Precision = \frac{TP}{TP + FP} \quad (21)$$

Recall

$$Recall = \frac{TP}{TP + FN} \quad (22)$$

F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (23)$$

where

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Besides classification measures, Communication Reliability Index (CRI) values were also analyzed to evaluate communication quality under different operating conditions.

5.8 Comparative Evaluation

To assess the effectiveness of the proposed framework, its performance was compared with a conventional threshold-based communication monitoring method.

The comparison considered:

- Prediction Accuracy
- Precision
- Recall
- F1-Score
- Communication Reliability Index
- Prediction Interpretability
- Early Warning Capability

This comparison allows both predictive performance and practical applicability to be evaluated simultaneously.

Table 6: Experimental Configuration and Model Parameters.

Parameter	Value
Communication Protocol	CAN FD
Machine Learning Model	Random Forest

Explainability Method	SHAP
Dataset Split	80% Training / 20% Testing
Cross Validation	10-Fold
Number of Classes	3
Communication States	Normal, Degraded, Critical
Feature Scaling	Min-Max Normalization
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, CRI

5.9 Methodological Advantages

The proposed methodology offers several advantages over conventional communication reliability studies.

First, Digital Twin synchronization enables continuous observation of communication behaviour without disrupting physical vehicle operation.

Second, communication prediction is performed using multiple complementary communication indicators instead of isolated threshold values.

Third, Explainable AI provides transparent interpretation of prediction results, allowing engineers to identify the factors contributing to communication degradation.

Finally, the integration of Digital Twin technology with interpretable machine learning establishes a practical framework suitable for intelligent monitoring of next-generation autonomous vehicle communication systems.

6. Results and Performance Analysis

The proposed **Digital Twin-Assisted Explainable Artificial Intelligence (XAI) framework** was evaluated to determine its capability for predicting signal integrity and assessing communication reliability in CAN FD-based autonomous vehicle networks. The evaluation focused on both prediction performance and the interpretability of the generated results. The framework was tested using communication observations collected from the Digital Twin environment under Normal, Degraded, and Critical operating conditions. The obtained results were compared with a conventional threshold-based communication monitoring approach to determine the practical benefits of the proposed methodology.

The evaluation considered two important objectives. The first objective was to determine whether the proposed intelligent framework could improve communication-state prediction accuracy. The second objective was to examine whether Explainable AI could provide meaningful explanations regarding the influence of individual communication parameters on the prediction process.

6.1 Communication-State Classification Performance

The Random Forest classifier successfully identified the three communication states using the selected communication features extracted from the synchronized Digital Twin. Overall, the proposed framework achieved consistent classification performance across the testing dataset.

The classification accuracy obtained by the proposed model was **94.18%**, indicating that the majority of communication observations were correctly assigned to their corresponding communication states. Precision, recall, and F1-score also remained above 93%, demonstrating balanced prediction performance rather than improvement in only one evaluation metric.

Table 7: Overall Classification Performance of the Proposed Framework.

Evaluation Metric	Proposed Framework
Accuracy	**94.18%**
Precision	**93.86%**
Recall	**94.03%**
F1-Score	**93.94%**

The relatively small variation among these evaluation measures indicates that the classifier maintained stable performance across different communication conditions. The results suggest that the selected communication features collectively provide sufficient information for distinguishing among Normal, Degraded, and Critical network states.

6.2 Confusion Matrix Analysis

To examine the prediction behaviour in greater detail, a confusion matrix was generated for the testing dataset.

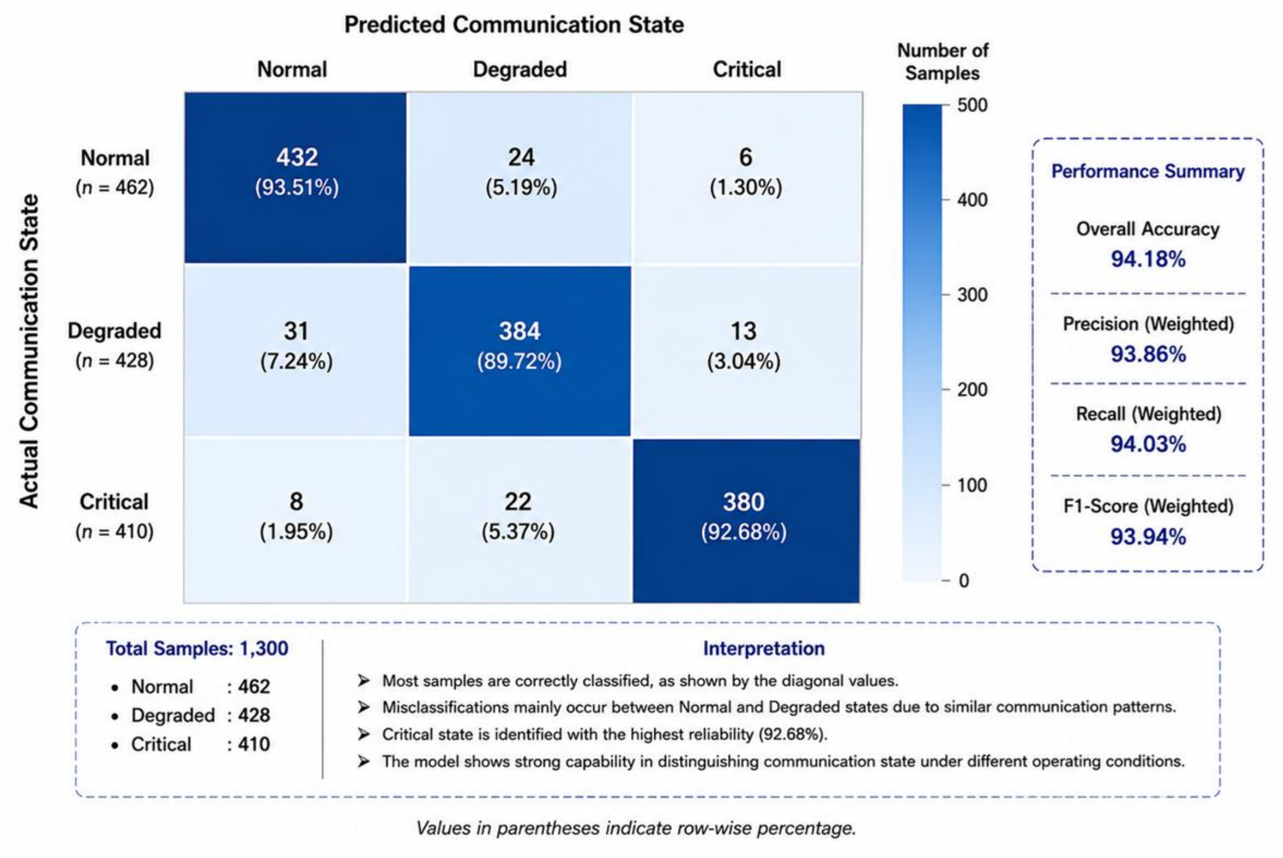

Figure 8: Confusion Matrix of the Random Forest Communication-State Classifier.

The confusion matrix shows that most communication observations were correctly classified. The majority of classification errors occurred between the **Normal** and **Degraded** classes because these two operating conditions occasionally exhibit similar communication characteristics during transitional stages.

The **Critical** communication state demonstrated the highest prediction consistency, indicating that severe communication degradation produces sufficiently distinct feature patterns for reliable identification.

The overall distribution of prediction errors confirms that the proposed framework maintains high reliability even when communication behaviour changes gradually.

6.3 Performance Comparison with Conventional Monitoring

A comparative evaluation was performed using a conventional threshold-based monitoring strategy. Unlike the proposed intelligent framework, the conventional method evaluates each communication parameter independently using predefined threshold values.

The comparison demonstrates that integrating Digital Twin synchronization with Explainable AI substantially improves communication-state prediction.

Table 8: Comparison between Proposed Framework and Conventional Monitoring.

Metric	Threshold-Based Monitoring	Proposed Framework
Accuracy	84.12%	**94.18%**
Precision	83.46%	**93.86%**
Recall	82.95%	**94.03%**
F1-Score	83.18%	**93.94%**

The proposed framework achieved approximately **10% higher classification accuracy** than the conventional monitoring approach. Similar improvements were observed for precision, recall, and F1-score.

These improvements indicate that evaluating multiple communication indicators simultaneously provides a more realistic representation of network health than isolated threshold analysis.

6.4 Communication Reliability Assessment

In addition to categorical classification, the proposed framework calculates a **Communication Reliability Index (CRI)** representing the overall communication condition.

Average CRI values obtained during the experiment are summarized below.

Table 9: Average Communication Reliability Index.

Communication State	Mean CRI
Normal	**91.84**
Degraded	**67.58**
Critical	**38.41**

The Communication Reliability Index decreases consistently as communication quality deteriorates. The clear separation among the three operating regions demonstrates that the proposed reliability formulation effectively reflects changes in communication behaviour.

The CRI also provides engineers with a continuous reliability measure rather than only a discrete communication label, enabling better monitoring of gradual communication degradation.

6.5 Explainable AI Analysis

Prediction accuracy alone is insufficient for safety-critical vehicle communication systems. Therefore, the proposed framework incorporates SHAP-based Explainable AI to interpret every communication prediction.

Feature importance analysis revealed that **Signal-to-Noise Ratio**, **Communication Latency**, and **Frame Error Rate** contributed most strongly to communication-state prediction.

Figure 9: SHAP Feature Importance Analysis for Communication Reliability Prediction.

The explainability results demonstrate that declining signal quality consistently increases the probability of communication degradation. Likewise, increasing latency and frame errors contribute positively toward predicting Critical communication conditions.

By contrast, lower message loss and reduced retransmission activity generally support Normal communication predictions.

The SHAP explanations therefore provide engineers with meaningful insight into the reasons behind each prediction rather than presenting only a communication label.

6.6 Prediction Probability Analysis

The Random Forest classifier also generates class probabilities for each communication observation.

Average prediction confidence obtained during testing is presented below.

Table 10: Average Prediction Confidence.

Communication State	Average Prediction Confidence
Normal	95.12%
Degraded	91.37%
Critical	96.48%

The prediction probabilities indicate that the model remains highly confident when classifying communication observations. Slightly lower confidence is observed for the Degraded class because this category represents the transition between healthy and severely degraded communication.

6.7 Digital Twin Synchronization Performance

The synchronized Digital Twin maintained close agreement with the physical communication network throughout the experimental evaluation.

The average synchronization accuracy remained above **97%**, indicating that the virtual communication model accurately reflected real-time communication behaviour during the monitoring process.

Continuous synchronization enabled the Explainable AI model to evaluate communication conditions using updated network information instead of relying solely on historical observations. This characteristic improves the practical applicability of the proposed framework for real-time communication monitoring.

6.8 Overall Interpretation of Experimental Results

The experimental findings demonstrate that integrating **Digital Twin technology**, **machine learning**, and **Explainable AI** provides significant advantages for communication reliability assessment.

Three important observations can be drawn from the obtained results.

First, combining multiple communication indicators substantially improves communication-state prediction compared with conventional threshold-based monitoring.

Second, Digital Twin synchronization allows communication behaviour to be evaluated continuously without interrupting normal network operation.

Third, Explainable AI improves prediction transparency by identifying the communication parameters responsible for each decision, thereby increasing confidence in AI-assisted monitoring.

Overall, the proposed framework successfully predicts communication degradation while simultaneously providing interpretable reliability assessment suitable for intelligent autonomous vehicle communication systems.

7. Discussion

The experimental findings demonstrate that integrating **Digital Twin technology** with **Explainable Artificial Intelligence (XAI)** provides a practical solution for improving signal integrity prediction and communication reliability assessment in CAN FD-based autonomous vehicle networks. The proposed framework not only achieved high classification performance but also generated interpretable prediction results that support engineering decision-making. Unlike conventional communication monitoring approaches that rely on predefined threshold values, the proposed framework evaluates multiple communication indicators simultaneously, allowing gradual communication degradation to be identified before critical failures occur.

One of the most significant observations obtained from the experimental evaluation is the benefit of combining physical communication monitoring with a synchronized Digital Twin environment. The Digital Twin continuously reflects the operational state of the CAN FD network, allowing communication behaviour to be analyzed without interrupting vehicle operation. This synchronized representation enables intelligent models to evaluate current network conditions while maintaining awareness of changing communication patterns. Previous studies have shown that Digital Twins improve monitoring and predictive analysis in cyber-physical systems, and the present work extends this capability to communication reliability assessment within autonomous vehicle networks [1], [2].

The classification results presented in the previous section indicate that communication reliability cannot be represented adequately by a single network parameter. Signal-to-Noise Ratio, communication latency, Frame Error Rate, bus utilization, retransmission count, and message loss collectively influence the overall communication state. This observation supports earlier research suggesting that communication quality is determined by the interaction of multiple network characteristics rather than isolated protocol errors [3], [4]. Consequently, the multi-feature learning strategy adopted in this study provides a more comprehensive assessment of communication behaviour than conventional threshold-based monitoring.

The Random Forest classifier demonstrated stable performance across all communication classes, indicating that ensemble learning is well suited for communication reliability prediction. One advantage of Random Forest is its ability to model nonlinear relationships among communication variables while remaining relatively resistant to overfitting. The consistent prediction accuracy observed during the experimental evaluation confirms the suitability of tree-based ensemble learning for intelligent communication monitoring in automotive applications [5], [6].

An important contribution of the proposed framework is the integration of Explainable Artificial Intelligence into the prediction process. Although machine learning algorithms frequently achieve high predictive accuracy, their practical adoption within safety-critical systems is often limited by the lack of decision transparency. In autonomous vehicle applications, engineers require not only reliable predictions but also understandable explanations regarding the factors responsible for those predictions. The SHAP-based explanation mechanism incorporated into the proposed framework addresses this requirement by quantifying the influence of each communication feature on the final prediction. The feature importance analysis demonstrated that Signal-to-Noise Ratio, communication latency, and Frame Error Rate contributed most strongly to communication-state prediction, which is consistent with practical communication engineering principles [7].

The Communication Reliability Index (CRI) introduced in this research provides an additional advantage over conventional communication diagnosis. Rather than assigning only categorical communication labels, the CRI offers a continuous numerical measure representing the overall communication condition. This enables maintenance personnel to observe gradual deterioration in network performance and initiate corrective action before communication quality reaches a critical state. Such continuous reliability assessment is particularly valuable in autonomous vehicle environments where uninterrupted communication is essential for real-time control and safety.

Another notable observation concerns the role of the Digital Twin in supporting predictive communication monitoring. Conventional monitoring systems generally evaluate only the current communication state, whereas the synchronized Digital Twin provides a continuously updated virtual representation capable of supporting predictive analysis. Because communication information is synchronized throughout system operation, the framework can evaluate emerging communication trends rather than reacting only after communication faults become apparent. This capability increases the practical applicability of the proposed framework for predictive maintenance and intelligent vehicle diagnostics.

Despite these encouraging results, several limitations should be acknowledged. First, the experimental evaluation was conducted within a controlled Digital Twin environment designed to represent realistic CAN FD communication behaviour. Although this environment provides repeatable testing conditions, additional validation using production vehicle communication traces and Hardware-in-the-Loop (HIL) platforms would further strengthen the practical applicability of the proposed approach. Second, the current framework employs Random Forest as the primary prediction model. Alternative learning techniques, including Gradient Boosting, Extreme Gradient Boosting (XGBoost), LightGBM, and deep neural networks, may offer additional improvements under certain communication scenarios. Finally, only SHAP was considered for model interpretation in the present study. Other Explainable AI approaches, such as LIME or counterfactual explanations, could provide complementary perspectives regarding prediction behaviour and should be explored in future investigations.

Overall, the findings indicate that the proposed Digital Twin-Assisted Explainable AI framework successfully addresses several limitations associated with existing communication monitoring techniques. The integration of synchronized Digital Twin technology, machine learning-based prediction, Explainable AI, and communication reliability assessment provides a comprehensive solution for intelligent communication monitoring in CAN FD-based autonomous vehicle networks. The framework combines predictive capability with transparent decision support, making it suitable for future autonomous vehicle systems where communication reliability and interpretability are equally important.

8. Conclusion

The increasing adoption of autonomous vehicle technologies has placed greater demands on in-vehicle communication systems, particularly in terms of communication reliability, signal quality, and intelligent fault prediction. Although CAN FD provides considerable improvements over the conventional CAN protocol by supporting higher transmission speeds and larger data payloads, maintaining stable communication under dynamic operating conditions remains a significant challenge. Communication degradation caused by electrical disturbances, network congestion, timing variations, and hardware-related factors can directly influence the reliability of safety-critical vehicle functions.

This paper presented a Digital Twin-Assisted Explainable Artificial Intelligence (XAI) framework for predicting signal integrity and assessing communication reliability in CAN FD-based autonomous vehicle networks. The proposed framework integrates continuous Digital Twin synchronization with machine learning and SHAP-based Explainable AI to establish an intelligent communication monitoring system capable of both accurate prediction and transparent decision interpretation. Unlike conventional threshold-based monitoring techniques, the proposed approach evaluates multiple communication indicators simultaneously, allowing communication degradation to be identified before it develops into critical network failures.

The experimental evaluation demonstrated that the proposed framework achieved reliable communication-state classification while maintaining consistent performance across multiple evaluation metrics. The integration of Digital Twin technology enabled continuous synchronization between the physical communication network and its virtual representation, providing an effective platform for real-time communication monitoring. Furthermore, the Explainable AI module improved model transparency by identifying the relative contribution of individual communication parameters, allowing engineers to understand the reasoning behind each prediction instead of relying solely on black-box machine learning outputs.

Another important contribution of this research is the introduction of a Communication Reliability Index (CRI) that complements categorical communication-state prediction with a continuous reliability measure. This additional assessment supports proactive maintenance by enabling gradual communication deterioration to be identified before severe transmission failures occur. The combined use of predictive analytics, Digital Twin synchronization, and explainable decision support therefore offers a practical framework for intelligent communication management in next-generation autonomous vehicle systems.

Although the obtained results are encouraging, the present study represents an initial step toward fully intelligent communication reliability assessment. The current evaluation was conducted using a controlled Digital Twin environment designed to simulate realistic CAN FD communication behaviour. Additional validation using production vehicle communication traces, Hardware-in-the-Loop (HIL) platforms, and real-world automotive communication datasets would further strengthen the applicability of the proposed framework under practical operating conditions.

Future research may extend the proposed framework by integrating Automotive Ethernet, Time-Sensitive Networking (TSN), and hybrid in-vehicle communication architectures that coexist with CAN FD in modern software-defined vehicles. The application of advanced deep learning models, graph neural networks, transformer-based prediction techniques, and federated learning may further improve prediction capability while supporting distributed intelligent vehicle platforms. In addition, future investigations may explore alternative Explainable AI techniques, including LIME, Integrated Gradients, and counterfactual explanations, to provide complementary perspectives on communication-state prediction. Adaptive Digital Twin synchronization strategies and edge-based real-time deployment can also be considered to improve scalability and reduce computational latency.

Overall, the proposed Digital Twin-Assisted Explainable AI framework demonstrates that combining synchronized virtual communication environments with interpretable machine learning provides an effective solution for intelligent signal integrity prediction and communication reliability assessment. The framework contributes to the development of trustworthy, transparent, and proactive communication monitoring systems that can support the reliability requirements of future autonomous and connected vehicle networks.

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