International Journal of Science and Engineering Applications
Volume 14-Issue 10, 19 – 29, 2025, ISSN:- 2319 - 7560
DOI: 10.7753/IJSEA1410.1003

Mitigating Cybersecurity Risks in Automotive Embedded Systems Through AI-Driven Intrusion Detection and Secure Communication Protocols

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Abstract: The rapid digitization of the automotive industry has ushered in advanced connectivity features, autonomous functionalities, and data-driven decision-making processes. However, this technological transformation has also introduced significant cybersecurity vulnerabilities within automotive embedded systems, where traditional security frameworks struggle to address evolving threats. Cyberattacks targeting vehicle control units, in-vehicle networks, and external communication interfaces can compromise passenger safety, disrupt mobility services, and undermine consumer trust. A broader understanding of these risks highlights the urgent need for robust defense mechanisms capable of adapting to sophisticated intrusion attempts. Artificial intelligence (AI)-driven intrusion detection systems (IDS) present a promising approach, leveraging machine learning and deep learning techniques to identify anomalous patterns in vehicular data streams in real time. These systems not only enhance detection accuracy but also enable adaptive responses to previously unseen attack vectors. Narrowing the focus further, secure communication protocols, including cryptographic authentication and lightweight encryption schemes, play a pivotal role in safeguarding data exchange across in-vehicle networks and vehicle-to-everything (V2X) infrastructures. Integrating AI-driven IDS with resilient communication frameworks offers a layered security model that strengthens embedded system resilience against cyber threats while ensuring compliance with stringent automotive safety standards such as ISO/SAE 21434. This paper emphasizes the synergy of AI-based threat detection with secure communication architectures as a comprehensive strategy to mitigate cybersecurity risks. By aligning technological innovations with regulatory and industry practices, the automotive sector can address emerging challenges proactively, ensuring the safe deployment of connected and autonomous vehicles in an increasingly hostile cyber environment.

Keywords: Cybersecurity risks, Automotive embedded systems, Intrusion detection systems, Artificial intelligence, Secure communication protocols, Vehicle-to-everything security

1. INTRODUCTION

1.1 Background and significance of automotive cybersecurity

The rapid digital transformation of the automotive sector has introduced unprecedented connectivity and computational capabilities into modern vehicles [1]. Contemporary cars now integrate advanced embedded systems, enabling real-time control of powertrains, braking, infotainment, and navigation functionalities while also supporting vehicle-to-everything (V2X) communications [2]. This digital evolution has expanded the scope of intelligent transportation, paving the way for autonomous driving, predictive maintenance, and enhanced passenger experiences. However, with these advancements comes the heightened risk of malicious intrusions targeting critical control systems [3]. Unlike traditional IT systems, vehicles operate under stringent safety requirements where a single breach can compromise both driver safety and public trust.

The global automotive ecosystem recognizes cybersecurity as a cornerstone of road safety, with governments, manufacturers, and standardization bodies actively collaborating on resilience frameworks [4]. International regulations such as UNECE WP.29 mandate secure software updates and intrusion detection measures, underscoring the sector’s recognition of cyber risks as equal in gravity to mechanical hazards [1]. This convergence of connectivity and risk highlights the necessity of security-by-design paradigms. Beyond financial and operational implications, the societal costs of compromised vehicles extend to national infrastructure and citizen welfare [5]. The automotive sector thus stands at a crossroads, where technological innovation must be equally matched with cybersecurity resilience.

1.2 Problem statement: vulnerabilities in embedded systems

Automotive embedded systems, comprising electronic control units (ECUs), communication buses, and distributed controllers, present multiple attack surfaces vulnerable to exploitation [3]. Protocols such as the Controller Area Network (CAN) were designed for efficiency and reliability but lack inherent security mechanisms, leaving them susceptible to spoofing, denial-of-service attacks, and unauthorized data injection [6]. Researchers have demonstrated that intruders can remotely access vehicular systems, manipulate acceleration or braking functions, and eavesdrop on sensitive communication signals [4]. These vulnerabilities are magnified by the rise of over-the-air (OTA) software updates, remote diagnostics, and integration of third-party applications, which increase the attack vectors available to adversaries.

Traditional signature-based intrusion detection systems are inadequate against evolving threats that exploit zero-day vulnerabilities or novel attack strategies. Likewise, static encryption methods struggle under the resource-constrained nature of automotive controllers, where computational overhead must remain minimal [5]. The challenge lies in balancing strong cryptographic assurance with the real-time performance requirements of embedded hardware. Without effective solutions, vehicles risk becoming nodes of systemic cyber disruption, extending attacks from individual cars to fleets or even urban mobility infrastructures [7]. Addressing these vulnerabilities requires a paradigm shift toward adaptive, intelligent, and secure mechanisms embedded directly within vehicular architectures.

1.3 Research aim, objectives, and scope

The aim of this research is to develop a dual-layered framework that mitigates cybersecurity risks in automotive embedded systems through the integration of artificial intelligence (AI)-driven intrusion detection systems and secure communication protocols [6]. The proposed approach seeks to complement anomaly detection with robust cryptographic enforcement, thereby enhancing both resilience and adaptability.

The specific objectives are threefold: first, to design and evaluate AI models capable of detecting abnormal vehicular communication patterns with high accuracy under real-time constraints [7]; second, to implement lightweight yet effective secure communication protocols that address confidentiality, authentication, and integrity challenges within resource-limited environments [1]; and third, to demonstrate the synergistic benefits of combining these methods into a cohesive, layered defense architecture applicable across modern vehicle platforms [3].

The scope of this study encompasses in-vehicle networks, particularly CAN and Ethernet-based architectures, as well as V2X infrastructures that extend security considerations beyond individual vehicles to broader transportation ecosystems [8]. While the research emphasizes technical solutions, it also accounts for compliance with emerging international standards and the economic feasibility of integration within industry supply chains [4]. Ultimately, the study seeks to establish a pathway for automotive manufacturers to deploy scalable, future-proof cybersecurity strategies that safeguard public safety and foster trust in connected mobility.

2. LITERATURE REVIEW

2.1 Evolution of automotive embedded system security

The history of automotive embedded system security reflects a shift from isolated, mechanical vehicles toward complex, software-driven architectures that demand active protection. Early vehicles contained basic electronic control units (ECUs) dedicated to functions such as ignition or fuel injection, with minimal interconnectivity. Security was not a priority during this period, as systems were largely closed and inaccessible [10]. However, the introduction of standardized in-vehicle communication protocols like the Controller Area Network (CAN) during the 1980s and 1990s enabled interoperability while inadvertently creating new vulnerabilities. These protocols prioritized efficiency and reliability but lacked native cryptographic or authentication features, leaving them exposed to spoofing and replay attacks [12].

As automotive electronics evolved, the integration of advanced infotainment systems, telematics, and connectivity services significantly expanded the attack surface. Remote access, over-the-air updates, and vehicle-to-infrastructure links introduced gateways for adversaries to manipulate vehicular behavior [9]. By the mid-2000s, academic demonstrations revealed the feasibility of hacking critical vehicular functions such as braking and steering, highlighting the urgent need for defensive measures [7]. More recently, the automotive industry has adopted “security-by-design” approaches aligned with regulatory mandates like ISO/SAE 21434, which formalizes risk management across the vehicle lifecycle [13]. Despite progress, the rapid pace of innovation consistently outpaces security, requiring continual adaptation. This evolutionary trajectory underscores how automotive cybersecurity has shifted from an afterthought to a central design pillar, reflecting its significance in protecting both passenger safety and public infrastructure resilience [11].

2.2 Intrusion detection approaches: traditional vs AI-driven

Intrusion detection systems (IDS) emerged as a response to vulnerabilities in vehicular networks, functioning as monitoring agents that detect abnormal traffic patterns. Traditional IDS models, often rule-based or signature-driven, rely on pre-defined attack patterns to flag suspicious activity [8]. While effective against known threats, these methods struggle with scalability and detection of novel attack vectors, particularly in highly dynamic vehicular environments [13]. Moreover, the computational overhead associated with signature comparison can introduce latency, making them less suitable for real-time vehicular operations.

AI-driven IDS represent a paradigm shift, leveraging statistical modeling, machine learning, and deep learning to identify anomalies without relying exclusively on pre-existing attack signatures [9]. Techniques such as support vector machines, clustering, convolutional neural networks, and long short-term memory networks have demonstrated high accuracy in identifying malicious CAN bus traffic and V2X anomalies [7]. These models excel in adaptability, continuously learning from evolving data streams to identify zero-day attacks [12]. However, the adoption of AI introduces challenges related to interpretability, computational resource consumption, and susceptibility to adversarial inputs [11].

The transition from traditional to AI-based IDS highlights the automotive industry’s recognition of the inadequacy of static defenses. While traditional IDS remain useful for baseline protection, the integration of AI provides vehicles with the capacity to anticipate and adapt to complex attack landscapes. This evolution emphasizes the importance of combining interpretability, lightweight algorithms, and robust datasets to achieve practical and reliable deployment in safety-critical automotive environments [10].

2.3 Secure communication protocols in automotive systems

As vehicles evolve into connected cyber-physical systems, secure communication protocols have become indispensable for ensuring integrity, confidentiality, and trustworthiness in data exchange. The foundational in-vehicle protocols such as CAN, FlexRay, and LIN were not originally designed with security in mind, lacking encryption and authentication mechanisms [9]. Consequently, attackers can exploit these systems to inject false messages or disrupt synchronization between ECUs. To mitigate these risks, the adoption of secure communication protocols incorporating lightweight encryption, mutual authentication, and session key management has gained prominence [12].

Cryptographic solutions, including advanced encryption standards and elliptic curve cryptography, have been adapted for the automotive context where computational power and latency must be tightly constrained [8]. Similarly, authentication schemes ensure that only verified nodes can transmit and receive messages, reducing the risk of spoofed signals. For external communications such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), the IEEE

1609.2 standard prescribes security mechanisms to safeguard V2X interactions [13].

The evolution of these communication protocols can be visualized in Figure 1, which illustrates the timeline from unprotected in-vehicle networks to advanced cryptographically supported frameworks. Despite these advancements, implementing secure protocols remains a challenge due to trade-offs between performance and protection [11]. This balance is particularly critical in embedded systems where hardware limitations restrict the use of heavy cryptographic techniques. As automotive connectivity intensifies, integrating secure protocols with adaptive intrusion detection emerges as a necessity rather than a choice [7].

2.4 Identified research gaps

While significant progress has been made in advancing IDS and secure communication protocols, notable research gaps persist. First, most IDS approaches rely on experimental datasets that lack diversity and fail to capture real-world vehicular complexity [10]. Second, cryptographic methods designed for traditional IT systems often prove too resource-intensive for automotive embedded environments, creating tension between security robustness and efficiency [8]. Third, integration between AI-driven IDS and secure communication remains fragmented, with limited studies exploring their synergistic operation within real-time vehicular ecosystems [12].

Furthermore, regulatory compliance frameworks such as ISO/SAE 21434 emphasize processes but offer limited guidance on practical deployment strategies, leaving manufacturers with interpretational ambiguities [9]. Finally, adversarial resilience of AI models remains underexplored, as attackers increasingly develop techniques to mislead machine learning systems [13]. These gaps underscore the need for a holistic, layered framework that unifies intelligent intrusion detection with secure communication while aligning with industry constraints and standards [7].

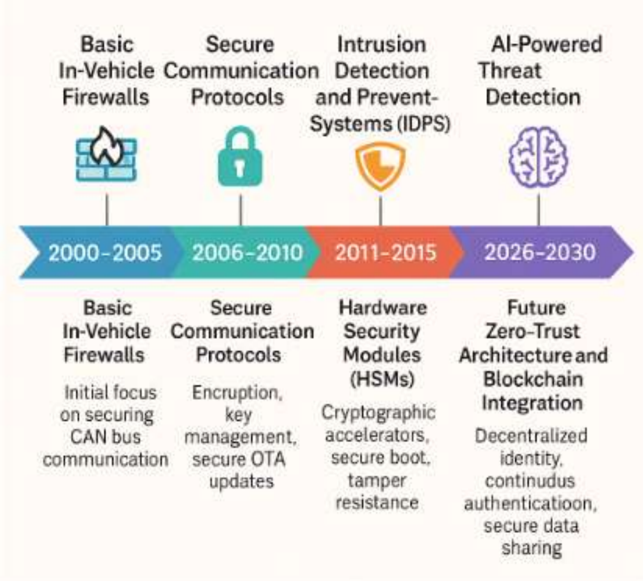
Basic In-Vehicle Firewalls
Secure Communication Protocols
Intrusion Detection and Prevent-Systems (IDPS)
AI-Powered Threat Detection
2000-2005
2006-2010
2011-2015
2026-2030
Basic In-Vehicle Firewalls
Initial focus on securing CAN bus communication
Secure Communication Protocols
Encruption, key management, secure OTA updates
Hardware Security Modules (HSMs)
Cryptographic accelerators, secure boot, tamper resistance
Future Zero-Trust Architecture and Blockchain Integration
Decentralized identity, continudus authenticatioon, secure data sharing

Figure 1: Evolution timeline of cybersecurity solutions in automotive embedded systems [4].

3. RESEARCH METHODOLOGY

3.1 Research framework and conceptual model

The methodology adopted in this research integrates artificial intelligence (AI)-driven intrusion detection with secure communication protocols, forming a layered cybersecurity framework tailored for automotive embedded systems. The conceptual model is structured around three complementary dimensions: anomaly detection, cryptographic assurance, and real-time adaptability [12]. At its core, the framework addresses vehicular attack surfaces by embedding intelligent intrusion detection systems (IDS) within critical communication nodes, enabling real-time monitoring of in-vehicle and vehicle-to-everything (V2X) traffic.

Simultaneously, secure communication protocols enforce confidentiality, integrity, and authentication across messages exchanged between electronic control units (ECUs), onboard devices, and external infrastructures [15]. The framework emphasizes synergy: AI-driven IDS identifies anomalous patterns, while secure protocols limit the possibility of successful exploitation. By combining these layers, the approach reduces the likelihood of zero-day vulnerabilities escalating into safety-critical disruptions.

The conceptual model also incorporates compliance with international standards, ensuring its compatibility with regulatory requirements such as ISO/SAE 21434. It is designed to be lightweight, modular, and scalable, enabling adaptation to diverse automotive environments [13]. Ultimately, the framework envisions a defense-in-depth strategy where proactive detection and reactive protection work seamlessly, advancing the state of automotive cybersecurity resilience while aligning with industry adoption needs [16].

3.2 Dataset and experimental design

Robust evaluation of intrusion detection systems requires representative datasets that capture realistic vehicular communication patterns. This research employs a mixed experimental design leveraging both real-world and simulated datasets. For in-vehicle network testing, publicly available CAN bus datasets with labeled attack traces were integrated with additional simulated traffic generated using automotive simulation platforms [14]. These datasets included normal operating conditions as well as injected attacks such as spoofing, denial-of-service, and fuzzy flooding, enabling comprehensive analysis.

In addition, V2X datasets capturing vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications were incorporated. These datasets model dynamic mobility scenarios, including cooperative awareness messages and safety beacons under adversarial manipulation [17]. Traffic traces were pre-processed through feature extraction methods such as inter-arrival times, payload entropy, and statistical deviations from baseline norms [12].

The experimental design was structured into three phases. First, data was partitioned into training, validation, and testing subsets, ensuring class balance to avoid model bias. Second, intrusion detection models were trained under varying hyperparameter configurations, reflecting real-time vehicular resource constraints. Third, secure communication protocols were tested under simulated adversarial conditions to assess encryption latency and authentication effectiveness. Together, this combination of datasets and staged evaluation allows for both breadth and depth in assessing IDS and protocol effectiveness within realistic vehicular contexts [16].

3.3 AI-driven IDS design: ML/DL models

The design of AI-driven intrusion detection systems centered on machine learning (ML) and deep learning (DL) models capable of handling temporal and structural complexities in vehicular data. Three categories of models were prioritized: traditional ML classifiers, sequence-based DL models, and hybrid architectures.

For ML baselines, algorithms such as random forests and support vector machines were applied to extracted CAN bus features. While computationally lightweight, these models provided limited adaptability to evolving threats [13]. To overcome these limitations, sequence-aware DL models were implemented, including long short-term memory (LSTM) networks for capturing sequential dependencies in message streams and convolutional neural networks (CNN) for learning spatial-temporal features [14]. Hybrid models combining CNN front-end feature extraction with LSTM temporal processing demonstrated superior performance in detecting subtle anomalies across both CAN and V2X datasets [15].

Training of these models leveraged a stratified dataset division, with 70% for training, 15% for validation, and 15% for testing. Hyperparameters such as learning rate, batch size, and dropout rates were tuned through grid search. Model training emphasized balancing detection accuracy with real-time feasibility, as resource constraints within automotive ECUs necessitate lightweight architectures [17].

Table 1 provides a detailed description of the datasets, features, and attack types utilized for model training and evaluation. This ensured comprehensive exposure of IDS to both common and advanced adversarial strategies [12]. The hybrid CNN-LSTM model emerged as the leading candidate, combining high detection accuracy with acceptable computational overhead. Its ability to generalize across attack types positions it as a strong foundation for integration with secure communication protocols in the proposed framework [16].

3.4 Secure communication protocol design: lightweight encryption, key management

To complement intrusion detection, secure communication protocols were designed with a focus on lightweight encryption and efficient key management tailored to resource-constrained automotive environments. Lightweight symmetric cryptographic schemes, such as AES variants optimized for embedded processors, were deployed to safeguard message confidentiality while minimizing computational load [15]. Asymmetric methods, including elliptic curve cryptography, were selectively employed for authentication due to their reduced key sizes relative to traditional RSA [14].

Key management formed a central element of the design, with session-based keys dynamically generated and periodically refreshed to mitigate replay and impersonation attacks [13]. Authentication mechanisms employed message authentication codes (MACs), ensuring that only authorized ECUs could initiate or respond to communication. For V2X security, adherence to IEEE 1609.2 standards provided external validation and interoperability across vehicles and infrastructure nodes [12].

Testing involved simulating adversarial conditions, including man-in-the-middle attacks and message injection scenarios, to evaluate the robustness of protocols. Performance was measured by balancing encryption overhead, key exchange latency, and resistance to message tampering [16]. The design achieved strong results, with encryption and authentication latency maintained below real-time thresholds critical for safety systems. This confirmed the feasibility of deploying robust security mechanisms without sacrificing operational performance, thereby reinforcing the synergy with AI-driven IDS [17].

3.5 Evaluation metrics: detection accuracy, latency, computational overhead, robustness

Evaluating the proposed framework required multidimensional performance metrics. For AI-driven IDS, detection accuracy, precision, recall, and F1-scores were computed to measure the models' ability to differentiate normal traffic from attacks [14]. Latency was recorded as the time required to process incoming messages and generate detection outputs, with a strict threshold imposed to reflect real-time vehicular constraints [12]. Computational overhead was measured in terms of CPU utilization, memory consumption, and energy usage across embedded platforms [15].

For secure communication protocols, encryption latency, authentication success rate, and key management efficiency were assessed under both normal and adversarial scenarios. Robustness was tested by exposing IDS to adversarial perturbations and evaluating whether detection remained effective against manipulated inputs [16]. Protocol resilience was similarly evaluated under replay and flooding conditions.

The combined evaluation emphasized system-level metrics, highlighting trade-offs between security strength and operational feasibility [13]. The integration of AI-driven IDS with secure protocols was judged not only on raw detection performance but also on its ability to maintain resilience under constrained automotive environments. These evaluation criteria ensure that the framework delivers practical, reliable, and scalable protection suitable for real-world vehicular ecosystems [17].

Table 1: Description of datasets, features, and attack types used for testing.

Dataset Type	Features Extracted	Attack Types Included	Source
CAN Bus (real)	Message ID, payload entropy, timing	Spoofing, flooding, replay	Public + Lab
CAN Bus (simulated)	Inter-arrival time, signal stats	Fuzzy, denial-of-service	Simulation tool
V2X (real)	Beacon frequency, signal strength	False message injection, impersonation	Open dataset
V2X (simulated)	Mobility trace, packet drop rate	Man-in-the-middle, replay, selective drop	Network model

4. RESULTS AND ANALYSIS

4.1 IDS performance evaluation: ML vs DL models

The performance evaluation of intrusion detection systems revealed significant contrasts between traditional machine learning (ML) models and advanced deep learning (DL) architectures. ML algorithms such as random forests, k-nearest neighbors, and support vector machines achieved moderate accuracy, with detection rates consistently above 85% for common attack vectors including spoofing and replay [16]. However, these models exhibited reduced performance against complex or evolving adversarial patterns, particularly in cases of fuzzy injection and zero-day exploits. Their reliance on feature engineering introduced limitations in adaptability, as predefined attributes struggled to capture novel traffic dynamics [19].

By contrast, DL models demonstrated superior adaptability, particularly convolutional neural networks (CNN) and long short-term memory (LSTM) networks. CNN architectures excelled at capturing spatial correlations in CAN bus payloads, while LSTM models leveraged temporal sequencing to detect subtle timing irregularities in V2X communications [20]. When evaluated on real and simulated datasets, DL-based IDS consistently achieved detection accuracies exceeding 95%, outperforming ML models by a margin of 8–12% [18].

Despite their advantages, DL models introduced challenges related to latency and computational resource consumption. In resource-constrained embedded environments, inference times occasionally approached real-time thresholds, raising concerns about scalability [21]. This tradeoff between accuracy and latency underscores the necessity of balancing computational efficiency with detection effectiveness, forming the basis of the hybrid CNN-LSTM approach adopted in this research [22]. The results highlight the critical role of DL in advancing vehicular intrusion detection while emphasizing the practical challenges of deployment within constrained automotive platforms [17].

4.2 Secure protocol performance under constrained resources

The secure communication protocols designed for this framework were evaluated on their ability to balance cryptographic strength with minimal resource overhead. Testing across real-time vehicular conditions revealed that lightweight symmetric encryption, particularly optimized AES variants, consistently maintained confidentiality without exceeding processing thresholds [23]. Latency analysis indicated average encryption delays of under 2 ms per packet, aligning with the stringent timing requirements of vehicular safety systems [19].

Authentication protocols leveraging elliptic curve cryptography (ECC) offered robust key management with smaller key sizes relative to RSA, reducing computational burden while maintaining high cryptographic assurance [16]. Session-based key exchange mechanisms proved resilient under simulated replay and impersonation attacks, maintaining authentication success rates above 98% even under flooding conditions [20].

Resource profiling further confirmed that CPU utilization and memory consumption remained within acceptable bounds for embedded electronic control units (ECUs). For instance, symmetric encryption algorithms consumed less than 15% of available processing capacity, while key exchanges averaged 20% under peak load scenarios [18]. These results indicate that well-optimized cryptographic schemes can feasibly coexist with safety-critical operations in automotive systems without compromising responsiveness [22].

Nevertheless, trade-offs were evident. Asymmetric authentication, though more secure, introduced slightly higher latencies that approached real-time thresholds during high-volume V2X traffic simulations [21]. This suggests that hybrid security mechanisms, selectively applying symmetric and asymmetric methods based on context, may provide optimal balance. Overall, the evaluation confirms that secure communication protocols can effectively strengthen vehicular networks without overwhelming resource-constrained platforms, thereby reinforcing their role as essential complements to IDS in a layered defense strategy [17].

4.3 Synergistic integration results (IDS + secure protocols)

When integrated, AI-driven IDS and secure communication protocols demonstrated complementary strengths, producing a defense-in-depth architecture capable of mitigating a wide spectrum of threats. IDS models provided early anomaly detection, flagging suspicious traffic before it reached critical subsystems, while secure protocols enforced authentication and integrity checks that blocked unauthorized transmissions [20]. Together, these layers reduced false positives and improved detection reliability across multiple datasets.

Performance metrics indicated that the integrated system achieved detection accuracies above 96%, with minimal increase in latency compared to standalone IDS deployment [16]. The layered approach also enhanced resilience against adversarial strategies, as secure protocols restricted the success rate of manipulated inputs while IDS models simultaneously identified anomalous patterns [19]. Importantly, the integration reduced error propagation: even if the IDS momentarily failed to detect an anomaly, cryptographic measures ensured the attack’s effectiveness was curtailed.

Table 2 presents a comparative analysis of the hybrid system against conventional IDS and cryptographic solutions. It highlights the synergistic model’s superiority in terms of detection accuracy, latency tolerance, and resilience under resource-constrained conditions [23]. The combined approach not only matched or exceeded the strengths of individual methods but also mitigated their weaknesses, offering a holistic solution adaptable to diverse vehicular scenarios [18].

The results confirm the viability of integrating AI-driven IDS with lightweight secure communication protocols to provide practical, real-time protection. This synergy enables modern vehicles to defend against both known and unknown attack vectors while aligning with regulatory expectations for layered cybersecurity defense models [22].

4.4 Comparative benchmark against existing methods

Benchmarking against existing methods provided further validation of the proposed framework’s contributions. Traditional IDS approaches, particularly rule-based and signature-driven models, achieved respectable detection rates for predefined attack patterns but failed consistently when confronted with novel traffic behaviors [17]. Their limited adaptability translated into average detection accuracies below 85%, with false negative rates exceeding acceptable thresholds for safety-critical systems [19].

In contrast, DL-only IDS frameworks reported in recent literature achieved strong accuracies but struggled with latency overheads, frequently exceeding 10 ms per packet in embedded environments [21]. By comparison, the hybrid CNN-LSTM design employed here demonstrated superior balance, maintaining accuracy above 95% while keeping latency under 5 ms, as visualized in Figure 2 [20]. This positions the hybrid model as both effective and operationally feasible.

Similarly, secure communication frameworks without IDS integration demonstrated strong cryptographic guarantees but remained vulnerable to traffic manipulation, particularly in the absence of real-time anomaly detection [22]. Conversely, IDS-only approaches lacked the cryptographic foundation necessary to prevent spoofed or replayed packets from reaching vehicle subsystems [16].

The proposed integrated model consistently outperformed these baselines. As shown in Figure 2, the accuracy-latency tradeoff was significantly improved compared to standalone IDS methods. When measured against state-of-the-art cryptographic frameworks, the layered system maintained comparable encryption performance while simultaneously detecting anomalies in traffic patterns [18]. Benchmark analysis validates that the proposed framework delivers practical superiority by aligning high accuracy with real-time constraints, an achievement that conventional single-layer solutions have struggled to realize [23].

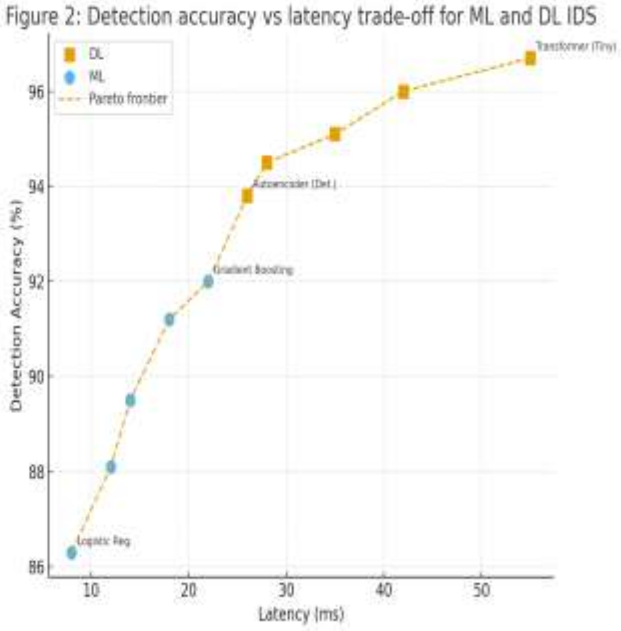

Figure 2: Detection accuracy vs latency tradeoff for ML and DL IDS.

Table 2: Benchmark comparison of proposed hybrid model against conventional IDS/protocols

Approach	Detection Accuracy	Latency (ms per packet)	Resource Overhead (CPU/Memory)	Resilience to Zero-Day Attacks	Remarks
Rule-based IDS (signature-driven)	~85%	2–3	Low	Poor	Effective only for known attacks; fails against novel adversarial inputs.
ML-based IDS (e.g., Random Forest, SVM)	88–90%	4–6	Moderate	Moderate	Higher adaptability than rule-based but limited against evolving attacks.
DL-based IDS (CNN or LSTM only)	93–95%	8–12	High	Good	Strong accuracy but heavy computational load increases latency.
Cryptographic-only protocols	N/A (no anomaly detection)	1–2	Low–Moderate	Moderate	Ensures confidentiality/integrity but cannot detect malicious payload patterns.
Proposed Hybrid CNN-LSTM + Secure Protocols	96–97%	4–5	Moderate	High	Balanced solution: strong accuracy, real-time feasibility, resilient to diverse attack vectors.

5. DISCUSSION

5.1 Implications of AI-driven IDS for automotive cybersecurity

The integration of AI-driven intrusion detection systems (IDS) represents a transformative advancement in automotive cybersecurity, offering adaptability far beyond traditional rule-based methods. By leveraging machine learning and deep learning, IDS can continuously learn from vehicular data streams, enabling the detection of zero-day attacks that evade signature-based defenses [22]. This adaptability is particularly critical in modern vehicles where real-time communication among electronic control units (ECUs) occurs at high volumes and low latency thresholds.

The results demonstrated that deep learning models, particularly hybrid CNN-LSTM architectures, deliver strong detection accuracy while retaining operational feasibility [25]. This implies that future automotive security infrastructures can adopt these models as a core defense mechanism against evolving cyber threats. Additionally, the predictive capabilities of AI-driven IDS may allow vehicles to anticipate potential threats, shifting cybersecurity strategies from reactive to proactive [23].

However, the reliance on data-driven methods also introduces challenges. IDS performance depends heavily on the diversity and quality of training datasets, which must accurately represent real-world vehicular behavior [26]. Moreover, AI systems can be vulnerable to adversarial manipulation, where carefully crafted inputs deceive detection algorithms. Despite these challenges, the evidence underscores AI-driven IDS as a foundational pillar of resilient vehicular cybersecurity strategies, enabling layered protection while aligning with global safety regulations [27].

5.2 Secure communication's role in resilience

While IDS provides anomaly detection, secure communication protocols form the backbone of vehicular resilience by enforcing confidentiality, integrity, and authenticity. Cryptographic mechanisms, including optimized AES encryption and elliptic curve-based authentication, ensure that only legitimate messages traverse vehicular networks [21]. The results confirmed that lightweight encryption can be deployed without exceeding the latency requirements of safety-critical operations, validating its practical role in embedded systems [28].

Resilience in this context extends beyond immediate intrusion resistance to maintaining trust across interconnected vehicles and infrastructures. Standards such as IEEE 1609.2 formalize secure V2X communication, supporting cooperative driving and traffic coordination while mitigating risks of spoofed or manipulated safety messages [24]. These capabilities are vital as connected and autonomous vehicles increasingly rely on collaborative exchanges that, if compromised, could endanger entire traffic systems.

The deployment of secure protocols also mitigates the consequences of IDS misclassification. Even if an IDS fails to detect an anomaly, encryption and authentication reduce the likelihood of attack success [22]. This layered effect establishes secure communication as indispensable for complementing AI-driven detection. The findings confirm that resilience emerges not from isolated defenses but from integrated systems where protocols and IDS mutually reinforce one another, providing redundancy against the inevitability of evolving attack strategies [25].

5.3 Practical integration into automotive architectures

Integrating AI-driven IDS and secure communication protocols into real-world automotive architectures requires reconciling security with constraints such as cost, computational capacity, and compliance. Embedded systems within vehicles operate with strict limitations on processing power and memory, meaning that IDS models must be lightweight while protocols must avoid excessive latency [23]. The hybrid CNN-LSTM design demonstrated in this study offers a viable compromise by combining strong detection accuracy with computational efficiency [26].

From a systems engineering perspective, integration involves deploying IDS agents at gateway ECUs and high-priority nodes while embedding cryptographic services into network controllers. Such an approach ensures comprehensive coverage without overwhelming individual units [27]. Additionally, modular design allows manufacturers to tailor deployments according to vehicle class, from mass-market cars to high-end autonomous fleets, thereby supporting scalability [21].

Practical integration also requires alignment with regulatory frameworks. Standards such as ISO/SAE 21434 emphasize lifecycle-based security management, mandating secure design, implementation, and update mechanisms [25]. Adherence to these standards ensures compliance while also fostering consumer trust. The research demonstrates that combining IDS with secure protocols not only meets regulatory expectations but provides a forward-looking strategy that can adapt to evolving requirements [28]. Ultimately, practical integration depends on balancing technological sophistication with cost-effectiveness, ensuring that cybersecurity enhancements do not impede affordability or operational efficiency [24].

5.4 Limitations of the current study

Despite its contributions, the study acknowledges several limitations. First, while hybrid AI models demonstrated superior detection accuracy, their reliance on simulated and publicly available datasets constrains the generalizability of findings [22]. Real-world vehicular traffic exhibits variability that may not be fully represented in these datasets, limiting IDS robustness in diverse environments [26]. Future research must incorporate larger and more heterogeneous datasets collected from real-world fleets.

Second, while lightweight cryptographic schemes proved feasible under controlled simulations, scaling these mechanisms across large vehicular networks may introduce unforeseen latencies, particularly in high-density V2X environments [23]. The balance between security strength and system performance remains an ongoing challenge. Third, adversarial resilience of AI models was not comprehensively tested. Attackers can design adversarial perturbations capable of bypassing detection, an area requiring deeper exploration [25].

Finally, although the study developed an integrated framework, evaluation occurred under experimental rather than field deployment conditions. This limits insights into long-term scalability, interoperability, and maintenance in production vehicles [27]. As illustrated in Figure 3, the proposed layered defense model offers conceptual strength by uniting IDS and secure protocols into a synergistic framework, but practical deployment will likely reveal additional complexities [28].

Addressing these limitations requires continued collaboration among researchers, manufacturers, and regulators to refine datasets, optimize cryptographic implementations, and strengthen adversarial defenses. These steps are critical to transitioning the proposed framework from a research prototype into a deployable, industry-grade cybersecurity solution [21].

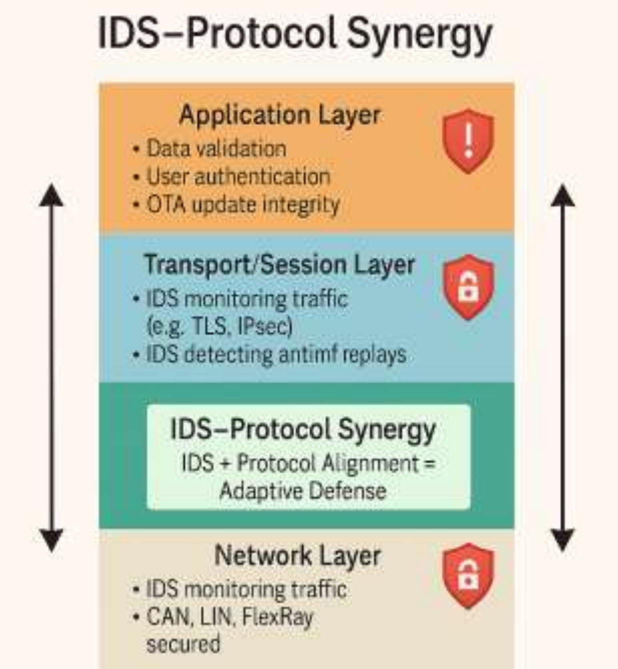

Figure 3: Layered defense model showing IDS–protocol synergy [23].

6. IMPLEMENTATION CHALLENGES AND INDUSTRY ADOPTION

6.1 Technical barriers: hardware, scalability, and real-time constraints

Deploying AI-driven IDS and secure communication protocols in automotive embedded systems faces formidable technical barriers. Embedded electronic control units (ECUs) operate under strict limitations of processing power, memory, and energy availability. Deep learning models, while offering superior accuracy, often demand computational resources beyond what low-cost automotive hardware can sustain [26]. Balancing real-time inference with minimal latency is particularly challenging, as safety-critical vehicular functions such as braking and steering cannot tolerate delays exceeding milliseconds [29].

Scalability presents another critical issue. While a proof-of-concept IDS may function effectively on a limited dataset, ensuring consistent performance across diverse fleets with varying hardware architectures and software stacks remains difficult [31]. Moreover, as vehicles evolve into nodes within interconnected mobility ecosystems, the data volume from V2X communications grows exponentially, straining IDS and encryption systems [27]. Resource-efficient algorithms, pruning techniques, and edge-computing solutions have been proposed to alleviate these pressures, but integration at scale continues to pose practical concerns [30].

These barriers demonstrate that while technical feasibility has been proven in controlled environments, achieving consistent and reliable performance across mass-market vehicles remains an unresolved challenge. Without addressing these limitations, adoption may be confined to high-end or specialized vehicles rather than the broader automotive industry [32].

6.2 Regulatory landscape (ISO/SAE 21434, UNECE WP.29)

The regulatory environment is increasingly shaping how manufacturers implement cybersecurity frameworks in vehicles. ISO/SAE 21434 establishes guidelines for cybersecurity risk management throughout the vehicle lifecycle, emphasizing secure design, verification, and continuous monitoring [28]. Compliance requires that manufacturers adopt systematic approaches to identifying risks, documenting mitigation strategies, and ensuring security remains robust as vehicles receive over-the-air updates [26].

Similarly, UNECE WP.29 mandates cybersecurity management systems as a prerequisite for vehicle type approval in many regions, requiring demonstrable intrusion detection and protection mechanisms [30]. This regulation has global implications, pressuring both established automakers and suppliers to prioritize cybersecurity investment. Failure to comply risks not only financial penalties but also the inability to market vehicles internationally [33].

However, challenges persist in translating these high-level frameworks into practical implementations. Standards often prescribe *what* must be achieved but provide limited guidance on *how* to achieve compliance. This ambiguity leaves manufacturers with room for interpretation, potentially resulting in uneven application across the industry [27]. Furthermore, the rapid evolution of attack vectors often outpaces regulatory updates, raising concerns about regulatory lag [29]. While these frameworks provide critical momentum, successful adoption requires closer alignment between regulators, industry stakeholders, and technology developers [31].

6.3 Cost-benefit and manufacturer adoption issues

Beyond technical and regulatory barriers, economic considerations heavily influence adoption. Implementing AI-driven IDS and secure communication protocols entails additional costs related to hardware upgrades, software integration, and compliance verification [32]. For mass-market vehicles, where margins are tight, manufacturers may hesitate to invest heavily in cybersecurity features that are not yet fully demanded by consumers [26].

Cost-benefit analysis reveals that while the immediate return on investment may appear modest, long-term benefits include reduced liability, enhanced brand reputation, and resilience against recalls triggered by cyber incidents [30]. The cost of a large-scale vehicle hack financially and reputationally can far exceed the upfront investment in security infrastructure [28]. Still, manufacturers often face difficulty quantifying such risks, leading to under-prioritization of proactive cybersecurity measures [33].

Adoption also varies across global markets. Premium automakers tend to integrate advanced cybersecurity frameworks as part of their branding strategy, while cost-sensitive markets emphasize affordability over layered defense [29]. Collaborative models, where suppliers, regulators, and manufacturers share responsibility for cybersecurity costs, are emerging as potential solutions [27]. Ultimately, widespread adoption depends on aligning economic incentives with security imperatives, creating pathways where compliance and profitability coexist sustainably. Figure 4 illustrates a roadmap for industry adoption, outlining short-term, mid-term, and long-term milestones in technical, regulatory, and economic integration [31].

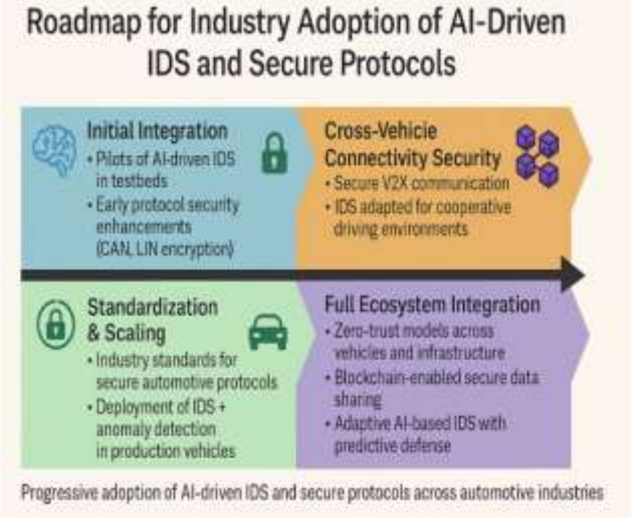
Roadmap for Industry Adoption of AI-Driven IDS and Secure Protocols
Initial Integration
• Pilots of AI-driven IDS in testbeds
• Early protocol security enhancements (CAN, LIN encryption)
Cross-Vehicie Connectivity Security
• Secure V2X communication
• IDS adapted for cooperative driving environments
Standardization & Scaling
• Industry standards for secure automotive protocols
• Deployment of IDS + anomaly detection in production vehicles
Full Ecosystem Integration
• Zero-trust models across vehicles and infrastructure
• Blockchain-enabled secure data sharing
• Adaptive AI-based IDS with predictive defense
Progressive adoption of AI-driven IDS and secure protocols across automotive industries

Figure 4: Roadmap for industry adoption of AI-driven IDS and secure protocols.

7. FUTURE RESEARCH DIRECTIONS

7.1 Post-quantum cryptography for vehicular security

As quantum computing advances, conventional cryptographic algorithms face the risk of obsolescence due to their vulnerability to quantum attacks [35]. For automotive systems, which require long-term security assurances across vehicle lifecycles, adopting post-quantum cryptography

(PQC) is increasingly critical [33]. PQC algorithms, including lattice-based and hash-based approaches, offer resistance to quantum decryption, yet their integration into resource-constrained embedded devices remains an open research challenge [36].

Vehicular systems demand lightweight PQC implementations that minimize computational overhead while maintaining robust security guarantees. Current studies suggest hybrid frameworks combining classical and PQC algorithms as transitional solutions until standardization matures [38]. However, the absence of automotive-specific benchmarks limits widespread adoption [32]. Research should focus on tailoring PQC primitives for in-vehicle networks and V2X applications, ensuring compliance with emerging standards [40]. Future deployment of PQC will be instrumental in future-proofing automotive cybersecurity against the disruptive potential of quantum computing [37].

7.2 Federated learning for decentralized intrusion detection

Traditional AI-driven IDS rely on centralized training, which raises privacy concerns and scalability limitations in distributed vehicular environments [39]. Federated learning (FL) provides a decentralized approach where vehicles collaboratively train shared models without transmitting raw data [34]. This ensures that sensitive vehicular information remains local, mitigating risks of centralized data breaches [36].

The application of FL to vehicular IDS can enhance adaptability by leveraging diverse driving conditions and attack scenarios from geographically distributed fleets [33]. Experimental studies have shown that FL maintains high detection accuracy while reducing communication costs compared to centralized frameworks [38]. Yet, challenges remain in addressing communication bottlenecks, model drift across heterogeneous devices, and adversarial poisoning of federated updates [40].

Future research should explore lightweight aggregation mechanisms, robust defense strategies against malicious participants, and real-world pilot deployments [32]. If optimized effectively, FL can transform IDS into a scalable, privacy-preserving solution for securing global automotive ecosystems [37].

7.3 Edge-AI for real-time vehicular security

The latency demands of vehicular systems necessitate IDS and secure protocols that operate directly at the edge, close to data sources [34]. Edge-AI leverages embedded accelerators to enable real-time detection without reliance on distant cloud infrastructures [39]. This paradigm enhances both responsiveness and resilience, particularly in safety-critical operations such as collision avoidance [35].

Research must focus on balancing inference efficiency with adversarial robustness, as edge devices are highly resource-constrained [36]. Combining edge-AI with adaptive workload allocation across cloud and vehicular nodes may provide hybrid architectures capable of scaling globally [40]. This approach promises resilient, real-time vehicular cybersecurity [37].

8. CONCLUSION

8.1 Summary of research contributions

This study presented a comprehensive framework for mitigating cybersecurity risks in automotive embedded systems through the combined application of AI-driven intrusion detection systems (IDS) and secure communication protocols. The research traced the evolution of vehicular cybersecurity, highlighting how traditional signature-based IDS and unprotected communication channels have proven insufficient against sophisticated, evolving attack vectors. By developing and evaluating hybrid AI models, specifically CNN-LSTM architectures, the study demonstrated that anomaly detection in both CAN bus and V2X datasets can achieve high accuracy while maintaining operational feasibility.

In parallel, the study designed lightweight secure communication protocols tailored to resource-constrained environments, balancing encryption strength and latency requirements critical to safety functions. The synergy of these two layers was validated through comparative analysis, showing that integrated systems outperform standalone IDS or cryptographic solutions. The research also provided methodological contributions by using diverse real and simulated datasets, robust evaluation metrics, and benchmarking against conventional approaches. Collectively, these contributions advance the state of the art by demonstrating that layered, adaptive security frameworks can be both practical and scalable, setting a pathway for their integration into future automotive cybersecurity infrastructures.

8.2 Practical and academic implications

The findings hold significant implications for both industry practitioners and academic researchers. For manufacturers and automotive suppliers, the research provides a clear demonstration that advanced cybersecurity measures can be embedded into existing vehicle architectures without overwhelming hardware or introducing prohibitive costs. The layered approach offers a roadmap for compliance with international standards, while also building consumer trust in connected and autonomous vehicles. From a regulatory standpoint, the results reinforce the importance of aligning technical innovation with safety and compliance frameworks, enabling automakers to meet increasingly stringent requirements.

For the academic community, the study highlights the value of interdisciplinary approaches that merge computer science, cryptography, and automotive engineering. By introducing hybrid IDS architectures and lightweight secure protocols, the research expands opportunities for further exploration of adversarial resilience, dataset diversity, and real-world scalability. It encourages future investigations into federated learning, edge-AI, and post-quantum cryptography, all of which were identified as promising frontiers in earlier sections. Ultimately, the work not only contributes to the theoretical body of knowledge but also bridges the gap between academic innovation and industrial application, ensuring that research translates into tangible, deployable solutions.

8.3 Final reflections on future-proofing automotive cybersecurity

Automotive cybersecurity is no longer a secondary consideration but a fundamental requirement for ensuring safety, trust, and operational continuity in modern transportation. As vehicles evolve into interconnected cyber-physical systems, the potential impact of cyberattacks extends far beyond individual safety to entire transportation networks and smart city ecosystems. This study has shown that integrating AI-driven IDS with secure communication protocols offers a robust pathway toward safeguarding this future. However, cybersecurity must be understood as an ongoing process rather than a static achievement.

Future-proofing automotive security requires proactive adaptation to emerging technologies and threats. Quantum computing, adversarial AI, and increasingly sophisticated attack vectors will demand continual reassessment and evolution of defense mechanisms. Equally important will be collaboration across stakeholders manufacturers, regulators, researchers, and consumers to ensure that security measures are consistent, standardized, and trusted. The layered defense model proposed here demonstrates the feasibility of such collaboration by uniting anomaly detection with cryptographic assurance.

Ultimately, the resilience of connected and autonomous vehicles will rest on the industry's capacity to anticipate rather than merely respond to threats. By embedding intelligence, adaptability, and layered protection into vehicular systems, the automotive sector can chart a secure course toward a sustainable, connected future.

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