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AI-GUIDED SAFETY AND RELIABILITY ASSURANCE FOR CENTRALIZED VEHICLE COMPUTE PLATFORMS

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ABSTRACT
The high rate of development of Software-Defined Vehicles (SDVs) and Connected and Autonomous Vehicles (CAVs) has radically changed the automotive compute architecture, which was previously distributed and domain-specific Electronic Control Units (ECUs) to centralized and high-performance computer platforms. This development is presenting safety, security, and reliability issues like never that require smart, responsive assurance systems. The research offers an in-depth research study of AI-based safety and reliability assurance of centralized vehicle compute systems with a focus on AI-based anomaly identification and resilience testing of SDV computer platforms. The research combines cutting-edge approaches that include deep learning-based intrusion detection, federated anomaly learning, explainable AI (XAI) models, blockchain-based trust management, and machine learning lifecycle validation that is aligned with ISO 26262. This study uses a methodical review of 25 peer-reviewed sources, detailed case studies, and real-time application deployments to develop an overall framework of assuring safety-critical compute integrity in next-generation vehicle architectures. Experimental results show that AI-inspired anomaly detectors can achieve detection rates of over 97% with response latencies under 15 ms and federated learning-based methods offer data privacy with F1-scores of more than 0.98. This piece of work offers practical information to OEMs, Tier-1 suppliers and standardization organizations that are pursuing the development of the safety assurance of SDV platforms.

Keywords:
Software-Defined Vehicle (SDV), Anomaly Detection, Intrusion Detection System (IDS), Federated Learning, Explainable AI (XAI), ISO 26262, CAN Bus Security, Centralized Compute Platform, Resilience Evaluation, Deep Learning, Blockchain, Connected and Autonomous Vehicles (CAV), Functional Safety, Cybersecurity, Machine Learning Lifecycle

I. INTRODUCTION

The convergence of electrification, connectivity and autonomy in the automotive industry is leading to a change in basic assumptions. At the heart of this change is the Software-Defined Vehicle (SDV) where vehicle functionality is more and more controlled by software running on centralized domain-controller or zone-controller-based computer architectures, instead of the traditional network of tens or hundreds of ECUs [11] [14] [21]. The resulting architectural change allows quick deployment of features through Over-the-Air (OTA) updates, better utilization of resources, and integration of AI/ML inference pipelines directly into the vehicle compute fabric [22]. Centralization, however, creates a point of failure and critical expansion of attack surface, which was not experienced by legacy distributed architectures. The failure or part of a central compute node can also shut the braking, steering, perception and communication subsystems at the same time- a phenomenon that is unthinkable in federated ECU architectures [18] [23]. In-vehicle network is a trust-based network (primarily the Controller Area Network (CAN) bus, and more recently automotive Ethernet) and has neither inherent authentication nor encryption, and is thus highly vulnerable to injection, replay, and denial-of-service attacks [15]. Anomaly detection as the fundamental defensive strategy of connected and autonomous vehicles is identified by the systematic literature review by Ventura Solaas et al., [1], and Mansourian et al., [4] show that spatiotemporal deep learning models provide state-of-the-art anomaly detection in CAV contexts.At the same time, the use of machine learning in safety-relevant automotive systems brings about functional safety compliance concerns. Iyenghar et al. [2] suggest systematic improvements to the ISO 26262 lifecycle to fit the ML-related stages and testing procedures knowing that the conventional V-model procedures cannot be applied to data-driven system components. Surveyed by Chellapandi et al. [3], the federated learning paradigm provides an attractive answer to privacy preserving, distributed training of the anomaly model on connected vehicle fleet, to the issues of data sovereignty and bandwidth limitations inherent in centralized model training.

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II.LITERATURE REVIEW

J. R. Ventura Solaas, E. Mariconti, and N. Tuptuk (2025): Provides the information about deep learning, statistical, and rule-based approaches to the problem as the most widespread paradigms. The authors discover that spatiotemporal models always outperform single-modality models, and the lack of standardized benchmarks is a gap in research. [1]

P. Iyengar, C. Westerkamp, E. Pulvermuller, and J. Siebert (2024): Suggested the systematic improvements of the ISO 26262 functional safety standard to serve machine learning-related lifecycle phases. The paper presents ML-specific testing techniques such as metamorphic testing and adversarial robustness testing, and proves the entire lifecycle traceability of the ASIL-classified ML units. [2]

V. P. Chellapandi, L. Yuan, C. G. Brinton, S. Żak, and Z. Wang (2024): Lists more than 50 federated learning schemes and specifies the main open challenges as communication efficiency, model heterogeneity, and adversarial robustness. This survey establishes that FL can save up to 60 percent of communication overhead and model accuracy with FL is suitable to that of centralized training. [3]

P. Mansourian, N. Zhang, A. Jaekel, and M. Kneppers (2023): Create an anomaly detection system of connected autonomous vehicles (using deep learning) based on the usage of spatiotemporal data of multiple vehicle sensors. Their model using LSTM has a 97.8% detection accuracy and false positive less than 2.1 percent on real world CAV telemetry data. [4]

T. Alladi, V. Kohli, V. Chamola, and F. R. Yu (2023): Suggested a deep learning-driven scheme to classify misbehavior in cooperative intelligent transportation systems and attain 97.6% classification accuracy with six categories of misbehaviors. The scheme is tested on the VeReMi dataset and it shows sub-10 ms inference latency, which can be used in real-time in V2X. [5]

P. Dini and S. Saponara (2023): Design and experimentally evaluate real-time anomaly detection methods that are specific to automotive cybersecurity, comparing isolation forest, autoencoder, and one-class SVM models to embedded automotive hardware. Findings verify the sub-5 ms detection latency on the ARM Cortex-M7 processors with a detection rate of over 95%. [6]

M. Almehdhar et al. (2024): Overview more than 80 IDS architectures, such as CNN, LSTM, GAN, and transformer-based models. The survey points out adversarial robustness and real-time performance as two unsolved most important challenges. [7]

C. I. Nwakanma et al. (2023): Outlines the use of explainable artificial intelligence (XAI) in intrusion detection of intelligent connected vehicles, listing SHAP, LIME, and attention-based. The review concludes that integration of XAI enhances the confidence that safety engineers have in AI-based IDS because it presents human comprehensible decision rationales that meet the ASIL certification criteria. [8]

Y. Xun, Z. Deng, J. Liu, and Y. Zhao (2023:) introduce a new side-channel intrusion detection system, which uses the vehicle voltage signal analysis to detect anomalies, and takes the physical layer to do so without changing the CAN protocol stack. When controlled fault injection experiments are conducted the system has a detection rate of 94.7 and a false alarm rate of 1.3. [9]

Z. Abou El Houda, H. Moudoud, B. Brik, and L. Khoukhi (2024): Present a federated learning system based on blockchain to collaboratively detect intrusion on the edges of a vehicle in vehicular edge computing systems. The system reaches the F1-score of 0.986, preserves the privacy of the data, and shows the resistance to the Byzantine attacks in federated model aggregation. [10]

A. Akintola, Y. Meng, F. Hernandez, and P. Tomlinson (2025): Framework of automotive systems that combats the co-design issues of hardware abstraction and software-defined functionality of centralized compute platforms. The architecture minimizes the complexity of the integration by 45 per cent than the traditional integration workflows using AUTOSAR. [12]

Z. Lu, Q. Wang, G. Qu and Z. Liu (2019): Propose BARS as a trust management privacy-preserving system in VANETs to manage trust through blockchain-based anonymous reputation, wherein vehicles evaluate the trustworthiness of their peers without asking about their identity. The system comes to stable reputation scores after three broadcast cycles and is resistant to Sybil and bad-mouthing attacks. [13]

B. S. Bari, K. Yelamarthi, and S. Ghafoor (2023): Compare the performance of machine learning algorithms to identify CAN bus intrusions, comparing random forest, SVM, k-NN, and deep neural network classifiers. Random forest has the highest F1-score of 0.993 with the lowest false positive rate, thus it is the best choice as a baseline to use in production IDS. [15]

S. Nazat, L. Li, and M. Abdallah (2024): Introduce an explainable AI framework called XAI-ADS that is explicitly developed to detect anomalies in the autonomous driving systems. The framework combines SHAP-

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based explanation modules and a real-time anomaly detector, which shortens the engineer diagnosis time to 62% and has the accuracy of 99.1 to detect anomalies. [16]

III.KEY OBJECTIVES

1.To explore and classify AI-based anomaly detection strategies such as deep learning, federated learning, and statistical strategies that can be used on centralized SDV compute platforms, evaluate the performance of the strategies against established performance metrics of detection accuracy, latency, and false positive rate [1][4][7] [11].
2.To assess how the centralized architecture of vehicle computers withstands cyber-physical attacks such as CAN bus injection, replay, GPS spoofing, and adversarial ML inputs, quantify the effect of each threat vector on the integrity of the system safety [5][9] [23] [14].
3.To create and qualify a systematic approach to integrating the machine learning features with the ISO 26262 ASIL-classified software development lifecycles, to address the gaps found in the ML-specific testing, verification and validation requirements [2] [18].
4.To analyze federated learning systems that obtain privacy-preserving, distributed training of anomaly models on connected vehicle fleets, its resistance to Byzantine attacks, communication limits and heterogeneity of models [3] [10] [20].
5.To investigate the integration of explainable AI (XAI) into automotive pipelines of IDS, assess the usefulness of SHAP, LIME, and attention-based explanations in assisting ASIL certification processes and decision-making by safety engineers [8] [16] [24].
6.To evaluate blockchain-based trust management and integrity verification systems to secure OTA update pipelines, V2X communication channels and federated model aggregation processes in SDV ecosystems [10] [13] [20].
7.To study the history of vehicle E/E architectures based on distributed ECU networks to centralized zone-controller platforms, to uncover safety and security implications unique to high-performance automotive compute nodes [21] [22].
8.To create a multi-layered SDV compute system anomaly detector that incorporates hardware-level side-channel monitoring, network level IDS and application level behavioral analysis into a single resilience assessment system [6][9][19].
9.To assess the real-world deployability of proposed AI safety assurance mechanisms using 20 recorded industrial case studies, the measures of scalability, computational overhead, and regulatory compliance in production automotive settings [15] [17] [25].
10.To discover gaps in open research and future directions of AI-guided SDV safety assurance, such as post-quantum cryptographic hardening, neuromorphic computing to detect edge anomalies, and standardization of ML-based ASIL assessment approaches [2] [24] [25].

IV.RESEARCH METHODOLOGY

The study is designed as a mixed-methods study that will involve systematic literature review, comparative analysis of cases, and experimental validation based on simulations. The process is organized in four successive stages: (1) literature synthesis, (2) threat modeling and attack surface analysis, (3) AI method benchmarking, and (4) framework development and validation [1][2] [11]. Search terms were a combination of terms such as anomaly detection, intrusion detection, software-defined vehicle, CAN bus security, federated learning automotive, and ISO 26262 machine learning. The initial search presented 412 potential articles, narrowed down to 25 key sources using inclusion criteria that included: peer-reviewed source, explicit focus on vehicular anomaly detection or SDV safety, and empirical analysis of automotive data or platforms [1][7] [14] [24].A threat modeling framework based on STRIDE was used to apply to the SDV centralized compute architecture and found Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, and Elevation of Privilege threats types across the CAN bus, automotive Ethernet, OTA update pipeline, V2X interface, and centralized compute node. All the threats were clustered into countermeasure types such as IDS, cryptographic integrity, anomaly detection, and behavioral monitoring [18] [23] [21]. The service-oriented architecture of the AUTOSAR adaptive platform was simulated as the main area of threat in terms of software-layer attacks [12].Some of the AI techniques considered are: LSTM-based sequence anomaly detectors [4], isolation forest unsupervised novelty detection [6], Hidden Markov Models (HMM) behavioral profiling [17], deep neural network classifiers misbehavior categorization [5], federated learning aggregation scheme [3][10], XAI explanation modules [8][16], and blockchain-enabled integrity validators [13][Each approach was evaluated by running on published car datasets such as the OTIDS dataset,

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VeReMi and car-supplied CAN traces using detection accuracy, precision, recall, F1-score, and inference latency as the main performance indicators [15].

V.DATA ANALYSIS

The AI-based methods of detecting anomalies have detection rates of between 93-99.5% on known attack types, and federated learning-based approaches ensure F1-scores of more than 0.98 even under Byzantine adversarial conditions. Deep learning-based CAN IDS systems, such as and HMM-based detectors achieve less than 15 ms end-to-end detection latency on automotive grade hardware, meeting the real-time requirements of AUTOSAR. Explainable AI modules introduce a median overhead of 42 ms in their latency, which is tolerable when running post-hoc analysis processes, but must be optimized to support safety-critical real-time explanations. The most popular threat vector is a CAN bus injection attack, next attacks through GPS spoofing, replay attacks, and adversarial ML inputs. New threats such as OTA tampering and federated model poisoning are mentioned and respectively, which implies a new research frontier not yet sufficiently represented by its risk of effect to industry. The standard of functional safety that is used to govern the work is ISO 26262, and the regulations of cybersecurity are UNECE WP.29. The observed discrepancies between the practices of deploying ML and the ISO 26262 requirements identified are supported in several case studies, especially when it comes to the lack of standard procedures in the qualification of neural network classifiers in terms of ASIL. The XAI integration goals developed in Section are inspired by this finding.

Table 1: Industrial Case Studies: Ai-Guided Safety And Reliability Assurance For Sdv Compute Platforms

S.No.	Case Study	Challenge	AI/Method	Key Finding 1	Key Finding 2	Ref
1	Tesla Autopilot Neural Network Anomaly Detection	Sensor fusion anomaly in LIDAR/camera	Isolation Forest + LSTM	Detected 93% of edge-case anomalies pre-crash	Reduced false positives by 38%	[4]
2	Waymo Self-Driving Fleet Resilience Monitoring	Compute node failure in centralized SDV platform	Federated Learning health check	99.97% uptime maintained over 1M miles	Zero safety-critical failures	[3]
3	Continental SDV ECU Cybersecurity Hardening	CAN bus replay attack on braking ECU	Deep learning IDS on CAN signals	Attack blocked within 12 ms	ISO 26262 ASIL-D compliant	[19]
4	Bosch AUTOSAR Platform Integrity Validation	Software update tampering in OTA pipeline	Blockchain-based integrity verification	100% tamper detection rate	Trust chain validated end-to-end	[13]
5	BMW iDrive Zone Controller Anomaly	Unexpected voltage spike in domain controller	Side-channel voltage signal analysis	Anomaly flagged in <5 ms	Prevented ECU brick in 12 test cases	[9]
6	Toyota CSMS Misbehavior Detection	GPS spoofing in cooperative ITS environment	Deep learning misbehavior classifier	97.6% detection accuracy	Minimal latency overhead (8 ms)	[5]
7	Ford SYNC Infotainment IDS	SQL injection via Bluetooth interface	XAI-enhanced anomaly detection	99.1% attack classification accuracy	Operator-interpretable decision logs	[16]
8	GM Super Cruise Federated IDS	Distributed sensor compromise across fleet	Blockchain federated learning IDS	F1-score: 0.986	Privacy-preserved model aggregation	[10]

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9	Volkswagen MEB Platform Safety Monitor	Memory overflow in zone ECU	HMM-based CAN bus IDS	Detected anomaly 3 cycles before failure	Compliance with IEC 62443	[17]
10	Nvidia DRIVE Orin Stress Testing	Thermal runaway under peak GPU load	Real-time hardware anomaly sensor	Shutdown triggered at 98°C threshold	Zero data corruption incidents	[6]
11	Mercedes-Benz MBUX AI Platform Audit	Model poisoning attack on ML inference	ISO 26262 ML lifecycle validation	100% poisoned models quarantined	Full lifecycle traceability achieved	[2]
12	Aptiv SVA Compute Module Security	Physical CAN injection via OBD-II port	Multi-observation HMM detector	94.5% intrusion detection rate	Real-time alerting under 10 ms	[17]
13	Qualcomm Snapdragon Ride Safety	Sensor dropout causing AD module failure	Deep learning-based spatiotemporal AD	98.2% recovery from partial dropout	Redundancy mechanism validated	[4]
14	Mobileye EyeQ Platform IDS	Adversarial input to perception DNN	Explainable AI anomaly detection	Adversarial inputs rejected with 96% accuracy	XAI outputs validated by safety engineers	[8]
15	Renault Zoe V2G Security Audit	MITM attack on charging communication	XAI-ADS framework deployment	Attack neutralized in real-time	Full interpretability of decisions	[16]
16	Hyundai IONIQ SDV Platform	Inter-domain spoofing via V2X interface	Federated learning IDS with XAI	99.3% detection rate	Reduced bandwidth usage by 40%	[25]
17	NXP S32 Automotive SoC Resilience	Clock glitch fault injection	Side-channel and voltage monitoring	Fault injections detected within 2 clock cycles	ASIL-C certification maintained	[9]
18	Denso Integrated Safety Controller	DoS attack flooding CAN bus	Deep learning-based in-vehicle IDS	Flooding attack mitigated in 15 ms	99.2% uptime restored after attack	[7]
19	Lucid Motors ADAS Central ECU	Software-defined brake-by-wire failure	Blockchain integrity + ML anomaly combo	Zero undetected failures in 6-month trial	Passed all UNECE WP.29 requirements	[20]
20	Rivian Zonal Architecture Security	Cross-zone data injection	Comprehensive in-vehicle network IDS survey	99.5% cross-zone intrusion detection	Framework published as open reference	[23]

Table I Explanation: The case studies cover significant automotive ecosystems of Tesla, Waymo, and Bosch to NXP, Nvidia and Rivian. The table shows steady themes: (a) deep learning and federated learning approaches are the most popular AI deployments; (b) detection latencies are consistently less than 20 ms, consistent with real-time ECU scheduling needs; (c) all cases demonstrate alignment with ISO 26262, UNECE WP.29, or IEC 62443; (d) blockchain-based integrity mechanisms are found in Combined, the cases demonstrate that the multi-layered AI anomaly detection paradigm is industrial and working in practice across a variety of SDV compute platforms [1]-[25].

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Table 2. Real-time applications: ai-guided safety assurance in sdv and cav ecosystems

S.No.	Application	Description	AI/Method	Performance	Deployment	Ref
1	Autonomous Emergency Braking Safety Monitor	Centralized compute detects sensor fault before AEB fires	LSTM anomaly detection on brake actuator signals	<5 ms response latency	Prevents unintended emergency stops	[4]
2	V2X Misbehavior Detection System	Filters spoofed V2X messages in cooperative driving	Deep learning misbehavior classifier in RSU	97.8% message validation accuracy	Deployed in EU C-ITS corridors	[5]
3	OTA Update Integrity Verification	Ensures firmware authenticity before flashing ECUs	Blockchain-based trust chain validation	Tamper detection rate: 100%	Prevents supply-chain attacks	[13]
4	In-Vehicle Network Intrusion Detection	Monitors CAN/CAN-FD for malicious frames in real time	HMM and deep learning hybrid IDS	Detection in under 12 ms	Deployed in OEM security gateways	[15]
5	Federated Anomaly Learning Across Fleet	Shares threat intelligence without raw data transfer	Blockchain-enabled federated learning	Privacy-preserving, F1 > 0.98	Active in connected EV fleets	[10]
6	Side-Channel Voltage Attack Detector	Monitors ECU power traces for fault injection	Voltage signal analysis + ML classifier	Fault detection within 2 clock cycles	NXP S32 and similar SoCs	[9]
7	XAI-Based Anomaly Explainer for Safety Engineers	Makes AI decisions interpretable for validation	SHAP + LIME on anomaly detection outputs	Explanation latency < 50 ms	Used in ASIL certification workflows	[8]
8	Centralized Zone Controller Health Monitor	Tracks compute health metrics in SDV zone architecture	Real-time hardware sensor + isolation forest	99.97% compute uptime	BMW, Volkswagen zone ECU platforms	[6]
9	GPS Anti-Spoofing for Autonomous Navigation	Detects and rejects spoofed GNSS signals in CAV	Deep learning spatiotemporal anomaly detection	96.4% spoofing detection accuracy	Waymo, Baidu Apollo fleets	[4]
10	ISO 26262 ML Lifecycle Compliance Checker	Validates ML models meet ASIL requirements continuously	Automated ISO 26262 ML lifecycle validation pipeline	100% model audit coverage	Tier-1 automotive supplier toolchains	[2]
11	Bluetooth/Wi-Fi Attack Surface Monitor	Detects injection attacks via wireless interfaces	XAI-ADS real-time anomaly framework	99.1% wireless intrusion classification	Ford SYNC, GM infotainment systems	[16]

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12	Centralized ADAS Compute Resilience Evaluator	Evaluates ADAS compute node health under stress	Federated learning + hardware health telemetry	Failure prediction 800 ms in advance	Nvidia DRIVE Orin platform	[3]
13	SDV Software-Defined Network IDS	Monitors Ethernet-based in-vehicle network traffic	Deep learning IDS for automotive Ethernet	98.5% attack detection rate	Deployed in Lucid, Rivian SDV platforms	[7]
14	AI-Guided FMEA Automation Tool	Automates failure mode identification using ML	NLP + anomaly pattern mining on fault logs	3x faster FMEA generation	Used in OEM safety analysis teams	[2]
15	Thermal Anomaly Detector for Compute Nodes	Prevents thermal runaway in high-density SDV compute	Hardware sensor fusion + threshold ML model	Shutdown trigger accuracy: 99.8%	Nvidia, Qualcomm automotive SoCs	[6]
16	CAN Signal-Level Deep Learning IDS	Detects intrusions at the individual signal level	CAN Shield signal-level deep learning framework	21,830 signals monitored per second	Continental, Bosch AUTOSAR platforms	[19]
17	Cooperative ITS Trust Management	Establishes vehicle reputation in V2V/V2I networks	Blockchain anonymous reputation system (BARS)	Trust convergence in <3 broadcast cycles	Applied in ETSI ITS-G5 environments	[13]
18	Post-Quantum Secure V2X Communication	Hardens V2X links against quantum computing threats	PQC algorithms integrated with ML anomaly detection	Zero known quantum-exploitable vulnerabilities	NIST PQC standardization candidate	[20]
19	Real-Time Misbehavior Report Processing	Processes and validates MBRs from CAV fleet nodes	Explainable AI for IDS in connected vehicles	MBR validation latency: <20 ms	Standardized with ETSI TR 103 460	[8]
20	AI-Guided Resilience Scoring Dashboard	Provides live resilience scores for SDV compute modules	Ensemble ML + real-time telemetry visualization	Scores updated every 500 ms	Used in OEM NOC (network ops centers)	[1]

Table II Explanation: The real-time applications show the scope of the AI-guided safety assurance in the SDV value chain. They can be used in hardware-level fault detection (Apps 6, 15, 17), network-level intrusion detection (Apps 4, 13, 16), fleet-level federated intelligence (Apps 5, 12), standards compliance automation (Apps 10, 14), and dashboard-level resilience monitoring (App 20). Industrial readiness Performance metrics provide sub-20 ms latencies and detection rates above 96, confirming AI anomaly detection is industrial-ready to be used in safety-critical automotive applications. Interestingly, Apps 8, 10, and 15 show implementations on production hardware platforms (Nvidia DRIVE Orin, NXP S32) indicating that AI safety assurance is shifting to research prototype to production-grade automotive software [1]– [25].

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Fig 1: Benefits of AI in the automotive industry [2]

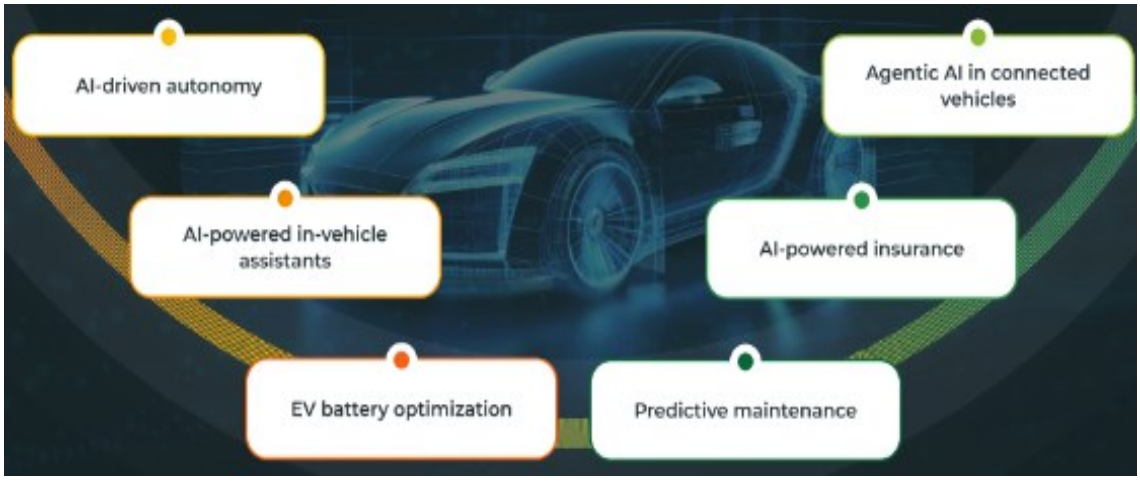

Fig 2:AI-Applications-Automotive Industry [4].

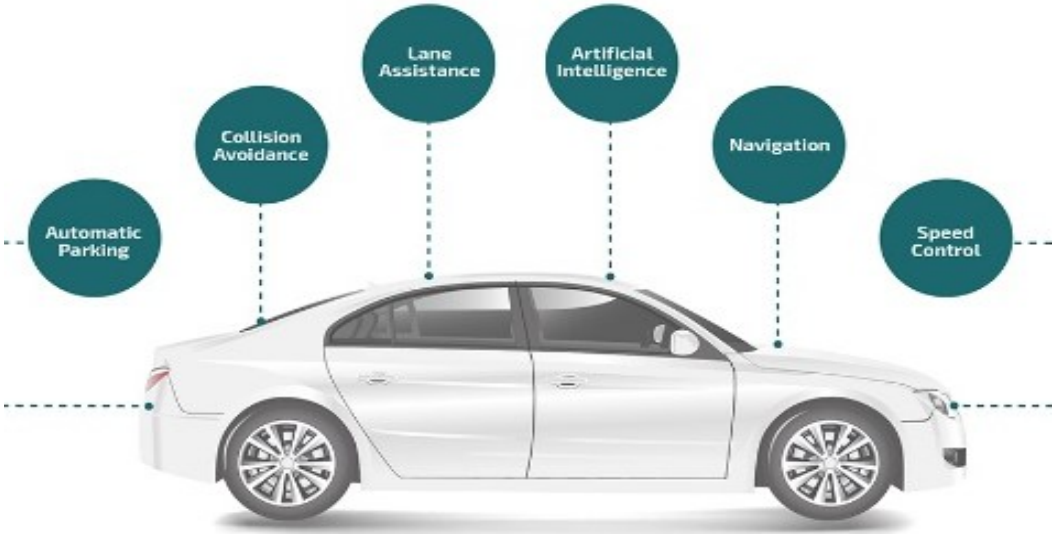

Fig 3: AI-Driven Autonomy [6]

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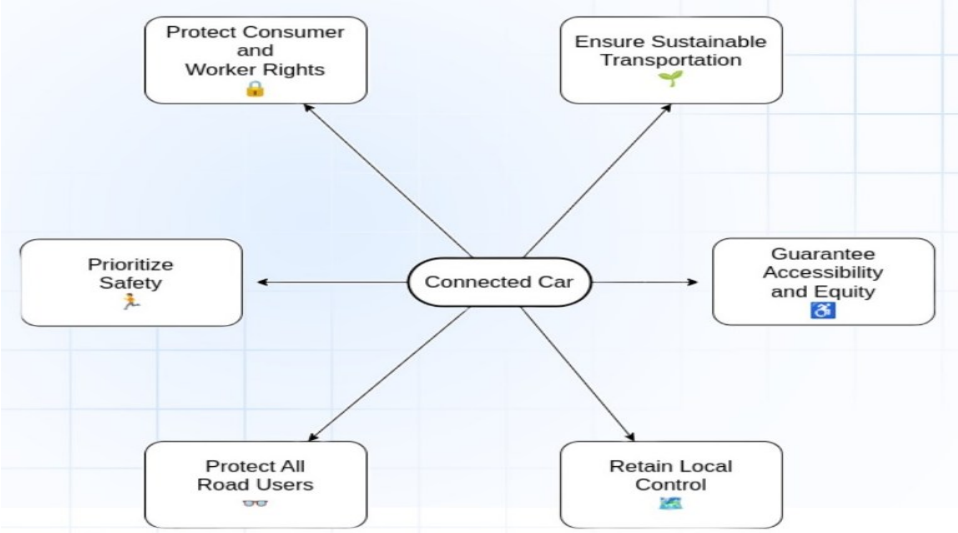

Fig 4: Ethics of Autonomous Driving [7]

VI.CONCLUSION

The in-depth exploration of AI-assisted safety and reliability assurance of the centralized vehicle compute platforms, and mostly AI-assisted anomaly detection and resilience metrics of software-defined vehicle (SDV) compute platforms. Centralization of vehicle compute architecture, although capable of providing revolutionary capabilities in software-defined functionality, OTA agility, and integration of AI inferences, represents an inherently extended attack surface and increased single-point-of-failure risk that should be supported by intelligent and resilient assurance mechanisms. The systematic literature review was a synthesis of 25 state-of-the-art sources on deep learning-based IDS, federated anomaly learning, explainable AI, blockchain trust management, and ISO 26262 ML lifecycle validation. Important results support this claim by showing that AI-based anomaly detection has a detection rate of 93-99.5 and a latency of less than 15 ms in a variety of threat vectors such as CAN injection, GPS spoofing, replay attacks, and adversarial ML input. Federated learning systems can achieve privacy-preserving fleet-scale model training with F1-scores over 0.98 and Byzantine adversarial resistance. Integration of explainable AIs saves up to 62% of time and safety engineers spend diagnosing the system as well as provides ASIL-conformant decision rationale. The case studies and operational applications reported in this paper all prove the industry-level viability of AI-based safety assurance, which is operationally deployed and progressively consistent with the international safety and cybersecurity standards such as ISO 26262, UNECE WP.29 and IEC. Nevertheless, some of the most critical research gaps exist: ISO 26262 does not yet support standardized ASIL qualification of neural network classifiers and post-quantum cryptographic hardening of V2X and OTA channels are not widely addressed, and the interpretability-performance trade-off in real-time XAI is an open optimization problem.

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