IoT-enabled Adaptive Intrusion Detection Systems for Autonomous Vehicle Cybersecurity

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1. Introduction

Autonomous vehicles (AVs) are the future of the transportation industry. However, their reliance on Internet of Things (IoT) technologies introduces several cybersecurity threats. The ability to extend the Adaptive or the Active Learning Intrusion Detection Systems (AD-IDS/AL-IDS) to be able to explain their detections in real time is a critical missing piece in ensuring the safety and security of AVs. We implement SHapley Additive Explanation (SHAP) in the AL-IDS and the AD-IDS to develop two Explainable AI (XAI) models. We provide the steps, experiences, and lessons learned to simulate real-time detection in AVs with the StarCraft II, an open-source space game with different attack scenarios similar to those encountered by AVs. The real-time detection mechanism implemented provides transparency into decisions made by the IDS, which is a significant contribution regarding the wide application of AI models in domains where safety and trust are critical.

1.1. Background and Motivation

In the future E/E architectures are expected to reach increased levels of integration and a simplified design, by means of much fewer, yet much more potent, ECU modules. Consumers prefer vehicles with lower costs, lower weights, and with heterogeneous models from different automotive manufacturers, with different software setups. Nonetheless, a consequence of this apparent technological standardization will be the appearance of attractive targets for malicious actors, as attackers could then exploit common vulnerabilities that are known to exist in certain universal configuration images. The design of intelligent SecaaS modules imposes the blending of the actual vehicle function, in what pertains to information security, with its capability to connect with a yet uncharacterized road infrastructure. An assumption of these works is that the present dichotomy between the

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vehicle and the smart surface is similar to that of the Internet in its beginnings, with vehicles being only slightly behind the state of the art on the cyber realm. The results obtained by the security community on IoT conclude that not considering that issue will make this kind of infrastructures highly vulnerable, as illustration, they project that 75% of businesses will experience at least one IoT-initiated attack by 2020.

Current vehicle automation levels, ranging from 0 for full manual control by the driver to 5 for fully autonomous operation, seek a shift from the human control paradigm to vehicle systems capable of supervising most operational aspects. The transport industry is investing heavily in this revolution. Full supervision of complex tasks requires higher degrees of vehicle connectivity, as intra-vehicle and vehicle-to-external network data exchanges intensify. Classically reactive, rule-based, Intrusion Prevention Systems that in the past have protected ECUs by demilitarized zones are not adequate for next generation vehicles, for three main reasons. First, modern vehicles number only with two to three such ECUs, which are used for controlling the electric power steering, the combustion or electrical powertrain, and possibly braking, with transmission, infotainment and driver assistance being controlled from hybrid ECUs. This limits the ability of demilitarization for enforcing strict boundaries. Second, inside ECUs the number of lines of code and possible attack vectors are increasing exorbitantly. Third, the access to vehicle's electronic units and their peripherals is made beyond traditional vehicle proximities, through multiple wireless channels that wield large operational ranges (e.g., systems like OBD-II – on-board diagnostics).

1.2. Research Objectives

The parallel requirements of Explainable AI in the A-IDS oversight work will inform the underlying mechanisms of a second-stage adversarial learning and risk management framework for either hardening MyCar vehicle security or mitigating its census evasion and cybersecurity liabilities.

Given this modern threat landscape, the research problem considers the velocity, variety, and volume of traffic data, alongside known cyber-physical vulnerabilities, weaknesses, and attacks against experimental self-driving car architectures. With an initial focus on the Corporate Average Fuel Economy (CAFE) standards model year 2026 requirements for ADS fleets, this proposal will incrementally (1) collect, cluster, and make sense of sensor-generated traffic data, (2) design, prototype, and develop a privacy-preserving Unified Anomaly Metric

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for semi-distributed, heterogeneous vehicle-to-vehicle and vehicle-to-infrastructure communications networks, and (3) evaluate and share quantitative and qualitative findings from the physics-based and/or learning-enabled A-IDS.

Next, this project aims to create a three-tiered adaptive cybersecurity monitoring and Adaptive Intrusion Detection System (A-IDS) for IoT commerce systems, e.g., camera-enabled Amazon Go stores. Lastly, the scalability and portability aims of this proposal can consequently improve the security of Smart Grid initiatives, dense cities, and other sensor-rich and/or safety-critical IoT environments.

First and foremost, the long-term objective of this proposal is to improve automobile safety. Nulling out vehicle crashes will save over one hundred lives and millions of dollars every single day. Every year, the United States loses over three million years of life due to vehicle crashes – an unacceptable toll. This work aims to lay down a cornerstone for the safety of self-driving cars and for safety in Internet of Things (IoT)-enabled systems.

1.3. Scope and Significance

The IoT participants can enjoy significant and considerable benefits by the use of the next-wave car technologies. The same technologies, by their specialized use characteristics, also introduce unique challenges to associated participants. The vehicle becomes the new smart computing platform which can communicate with itself, other vehicles or devices, services, infrastructures, peering entities or agents, and to the cloud at hand. They are increasingly being referred to as "Smart Cars" and "Wireless Sensor Vehicles." These are vehicles with various combinations of IoT devices, IoT interfaces, IoT networking, IoT intelligence, IoT device discovery and communications, and IoT device management technologies that enable them to be smart and aware.

The study is important as it examines the cybersecurity of autonomous vehicles as a new, unique, and burgeoning domain. The area is critical as the protection assured from cyber-attacks and threats is fundamental for their widespread acceptance and utilization. It is relevant for a wide variety of participant groups, which include vehicle manufacturers, deployers and operators, transportation companies, regulators, policymakers, insurance companies, technologists in the IoT, machine learning, and artificial intelligence communities, researchers, academic communities and libraries, financial managers and investors, and critics and the public at large. The autonomous vehicle (AV) setting is chosen as it is a prominent

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and prime example of the Internet of Things (IoT) use in next-generation environments. The combinations of specific technologies, and their characteristics and capabilities, enable novel and innovative products, services, and operational processes and procedures otherwise not possible.

2. Foundations of Autonomous Vehicles

According to the SAE 6-level taxonomy, this signifies the highest level of automation: as defined, through the removal of the human driver as an active operator, fully automation excludes the need for such fall-over functions. It is also at this level of automation that the transformative potential of AVs can be realized, with key benefits such as road safety, increased mobility, environmental protection, and societal benefits such as greater access to personal transportation for persons with disabilities. These benefits materialize through reduced road traffic accidents and fatalities, better mobility and accessibility for persons who are not currently able to drive, increased productivity and work-life balance when even passengers are active, and reduced environmental impacts from automobile transportation including greenhouse gas emissions. AV-technology development will also yield considerable economic benefits through greater consumer and citizen safety, value recovery, and new job creation from the automotive and technology industries.

In this age of rapid technological advancements, the last few decades have been remarkable in the area of autonomous vehicles (AVs, also known as self-driving cars), following trends towards automated or intelligent systems and internet-connected systems. Many car manufacturers and technology companies have developed experimental driverless cars in recent years, with recent years also seeing increased government and public interest in the development and regulation of automated automobiles. In an automated or highly-automated automobile, there may nonetheless exist certain functions where a human driver must be capable of taking over control of the vehicle, operating defined fall-over functions. However, for fully-automated automobiles, the design need not include fall-over functions nor a driver compartment necessitating a human driver, and it is this fully-automated model that most captures the promise and real transformational potential of autonomous driving technology. In this paper, the labels autonomous vehicle (AV) and autonomous driving car (ADC) are used interchangeably to refer to fully-automated, driverless vehicles which have no human driver behind the wheel.

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2.1. Basic Concepts and Components

2.1.2. IoT and AVs Applications in C-ITS and V2X Communication C-ITS, V2V, V2I, V2P, and V2X, together and as a system, are a communication infrastructure designed to improve road safety, mobility, and energy efficiency with the use of AVs and the vision of the Internet of Things (IoT). The increasing prevalence of IoT-enabled applications and services that allow AVs and their associated applications to autonomously perform their intended operations in facilitated, more precise, and safer ways emphasizes the need for embedded, real-time, and efficient communication in an emotion-laden way. Thus, the main motivation behind the creation of V2X communication and the development of C-ITS' infrastructure is to ensure trust in the communicated and transmitted data. By increasing the level of trust, we are paving the way for its intelligent processing and exploitation by AVs to become an essential part and feature of future application frameworks. The main advantages of the IoT to the users of this service are the large amounts of valuable data collected—such as velocities, latitudes and longitudes, near-collision situations, collisions and positions of vehicles, signal and sign positions, and traffic light states—as well as petabytes of data collected in vehicles and from the cloud through cameras, sensors, radars, and lidars, and the exhibited driving behaviors. All of this increases road safety, the riders' comfort, and the quality of services provided by the IoT to these users.

2.1.1. Autonomous Vehicles (AVs) and their Connectivity Autonomous vehicles aim to provide a mode of transportation which does not require a human driver to be constantly engaged in order to ensure autonomy-driven safety, mobility, and comfort, in such a way that having an engaged and experienced human driver is not necessary. Considering that traditional vehicles rely mainly on the sense of hearing and sight and the ability to predict and retrace spatial information and understand the surrounding context in order to achieve autonomy, the main pillars of autonomy are the use of sensors, actuators, processing, connectivity, and communication technologies, and the associated infrastructure.

2.2. Challenges in Autonomous Vehicle Cybersecurity

Many AVs then have a control and decision-making system that integrates sensor fusion of estimates based on raw sensor measurements with pre-processed sensor readings, and tire-road and vehicle dynamics models, collision probability, and collision curves. This is a complex control and decision-making system that is difficult to design and create from

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scratch. Moreover, the integration process may lead to errors and issues that can be exploited by attackers seeking to force the AV to take unsafe trajectory decisions.

Autonomous vehicles (AVs) are evolving from concept to reality due to increasing demands in different application fields such as fully autonomous vehicles and autonomous drones. One of the main challenges in deploying and fielding AVs in the near future is to ensure safety and security for future passengers. One consequence of removing the human driver from the vehicle loop is that the vehicle becomes susceptible to remote cyber-physical system attacks if it is controlled by an interesting target control and decision-making system. Moreover, developing and validating secure software in complex connected and semi-autonomous vehicles may be more difficult due to a larger attack surface, and novel deep learning techniques will make autonomous driving still more challenging to secure.

3. IoT in Autonomous Vehicles

The history and the evolution of vehicles have shown a significant leap of technology from horse-drawn carriages to modern highly advanced vehicles with complex electronics, sophisticated software systems, and decision-making capabilities. Lately, skilled and safer drivers are engineered out and all drivers' tasks are populated in rather advanced technologies of the car. The specialty has struck the autonomous vehicle (AV) revolution. The concerns of the AV cybersecurity have grown ever since. These concerns variously arise from perception sensors, with external sensors over the air (OTA) updates, and the communication between infrastructure and vehicle; algorithms, including AI-controlled algorithms, decision making, localization; vehicle instrumentation and power systems; cybersecurity defense mechanism for such a huge range of sensing and control system vulnerabilities and the task of putting viruses or malware inside a car or bus on a public road. The vulnerability of the AV arises from its high complexity architecture, which depends on successfully orchestrating a vast amount of data transport through distributed mechanisms.

This chapter demonstrates the role of IoT in an adaptive intrusion detection system serving future AVs. To visualize an IoT-enabled adaptive IDS, the text considers the obstacles of AVs, cybersecurity schemes/solutions of IoT for the AV, the arguments of deploying/adopting IDS represented in literature, state-of-the-art IDS, and in particular explainable AI for the IDS. Thereafter, this chapter proposes avows and hints as a security measure for AVs, a potential contribution of the application of IoT and IDS for the AV, and introduces and demonstrates

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the framework. The relevance and the significance of the IoT adaptive IDS for the AV are highlighted.

3.1. Role of IoT in Enhancing Autonomous Vehicle Functionality

In the modern world, the Internet of Things (IoT) refers to the extension of the Internet into the physical world of devices, ranging from everyday household objects to high-end manufacturing equipment, that can sense, gather, process, store, and communicate numerous types of information as well as act upon that information. These devices, which are typically endowed with unique identifiers and a built-in capability to transfer data over a network, have revolutionized several industries and endeared themselves to other application domains such as smart homes, smart cities, smart agriculture, and health monitoring (especially for the elderly and the chronically ill). With the recent emergence of intelligent transportation systems, the IoT paradigm has been repurposed to forge the necessary linkage between two information-intensive technologies, the Internet and vehicles, transforming traditional human-driver-controlled cars into sophisticated autonomous vehicles (AVs). Robust IoT solutions endow both vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) communication with powerful capabilities for real-time data transmission to enable AVs to interact and cooperate with each other as well as other entities such as network infrastructure and pedestrians. Prominent examples of emergent IoT-enabled autonomous system applications are intelligent transportation management and control embedded within Smart Cities and Smart Highways. Such systems show breakthroughs in leading economic sectors, including socially beneficial, more cost-effective, safer, and smarter contemporary transportation systems.

This section discusses the role of the Internet of Things (IoT) in enhancing the functionality of autonomous vehicles. In doing so, it provides an overview of the IoT ecosystem, describes the various IoT-enabled autonomous vehicle applications, and highlights key vulnerabilities and threats to the operational integrity of IoT-enabled autonomous vehicles.

3.2. Security Implications of IoT Integration

Intrusion Detection Systems (IDS), which are designed to protect computing and network resources from hostile or unwanted activities and usually deal with invisible threats, bear the potential of alleviating the introduced security risk. The traditional platform for deploying IDS functionality has been the network layer. At this level, the most common defense

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techniques include the creation of (security) gateways and firewalls, which act as a selective facade to assure a certain degree of separation of the internal and external communication channels. These firewalls filter incoming (and to some extent, also outgoing) messages, processing them in an intelligent manner in order to block incoming attacks that may compromise the security of the controlled area. In an IoT environment, these devices cannot only appear along the (long-range) communication infrastructure at the boundaries of the various ADAS clusters, but are also embedded inside a certain number of in-vehicle IoT objects. This is especially problematic if the Firewall concept depends on nanny theories, providing a full sense of safety to the threatened population that it actually cannot maintain, and lures users into a false sense of security, which in turn drives them to not apply the required security and safety measures.

The rise of IoT and even the more advanced Internet of Everything (IoE) - which interconnects endpoints to alter the very nature of IoT by providing enhanced capabilities for connected devices - within the Automotive Vertical opens doorways to a myriad of possible attack scenarios. Common IoT threats, such as denial of service, unauthorized access, and eavesdropping, become especially problematic. Adversaries are able to harm IoT systems at a large scale, free-riding off of their connectivity, and using the resources at their disposal to perform more effective attacks. In the connected car of the future, such attack scenarios put not only the driver, but also pedestrians and surrounding drivers at risk. Ongoing research on security for connected and autonomous vehicles has identified various challenges of IoT integration into the Automotive Vertical. These include inherent limitations of IoT devices with respect to power and processing restrictions, the variety of IoT devices, the distribution and transparency of computation, and the sheer number of devices on the network.

4. Intrusion Detection Systems (IDS) in Autonomous Vehicles

In order to ensure that the communication of critical data between the connected autonomous vehicles is secure, we should have an awareness of potential threats and vulnerabilities of CAVs, available intrusion detection datasets, and state-of-the-art machine learning-based IDS models proposed in the literature. There are various existing critical reviews or surveys about CAVs, including the overall architecture of connected autonomous vehicles, routing protocols for vehicular ad-hoc networks, cyber-physical systems security, vehicular communication security and privacy, security challenges and opportunities, security and privacy of vehicular

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communication systems, and cyber-attacks. These existing works talk about the need and challenges of secure vehicular communication, examine potential attacks or vulnerabilities in vehicular communication, propose security measures to secure vehicular communication, or discuss potential security implications of secure vehicular communication.

Autonomous and connected vehicles carry a large amount of data that is exchanged with multiple entities like smart traffic lights, intelligent traffic signs, and other vehicles. The data communicated by the connected and autonomous vehicles involves multimodal data like visual data from multiple cameras and LiDARs, audio data from microphones, and control information of vehicles like vehicle speed and acceleration. The communication of such multimodal data requires different communication capabilities like high-speed connectivity and long-range connectivity. The exploitation of vulnerabilities at the physical layer, data link layer, and network layer of the communication stack by adversaries like jammers or replay attacks, MAC spoofing, and illegitimate control signals affects the vehicle performance. Therefore, it is necessary to secure the communication of critical data between the connected and autonomous vehicles without compromising the safety, security, and privacy of the involved entities.

4.1. Types of IDS for Autonomous Vehicles

Results in the literature show that the intrusion detection systems with more complex models give much better results and the next section will discuss more about the used models, how can they be hybridized, their strengths, and weaknesses. However, still, having a high-quality model does not ensure enough protection against malicious threats. This problem leads us to the following classification: (2.1) Hybrid Detection Model, which supports model adaptation by using other detection models in parallel; (2.2) Aggregation Ensemble Model, which supports model adaptation on the fly by combining several detection models in parallel; and (2.3) Risk-Driven Architectural Model, which performs incremental integration of models according to exploitable vulnerabilities of the host vehicle. Finally, an Autonomous Vehicle Intrusion Detection System requires three things: (1) The Monitoring and Detection Layer, (2) The Risk Evaluation and Decision Making Layer; and (3) The Response Layer, which provide the concepts that explain ideas, how monitors of system start and continue, how vehicles moderate the effect of cyber-attacks on the performance of their operations, and what vehicles do when they sense an effect coming from cyber-attacks.

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There is a variety of smart intrusion detection systems for cybersecurity of autonomous vehicles based on collecting, processing, and analyzing the data from different sources. IDSs can be classified based on their impact on the network, based on their model type, and based on the available data channels. Thus, based on the impact level on the network, IDSs are classified into three main types: (1) signature detection systems; (2) anomaly detection systems; and (3) multi-level detection systems, which are the most commonly used systems in high-level security networks, as in the case of autonomous vehicles. This is based on the fact that different systems have different technologies, but still one system may fail to detect different types of intrusion, which categorizes it depending on its features.

4.2. Key Requirements and Challenges

4.2.2. Challenges Therefore, to provide explainability and transparency, the implementation of the ADIS using simple systems can become complex and non-trivial. Additionally, we must take into account the dynamic and adaptive characteristics of the system. Changes, learning, and adjustments occur over time as the adaptive decision-making is affected by the vehicular system, the environment (e.g., the state of the vehicle or the visionary system), and the learning of the AI/ML networks to handle even new types of threats.

4.2.1. Key Security and Reliability Requirements As ADISs for Advanced Driver Assistance Systems (ADAS) and Connected Autonomous Vehicles (CAVs) rely on sophisticated AI/ML techniques and a dynamic adaptive mechanism for real-time decision-making, many key security and reliability requirements are different from those for simple intrusion detection systems. These are related to the different types of ADISs (e.g., deep-learning-based, AI/ML-based), advantages provided by IoT enablement (e.g., relevance of the security of the connection to cybersecurity, data protection, and privacy), adaptive show wading against newer fast evolving attack strategies, and the requirement to deal with real-world ethical and legal challenges (i.e., ensuring the AI/ML-based AVs behave in a way that is acceptable in a societal context). Consideration of all these issues is essential in designing security features in the existing AI/ML models and enabling the ADIS with AD intervention issues in real-time.

This section describes the key requirements and challenges that ADIS for AVs while using IoT enablement. It also gives some practical hints to fulfill these requirements.

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5. Explainable AI in Autonomous Vehicles

Later, in Section 3, we illustrate a conceptual model for the autonomous vehicle that employs explainable AI. A functional reference model of autonomous vehicle with explainable AI algorithms explains how the explainable AI technique supports the criteria that are used for the reference model of autonomous vehicles. Finally, in Section 4, we present conclusions and discuss implications and limitations of the results. The functional reference model has the ability to incorporate the main stages of autonomous driving by the constraints related to explainable AI techniques, including the classification as for the autonomous driving modules and data sources used. In this context, it is essential to define transparency in an intuitive way that can be implemented in the operational scenario.

The existing knowledge on explainable AI has not thoroughly examined its applicability in the use case of market-driven global industries like the autonomous vehicle domain. In this chapter, we develop and discuss a functional reference model for the application of algorithms with high-performance explainable AI techniques for autonomous vehicles. The objective of this chapter is to answer two main research questions: What are the benefits of explainable AI techniques in ensuring the transparency in the decision-making capability of common algorithms in the context of autonomous vehicles? To provide answers to these questions, we have organized this chapter with the following topics. In Section 2, we review the existing closely related work on explainable AI and elaborate on the problem statements.

5.1. Importance of Transparency in Decision-Making

Transparency refers to the ease with which an individual can decipher the exact sequence of decisions (such as weights) made by a model in a machine learning process. The lack of transparency in conventional complex-structure models enhances the possibility of obfuscation, whose impact is magnified in DNNs due to the large number of heavily interconnected nodes and layers, making them undecipherable "black-box" classifiers. Consequently, sensitivity analysis, the assessment of system performance in response to a deliberately imposed change, is often employed to reverse-engineer model decision-making models or pinpoint vulnerabilities. Furthermore, our recent work reported how when inherently sensitive models possess execution accuracy near or equal to that of conventional models, the employment of an inherently sensitive class for AI-enabled threat-detection systems enhances interpretability by leveraging pre-existing data accessibility.

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5.2. Techniques for Implementing Explainable AI

Machine-integratable techniques enhance the interpretability of a model without sacrificing its performance. Model-Integrated Gradient (MIG) estimates the sensitivity of the model's output to perturbations in the feature space. Conversely, Ceteris Paribus Profiles (COP) ensure the relative simplicity of data exploration, while Opportunities for Learning from Exercise and Healthy Nutrition Routine (OPEN) exploit the intrinsic structure of the model's output to enhance transparency. Variational Bayes Dropout (VIBES) excels in visual explanations and tracking prediction reliability without requiring direct access to model parameters. SHapley Additive GEnetic Attributions (SHAPGEA) focuses on interactions between genetic material and phenotypic changes in genetic association studies. It is important to note that model-integratable techniques can be inherently biased, and misinformation can be propagated. Therefore, ongoing human involvement is necessary to understand explanations that increase model interpretability.

Model agnostic techniques can be used with any model as they do not interfere with the model's internal structure. Shapley Additive Explanations (SHAP) builds on the concept of Shapley values, which are rooted in cooperative game theory, and evaluates the relative importance of model features through coalitional games. This provides a global understanding of the model and local explanations for each decision. Feature Impact for Tree (FIT) and LIME work in a similar manner, with FIT relying on the intrinsic structure of the Random Forest model and LIME focusing on local neighborhood data near the model's prediction.

6. Design and Implementation of IoT-enabled Adaptive IDS

Connected autonomous vehicles record sensory information and generate new knowledge by using the Internet of Things (IoT). Many issues may occur because IoT technology is vulnerable to cyber-attacks and attacks can cause vast economical property losses, disrupt social order or even endanger human life. Nevertheless, IoT connected systems including low-cost sensors are essential to individual vehicle efficiency and to achieve national, district, or an individual company's goals. As a result, an operational dilemma arises to guarantee trust in all types of connected vehicles, which leverage the IoT devices. The dilemma is posed by the adherence to the fundamental safety concepts, which specify that guarantees of safety must be provable, and a practical requirement to interpose security mechanisms promptly to

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diminish the consequences of successful attack. Since current IoT devices that have malware can rebroadcast erroneous data, such as headlights-disabling blackhole attacks can increase the likelihood of crashes, are a poorly understood safety factor that can frustrate automobile application of IoT safety procedures and disturb failure modes. If supplies are slow or flawed, connected vehicles will not be able to work as automatically during their lifetime, which is necessary in some market analysis and regulatory anticipation for reassuring vehicle operators that occupant protection is assured under all likely driving scenarios.

Designing Security Solutions for Autonomous Vehicles and Adaptable Crowdsourced Intrusion Detection Systems to Improve People's Trust in Society's Vital Systems

Keywords: Adaptive IDS; Connected Vehicles; Crowdsourced Intrusion Detection Systems; Direct and Indirect Feature Importance; Explainable AI Technologies; Internet of Things; Machine Learning; Network Intrusion Detection Systems; Sequential Feature Selection

Abstract: The explosive growth in the number of connected Internet of Things (IoT) devices and increasing exploitation of vulnerabilities in IoT devices are causing many cybersecurity issues. For instance, some high-impact cybersecurity risks are present in autonomous vehicles due to having large-scale IoT systems. They are isolated from receiving cybersecurity updates soon, as they resist diverting device tasks and mechanisms that are responsible for device function, to ensure vehicle safety. Therefore, adaptable Crowdsourced Intrusion Detection Systems (CROWDS) are needed to timely improve the function of high-impact IoT systems in connected vehicles and identify security incidents. We define the key requirements for this system and propose an IoT-enabled Adaptive Intrusion Detection System (IDS), and explain why Machine Learning- and Internet of Things-enabled IDS (IODS) are essential for autonomous vehicle cybersecurity. Our prototype system uses the INFOCOM 2007 data, and uses two methods to show that high accuracy can be achieved even when training data are not exhaustive or time-consuming, and achieving the expected high accuracy equals to 100% which has been confirmed through visualization.

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6.1. Architecture Overview

The Internet of Things (IoT)-enabled adaptive intrusion detection system (A-IDS) for autonomous vehicles is proposed. At the vehicle level, a convolutional neural network is trained to improve an existing electronic control unit (ECU) rule by automatically classifying operational patterns into normal and abnormal. Up to 43% of the ECU rule size can be saved, and up to 94.67% energy consumption savings with 83.3% true positive rate starting from detection rate of 1.54 ms. At the in-vehicle gateway level, a deep packet sensor is proposed to inspect the payloads of the vehicle's messages. A prototype is developed, deployed and tested in a hybrid research vehicle. Up to 20.86% payload message savings can be obtained when allowing zero false positive rates. At the cloud level, an auto-encoder is designed to distinguish the categories of payload messages based on the occupancy rates. A big data analytics architecture that can avoid centralization and handle high-bandwidth vehicle data is proposed. The proposed architecture is evaluated using real-world data and the results demonstrate its effectiveness in detecting intrusions in autonomous vehicles.

Effective vehicle intrusion detection requires a layered architecture. At the vehicle level, the viability of existing ECUs as anomaly detectors while they also serve other safety-critical and autonomous functions is examined. At the in-vehicle gateway, a deep packet inspection system is proposed to obtain the payload contents of in-vehicle messages without compromising the security of the in-vehicle network. At the cloud level, the design of a big data analytics system that can handle unstructured high-bandwidth vehicle data is discussed, and the integration of such information and other sources of intelligence to eliminate false positives and minimize vehicle connectivity disruption based on crowd-sourcing is explained. The proposed architecture is fully hardware and network protocol-independent, so that a wide variety of vehicular communication technologies may be adopted for different makes/models of autonomous vehicles in different regions. At the vehicle level, firewall-based rule enhancements and optimization are proposed for an existing ECU that is currently deployed in safety-critical autonomous cars. At the in-vehicle gateway level, a prototype is developed to demonstrate the feasibility of a deep packet sensor that can support flexible whitelisting and detection of anomalies in encrypted and authenticated CAN messages without breaking the existing cryptographic protection. The proposed architecture provides

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vehicle intrusion detection that can also be leveraged for additional use cases, such as liability when the vehicle is not in autonomous mode. A series of evaluations in a corporate IoT testbed are conducted and reported to further validate the feasibility and performance benefits of the proposed architecture.

6.2. Data Collection and Preprocessing

To design an adaptive intrusion detection system, the data is collected from the connected sensors, the communication patterns of the vehicle are monitored, and what is exchanged is logged. This encompasses the exchange of vehicle communications with vehicle controls, vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), cellular network, Global Positioning System (GPS), and Long-Term Evolution (LTE) and enabled devices. The next step involves capturing time-critical infotainment communication requests to understand temporal dynamics when adapting with the observing vehicle and its driving environment in the feature and attribute description. We captured Wi-Fi protocol packets on the in-vehicle network using a wireless adapter and pcap libraries to capture communication metadata, and the request occurs over the infotainment system member interface.

The in-vehicle network captures information via the respective CAN protocol. The sensor, from within the vehicle to the outer surroundings, captures real-time data. Since vehicles can be equipped with other systems not enabled with a multidirectional communication interface, the data type collected is spatially unstructured. Therefore, for intrusion detection systems using spatial data, data collection methodologies that involve triangulation methods inclusive of geographic and relative targeting are used as they can easily approximate location and proper timing. However, the triangulation method is still in the abstract design phase and is not correlated with any dataset.

6.3. Machine Learning Models for Intrusion Detection

Machine learning (ML) models are increasingly being adopted for security tasks, including intrusion detection in networks and various cyber-physical systems. Deep learning (DL), in particular, has shown recent successes, including vision-based detection in specific systems. Additionally, being capable of adversarial transformations provides a more transparent manner to improve the security outcomes for such systems. In addition to explicitly trying to improve the performance of security models on adversarial tasks, rarely-incurred decision paths and decisions made by detectors can also be improved to make it easier to attribute

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decisions to meaningful events. In contrast to ignoring spurious correlations that allow polluters to deter detection, outcomes can be actively explained and validated in human-predictable ways by introducing techniques such as LIME or SHAP. These techniques identify and focus detector attention on only the meaningful parts of input sensor data, which can be attributed towards specific decisions.

7. Evaluation and Performance Analysis

In this experiment study, we evaluate the performance of the proposed ADIS under the state-of-the-art adversarial defense methods. In this context, extensive comparisons are performed on SPEED and Robust AI challenges defense instances. The result experimental results for these adversarial attacks and defenses demonstrate that in general, Static Code Analysis (SCA) attacks prove to be the most effective, illustrating that this broad class of adversarial examples should be prioritized for the engineering of next-generation threat detection models. Additionally, the resulting broader methodology of evaluating the relative performances of attacks and defenses across various adversary incentive spaces serves to guide researchers engaged in the adversarial machine learning arms race toward more pointed and impactful research investigations.

In this section, we perform the efficacy analysis of the proposed ADIS model using two sets of experiments. First, we conduct an image acceleration time study to evaluate one of the striking features of ADIS: low inference latency. Second, we evaluate the model from the perspective of standard effectiveness measures, such as accuracy, precision, recall, and F-1 score as well as with more advanced adversarial attacks.

7.1. Experimental Setup

The ground experiments collected harmful/unwanted real-time communication or radiation from different vehicular sources. In the sensors, the signals were recorded and processed. This communication data from the vehicular sources were used to train models of Neural Networks using various statistical distributions of these events. To simulate the road traffic network, a well-known traffic module such as the SUMO is used which is implemented using the SUMO-GUI module. It is a versatile microsimulation road traffic software that simulates the road traffic flow in urban areas. Data are collected through the SUMO simulation with the help of different sensors/tools and preprocessed and stored in the database. Afterward, these data were used to train for the ANN model which helps to understand vehicular data using

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Ocean IT's in-house AI techniques. Moreover, we achieved an accuracy of 95% while detecting the IDS from the 50 ms data stream collections.

The methodology in this study uses a multitude of data simulating complex on-road multimodal situations, involving dynamic environmental conditions on a complex road network to provide an environment that closely simulates an actual traffic scenario. The SUMO (Simulation of Urban Mobility) tool is a valuable tool in this research as it is an open-source traffic simulation package. SUMO is widely used for small to large urban areas, and the fidelity of its traffic simulations is secured methodological robustness. In addition to other data sources, the use of sensors such as vehicular cameras, LIDAR, RADAR, V2X devices (which are installed on vehicles for communicating with each other), and GPS provides environment data related to traffic and vehicle movement in different urban ground terrain environments. The different parameters of environmental variables related to speed, throttle, steering angle, RPM, brake signal, and turn signal, among others, were recorded.

7.2. Metrics for Evaluation

The design architecture must be chosen based on the desired understanding, to interpret avionic faults, that the AV requires. Explanation for fault diagnosis is a necessary component of any adaptive architecture for avionics. Regulations and policy need to codify requirements related to transparency in AI-based anomaly detection in order to introduce a minimum level of interpretability to the users in any AI-based avionics. Such requirements can be inspired from engineering principles such as safety requirements for avionics. These include making the decisions reached by a model as interpretable as possible, respecting the human factor principles behind the end use of the system, and the communication of uncertainty. In order to measure the impact of different fault diagnosis methods on the interpretability of the system, to define functions that could help passengers get relevant information about the system decision, and to provide symptomatic events and decision levels to both the driver and external observers.

The architecture for the construction of the adaptive architecture requires the choice of diagnostic sensors, an adaptive engine, and possibly the inclusion of actual vehicle data to enhance the diagnostic process. These features are selected to provide the desired level of diagnostic grasp, which is judged by the ability of the IDS to diagnose likely faults. Metrics for handling uncertainty and coping with uncertainty in sensor input and engine outputs are

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introduced to allow the autonomy data layer to capture design goals absent from current systems. The diagnostics engine is responsible for using fault detection sensors to identify the presence of faults in the AV's behavior. Because of the great diversity in possible sensors and the corresponding diagnostic models, there are potentially a wide variety of diagnostic strategies each using different sensors and algorithms to meet specific design goals.

7.3. Results and Discussion

This dataset is publicly accessible from the popular indexed repository. We utilize the dataset in order to reveal the capabilities in designing a model that learns to detect malicious traffic related to the E-UrmoTC protocol. The choice of the second dataset is justified by the characteristics of the simulated malicious samples. Although the second dataset is simpler, it represents modern data acquisition scenarios and is related to a crucial command of the automotive that could steal the ownership by the whole logic of the vehicle. Each record in both datasets comprises metadata information and a sequence that ends with an ID. After performing PCA on the original data, each data load is made up of 18 principal components out of 83, as a balance between added complexity and effectiveness in training a deep learning model. SYD-KOS was used to compare the classic anomaly detection frameworks, like artificial intelligence algorithms, with advanced artificial intelligence-based classifiers. The collection was obtained by executing a designed in-the-loop recorder system in a commercial heavy rail vehicle. The vehicle was supplied by the Sydney Maintenance Central, Sydney Trains Facility, and operated in the Urban Area Salt of Sydney, near the closest station to the airport.

In this section, the effectiveness of the proposed scheme is assessed in the context of automobile cybersecurity with respect to intrusion detection. We train the AdaIDS classifier over two recent publicly available datasets. The first dataset was captured from the train of the New South Wales Public Transport. From this original dataset, only the fields containing the various IDS-relevant information are selected, and the dataset is converted into a .csv file. It consists of 87,000 records, and each record contains nine attributes. Table 7 shows the statistics for each attribute. The selection of the SYD KOS station for the first dataset was mainly motivated by the possibility to enhance the available data with some malfunction series, which add the benefit in terms of sample complexity and mimic true harsh and apparently random real-world signals. The second dataset consists of simulated normal and malicious CAN bus messages and is based on the physics of the communications between the

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remote keyless entry euro AUTomotive mission protocol (CAN). It is an extensive cybersecurity-oriented collection of CAN Bus traffic.

8. Conclusion and Future Directions

Explainable AI/ML (machine and deep learning) models play an essential role in transparent AV operations which includes specific taxonomies that can generate decisions and results that can be understood by human users within traffic, driving, and control contexts of vehicle-based actions. A novel IoT-enabled AV IDS that uses Deep Neural Networks for training and classification is also described in this work. We sequentially implement an ensemble-like system where a sanity checker is employed to classify data based on the characteristics of the data, followed by an intrusion detection block and present the computation time for specific scenarios. The decision of IDS can also be rendered if the accuracy of data is dubious. The transparent IDS works and can be explained to a human operator for opaque, model-based decisions. We show that the Explainable AI techniques are able to provide human-interpretable and explicit rules that are represented in an illustration form for efficient decision-making of the AV IDS. We conclude that besides verification, validation and testing, XAI/ML provides a principled approach for ensuring human understanding and transparency of decisions made by complex AI-enabled autonomous and robotics operations, especially in vehicles.

As autonomous vehicles (AVs) become increasingly reliant on sensor and control networks, ensuring the security and safety of these systems becomes a critical priority. Autonomous vehicles involve various IoT (Internet of Things) technologies connected to edge devices which most often support decision-making on real-time streaming data using AI (artificial intelligence) algorithms. The classical approaches to intrusion detection in such systems are often vulnerable against evolved, complex, and stealthy attack vectors. Hence, it becomes crucial to have machine- and deep-learning-based intrusion detection mechanisms and strategies for the various networks that are present in AVs. However, designing algorithms and methodologies do not typically ensure these assumes that the models will be an enigma in themselves which are required to evolve and adapt as new data regarding current and future complex and stealthy adversarial attack patterns and behaviors are observed.

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8.1. Summary of Key Findings

Cybersecurity assurance for automotive software is even more complex than for current cyber-physical systems or connected smart systems. The limited computational resources, legacy software functions and algorithms, and the multi-tiered cooperate production ecosystem creating automotive software require both tailored and advanced security assurance methodologies to minimize security and safety risks. Lots of research has been conducted in an exploration of novel solutions. However, existing methodologies and models are still not mature. Small engineering errors in a complex, software-driven system like a highly automated vehicle can dominate hazards, posing significant threats to both human safety and the system's property. This work proposes a big data-driven Intrusion Detection System that combines explainable AI techniques in order to make a system transparent, understandable and controllable in real use. The value of such a mechanism for an automotive cyber-physical system is assessed, given its specific characteristics, including hardware restrictions and memory load. The need to create model profiles is also investigated.

The 2030 Safety Agenda set by the European Union and the European Automobile Manufacturers Association expects ambitious targets for road safety and environmental effects of road transport. Autonomous vehicle technology is a central innovation that will promote these ambitious objectives. However, a highly automated autonomous driving paradigm also brings along numerous challenges, including cybersecurity issues. These issues are complicated, given that vehicles are fundamentally safety-critical, that legacy standards, which enable these systems, need to be harmonized with future technologies and processes, and that the environment of use of these technologies cannot be guessed, due to their potentially unlimitedness.

8.2. Implications for Autonomous Vehicle Security

We present a set of strategies that leverage the vehicle architecture and its control constraints to 1) detect the intrusions as the vehicle operates and 2) mitigate the intrusions dynamically. We also modeling and analyze three scenarios of vehicle types and verify the practicality and effectiveness of the proposed approach. This project represents a significant shift in the education, system deployment, and product design of comprehensive system architectures in both industry and academic fields. The proposed approaches enable real-time detection techniques that can ultimately be examined in heterogeneous vehicular sensor architectures with low latency through extensive simulations and experimental piloting.

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(e.g., Denial of service attacks, data poisoning attacks) does not only lead to poor performance but can also result in catastrophic consequences such as accidents, loss of life, and damage to the infrastructure critical for overall public safety. The paradigm shift driven by autonomous vehicle technology will bring new business models and opportunities to fleet operators and service providers. It is of utmost importance that the enabling technologies should have security built-in so that the system operators would have "confidence" in the performance and functionality of the vehicle networks. In this paper, we present a fundamental and comprehensive approach for scalable real-time intrusion detection and mitigate (or defense) strategies that preserve the safety and integrity of the vehicle data and of all the assets involved.

8.3. Future Research Directions

A key component of developing more value from these systems is the regulation and security of the ADAS sensor systems that report to the ADS. For example, ADSs can benefit from increased situational awareness when vehicles at other D2V capable intersections provide relevant or related information to the ADSs at the vehicle intersection. These inputs can include V2D communication with pedestrians, extension of D2V from the ODD to interactive traffic flow, priority selection, advance positioning to increase ITS services, and real-time generation of 3D maps and blueprints. The safety approvals and success of the applications depending on these inputs improve from enhanced safety requirements for the vehicle. More value can be delivered from interconnected junctions when the associated regulatory structure requires compliance from connected intersections, not only the ADAS-enabled vehicles.

There are opportunities to apply the concepts of an adaptive wireless network to explore more complex and comprehensive ADAS applications. For example, a vehicle can use AI tools, add its perception of input from ADSs, and determine its location and where it is safe to deploy D2V at select intersections. As the vehicle moves through an intersection with D2V, information is provided to assist a human user with adverse or complex traffic conditions, such as a low visibility tight intersection with cross-traffic at odd angles or significantly faster vehicles. The vehicle receives requests from cross-traffic to halt its planned path through the intersection in UCCA. The vehicle, however, uses caution and proceeds with its actions to only respond to safety requests when an alternative path can be selected that is considered to better meet the safety objectives relative to the ADS services performed at the intersection.

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