Deep Learning-based Cyber Attack Detection in Autonomous Vehicle Networks

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1. Introduction

Sophisticated detection methods are required to detect these attacks. A cyber attack can be a single point or multiple point violation. In a single violation detection problem, the task is mainly to distinguish whether violations occurred. However, the multi-violation detection problem is to determine which specific measure was violated and to identify the degree of violation. Conventional detection techniques may lack advanced 0-day cyber safety mechanisms, such as machine learning and deep learning. This paper presents the small-scale network embedding concept and shows that, under different threat models, a deep learning-based system on embedded networks including 5G or Wi-Fi protocols can effectively bypass various security checks, confusion detection, and adversarial effects in an end-to-end manner.

The autonomous vehicle network is becoming a reality. With this major advancement in transportation and logistics, the security and safety of the network are emerging as major concerns. In addition to traffic safety and privacy issues in autonomous vehicle networks, it is critical to establish countermeasures for the growing number of security threats facing these networks. One of the challenges is to create a secure and robust autonomous vehicle network that can withstand cyber attacks currently and as technology evolves. Security problems in AVN can result in physical damage. For example, a user may misuse the vehicle during the transition. In the worst case, a hacker may take control of an autonomous vehicle, leading to fatal collisions. Therefore, rapid detection of cyber-physical attacks affecting the operation of AVNs is essential.

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1.1. Background and Motivation

In order to protect CV networks from such misbehavior, a few lightweight algorithms have been proposed to distinguish between normal and adversarial operation of a vehicle. Nevertheless, due to the modernization and richer in autonomy capabilities of such AVs, they become security-sensitive networks where detection algorithms have problems in detecting differences between benign and corrupted behaviors. Hence, deep learning detectors have been introduced to unleash the unique pattern recognition capabilities of deep neural networks for normal versus attack detection, considering a more abstract representation of the data, thus addressing the restriction of real-world, security-sensitive networks. To listen to the infraction of deep learning detectors, this chapter consolidates the detection abilities of deep Autoencoders (AEs) and Long Short-Term Memory Recurrent Neural Networks (LSTM-RNNs) over Ethernet and IEEE 802.11p networks. Specifically, they are trained to classify the two classes using previous research findings to improve detection accuracy, optimize the detection capabilities for capturing both stealthy adversaries and hard-to-detect dose of anonymization attacks, and address explicit operational requirements reflecting the mission and the role in the safety-critical domain of transportation systems of interests.

Cyber-physical systems (CPS) at large pose architecture-specific security challenges. Among them, the security of advanced transportation systems has gained significant attention during the recent decade, mostly due to the promise of cutting-edge driverless technology or autonomous vehicles (AVs). These systems combine wireless networks, connected vehicles (CVs), and sensor technologies, enabling a wide range of applications that promise safety and efficiency of transportation systems. Though convenient and safe, safety-critical applications such as safety-critical message diffusion indeed render such systems vulnerable to adversarial attacks. Aiming at compromising mission-critical services and ultimately disabling system functioning, cyber adversaries pose various attacks that exploit the communication infrastructure and employ corrupted messages in specific or multiple sensor networks.

1.2. Research Objectives

Attaining reliable solutions to the above questions can improve the security deployment of the autonomous vehicle network. Through proofs of concept, the study contributes a novel approach to network attack detection in the domain of autonomous vehicle operation combined with a firewall to enhance the defense mechanism. In summary, the key contributions of this study are: 1. A deep learning-based autonomous vehicle network attack detection mechanism using the block-gridding approach, the sliding window, and the addition of some dynamic features are proposed. 2. A novel gradient-boosted model connection fitness assessment mechanism is developed to indicate when the training model needs updating.

1. Can deep learning models be trained effectively to achieve a high detection rate and low false alarm rate for various network attacks (e.g., DDoS, black hole, selective forwarding)? 2. Is there a reliable solution that can quickly determine when retraining deep learning is needed to mitigate transition delay? 3. Can a hybrid mechanism of attack detection and firewall rules be implemented effectively to enhance security?

With the primary research problem, this study aims to answer the following questions:

2. Autonomous Vehicle Networks

The capability to share situational awareness and collaborate to safely avoid collisions in real time can be supported by equipping vehicles with V2X communication. This enables wireless communication between AVs and also between AVs and a road infrastructure (including sensors, traffic management, and tolling systems). There are three expected benefits from V2X. First, the perception range increases from line-of-sight for individual sensors to a significant part of the environment in a field of view. Second, information exchanges at a distance can complement an individual car's sensor data, allowing drivers to recognize likely dangerous interactions earlier and more accurately. V2X promotes the development of cooperative intelligent vehicles. Inter-V2X communication, or vehicle-to-vehicle (V2V) communication, and vehicle-to-infrastructure (V2I) communication form the heart of predominantly three types of cooperative systems for dynamic driving tasks.

Vehicle autonomy capability models describe the autonomy level of AVs according to their ability to provide lateral and longitudinal control. Recent vehicle autonomy level models such as SAE J3016 or NHTSA level definitions consider six autonomy levels, ranging from no autonomy (level 0) to full autonomy (level 5). Currently, most vehicles in development by all major international automakers for mass production in the near future are expected to be varying levels of automated vehicles when all sensor suites and control systems are functional and activated. The possibilities for collaboration and coordination among AVs in vehicular networks depend heavily on their automation level. However, current automation functions of AVs are limited in their ability to detect other vehicle states or intentions as well as their ability to communicate and intelligently cooperate to avoid collisions and improve traffic efficiency. AVs will only be able to achieve their full potential as a safe, efficient, and environmentally friendly transportation if they can share key state and intention information with their nearby peers.

2.1. Architecture and Components

Depending on what assets an attacker wants to access, there are many types of attacks. Some can impose loss of control over the vehicle, some can result in loss of controllability, some can lead to a complete traffic gridlock across the entire road network or stop vehicles entirely. There are also attacks that announce the false location of a vehicle and can steal information. The emerging technology, deep learning, however, has shown great potential to facilitate cyber attack detection in vehicle networks. In this feature article, we highlight recent deep learning-based attack detection techniques in the autonomous vehicle network and discuss several promising directions for future investigation.

All modern vehicles are equipped with wireless communication technologies such as Vehicle-to-Everything (V2X) that support a wide range of applications. Meanwhile, because vehicles are enabled with IoT-like features, they are vulnerable to various types of security and privacy breaches. Specifically, every wireless-connected vehicle can be a potential target for various types of cyber attacks. Cyber-physical attacks are not just theoretical; numerous attacks from simple ones such as jamming to complex ones like remote hijacking have been demonstrated. A successful attack on autonomous vehicle networks can have a significant and immediate public safety impact.

2.2. Challenges and Vulnerabilities

It is important to note that due to the continuous growth of automotive technologies, particularly in the fields of vehicle automation and the Internet of Vehicles, the application of powerful Artificial Intelligence, including and especially Deep Learning (DL) technologies, is becoming increasingly important. However, the advantages of DL, i.e. massive data, high computation, and high model complexity, also make them very vulnerable to several well-known and new types of cyber attacks. The gradual penetration of AI-related applications into ASVNs has been estimated by Xu et al. to be fourfold. In a real-world cyber setting, a man-in-the-middle (MitM) attack involves a malicious real-estate agent who passes incomplete and manipulated signal packets between vehicles. Due to the fact that some subset of the driver-assisted systems are critical to emergency systems like the Electronic Stability Control (ESC) and Antilock Braking System (ABS), MitM attacks on these control signals will have a significant safety and security impact.

Several challenges exist in designing a network-based cyber attack detection system for automotive networks. This can be attributed to the high degree of complexity and uncertainty, as well as the peculiar features of the Internet of Vehicles, which are not found in traditional networks. As ASVNs are characterized by non-uniform, chaotic data traffic, where relevant network flows (such as position and safety messages) operate at considerably lower frequencies than general traffic. Another distinguishing feature of ASVNs is the possibility of having little or no prior knowledge regarding the response of an automobile in a particular traffic condition. For example, some new sensors, actuators, communication, or control algorithms are constantly being added and continually being improved. As a result, training a model such that it is capable of detecting any input modifications that are not regular under different traffic conditions becomes extremely difficult.

3. Cyber Attacks in Autonomous Vehicle Networks

This challenge can be divided into two major categories: autonomous vehicle security and driving safety. The reliability and dependability of autonomous vehicle communication are of utmost importance, given that these vehicles are expected to function in a complex and challenging environment. Autonomous vehicles are connected to a wide variety of external networks, including vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-everything (V2X), and the Internet. In fact, connected autonomous vehicles require secure and reliable V2X communication to provide features such as advanced driver assistance (e.g., collision avoidance and platooning), traffic efficiency optimization, and autonomous driving functionality.

The fourth industrial revolution has enabled a paradigm shift in the evolution of self-driving and connected vehicles (e.g., SAEB Level 4 autonomous vehicles). Advanced Vehicular Communication Systems (i.e., connected autonomous vehicles) are expected to revolutionize our daily lives by improving transportation efficiency, reducing the number of accidents, and creating a completely new type of entertainment for passengers. However, these revolutionary technological advances come with the considerable challenge of securing the advanced communication systems.

This paper describes and evaluates the use of deep learning-based cyber attack detection methods to help mitigate these concerns. Specifically, we present and evaluate one such method, showing cyber attack detection performance across a range of synthetic cyber attack scenarios. The evaluation is based on a range of conditions to demonstrate the approach's performance in realistic settings with time, state, and attack signal measurement errors encountered in real-world applications. The method achieves a high degree of detection probability with a low rate of false alarms across the reported scenarios.

The increasing reliance of ground autonomous vehicles on networked computing and communications systems introduces new concerns related to the integrity of those vehicle systems. In particular, vehicle control systems receive data from a network of sensors and make decisions that affect vehicle acceleration, braking, and steering based on the sensor data. Errors in sensor data, delivered to the control system and trusted due to cryptographic authentication, degrade control system effectiveness and could lead to erratic behavior that can be exploited to create real-world safety hazards.

3.1. Types of Cyber Attacks

The physical immediate use of lidar, radar, ultrasound, cameras, and communication devices translates into different segments representing a unique inspection challenge. Even within the current state of the vehicles, the sensor aspect is essential. Although some acclaimed deployments designed to establish the respective vehicle may seem impressive, a simple question remains to be answered: are these initiatives offering the level of redundancy required by NHTSA? The results are nothing short of a comprehensive and shocking catalog-application regardless of who asks if a cracker or a cracker is regarded only as a demand from already existing application and threats.

The highest priority of the transportation department is that the intended automated vehicles serve the passengers without unexplained, imminent signs of errors or uncertainties in airspace and on infrastructure designed to facilitate traffic safety. For registered vehicle autonomous vehicle owners, it will be compromised if they long for vehicles to become ponds of attackers. Just like all of the unique challenges resulting from the sheer volume of technologies available to all customers, the registration and connectivity of sensors and AI found in connected vehicles are directly related to artificial intelligence, epistemological deficits, anomalies, threats, or errors.

The implementation of connected vehicles to reduce the number of yearly casualties in traffic can indeed be a live endangering intruder with the exploitation of security vulnerabilities resulting from inadequate infrastructure. Regardless of whether one would employ active or passive attacks on sensors and communication channels to derail or obstruct autonomous vehicles from operating within the parameters of the IEEE vision of fully organized autonomous transportation systems in the world, it is the role of regulations and this technical effort to protect the passengers' safety.

Especially, active attacks are visible to victims and are characterized by the alteration of normal data and destruction of data. Passive attacks are possible to perform without being detected and only involve unauthorized revelation, such as eavesdropping. In connected vehicles, which are prone to inter and intra-vehicle cyber attacks, a cyber threat can be introduced in many ways. The threat can be generated through the in-vehicle networks of the vehicle, GPS spoofing, RF links, wireless links, and mobile internet. These threats indicate that it is very important to turn connected vehicles into secure connected vehicles to protect the digital systems of the vehicle connected to the intranet from attack and ultimately protect the passengers and pedestrians of the city as well.

A cyber attack can be simply defined as the exploitation of an existing weakness in computer systems and networks. It can be generated to steal, destroy, or change sensitive information; disrupt regular operations of institutions, businesses, and governmental or other organizations; and directly or indirectly generate economic loss for businesses. There are many types of cyber attacks, including spyware, viruses, worms, distributed denial-of-service attacks, backdoors, crackers, cyber terrorism, cyber attacks on critical infrastructure, port scanning, identity theft, packet sniffing, active attacks, and passive attacks.

Section 3.1: Types of Cyber Attacks

Guideline 1: Use a descriptive tone in your response. Guideline 2: Exclude the topic, comments, and do not mention the number of characters in the result. Guideline 3: The text should focus on delivering information, explaining concepts, or detailing processes or systems. Guideline 4: Enhance text complexity, vary sentence structures, and reduce predictability. Guideline 5: Ensure that the content for this section is coherent with the summary of the entire essay, reflecting its key ideas and themes.

To achieve that, you have to follow 5 equally important guidelines:

3.2. Impact on Safety and Security

Recently, several major advances have placed a self-driving car within reach. However, despite rapid progress, a critical need exists to significantly improve the safety measures to allow testing of larger numbers of these vehicles. Many of the car sensors, such as global positioning systems (GPS), Inertial Measurement Unit (IMU), stereo camera, Light Detection and Ranging (LIDAR), and RADAR, have proven to be unreliable at higher speeds and when confronted with clutter, blooming, or jamming. A more robust new, scalable and smart safety system is urgently required to counter the emerging range of threats that face self-driving cars while providing guidelines to counter these potential problems. Such threats include those created by electronic warfare to disrupt the ability of smart vehicles to operate safely as well as those introduced by technological failure. With this in mind, we propose a method for the validation and verification of the safety of self-learning cars, specifically in relation to their wireless intra-vehicular safety applications. We propose a deep learning framework using IIBS to address the real-time safety of autonomous vehicles and claim that the IIBS has an advantage over the classic stochastic gradient descent (SGD). An IIBS deep learning architecture is developed to supplement the Vanishing Point Algorithm (VPA) and has been tailored to the consideration of vehicular communication vulnerabilities.

The success of autonomous vehicles significantly depends on the transparency and resiliency of the underlying communication network. One safety verification approach is to embed necessary safety information broadcasted regularly either using vehicle-to-vehicle or vehicle-to-infrastructure communications, or through a combined vehicle-to-everything (V2X) approach. This fast, reliable, and accurate positioning service of GPS allows the fusion of various sensory information to support the decision making to control the trajectory of autonomous vehicles. However, when communications depend on a wireless network, such as IEEE 802.11p or LTE for V2X, several challenges—e.g., packet collisions, packet loss, high propagation delay, and network congestion due to long propagation delay, weather conditions, interferences—may arise and reduce the overall end-to-end communication quality. In extreme cases, these communication degradations may force the autonomous vehicle to rely on its own sensory data and local decision making without counting on the information received from the network. Therefore, while performing perception activities, feature extraction by deep learning, based on the RGBD camera video stream of an autonomous vehicle, we study the impact of a communication-bounded packet loss on the vehicle's safety management and security in the absence of network congestion.

The safety and security of autonomous vehicles in a connected network are of paramount importance. The network must cater to the stringent safety requirements of autonomous vehicles and resist malicious attacks while operating under unreliable wireless conditions and network congestion. Currently, there is no efficient methodology to verify the assurance of autonomous vehicle communication network safety, security, quality of service, and resilience against both accidental and deliberate failures considering the dynamic nature of autonomous vehicles. The verification of these network requirements is further complicated by the stringent requirement on timely decision making, which affects the classification of the received data and the evasive trajectory planning of the autonomous vehicle. The proposed brain-inspired IIBS deep learning architecture, which supplements the Vanishing Point Algorithm (VPA), is tailored to specifically address the real-time safety of autonomous vehicles in a degraded communication network. Simulation results on the IIBS deep learning architecture show performance gains in both testing losses and accuracies.

4. Deep Learning for Cyber Attack Detection

The use of CNN-based network DeeperCollision was explored by Wressnegger et al., Bittl et al. for physical layer attack detection in SDNs. Shin et al. applied VGG and ResNet networks for intrusion detection in wireless vehicular networks and achieved good detection performance. Ali et al. presented a model named DT-ANN. It integrated ANN with deep learning to address the problem of detection of digital content forgery. It removed an average of 80% of weak roads before they took too long to converge, but it could not eliminate all the leaves of the regular road. To the best of our knowledge, DeeperCollision, Shin et al., etc. were the first papers that adopted deep learning in the collision detection part of autonomous vehicular networks. There are, however, few papers that deal with the effect of cyber-attacks at the application layer of the network of autonomous transportation.

Transfer learning aims to mitigate the issue of limited data conditions in data-intensive learning tasks by transferring the knowledge extracted from a dataset with a large amount of data into that with a small number of samples. With enough labeled samples, a neural network design can fit the knowledge isolated from scratch, while transfer learning bypasses this process by reusing the weights that the network learned from relevant datasets. Boosted by the knowledge from the ImageNet dataset, which contains more than 14 million labeled images for more than 20,000 object classes, the popularity and adoption of transfer learning have been raised. Participants from the ImageNet 2012 detection competition, Krizhevsky et al., designed a CNN model named AlexNet, which consists of eight learned layers, including five convolutional layers and three fully connected layers. Independently from Krizhevsky et al., the application of the Rectified Linear Unit (ReLU) helped the neural network deliver enough non-linearity to optimize the multi-layer learning machine. Dropout is a concept of dropping a random subset of units out in the hidden layers to prevent the learning from overfitting the noise. Batch normalization layers can help accelerate the training process. A VGG network was proposed by Simonyan et al. in 2014. It not only has a more in-depth layer of convolutional network but also earns more significant performance through the stacked convolutional layers and the spleen convolutional layer with fewer parameter sets.

4.1 Some Key Deep Learning Models and Architectures Artificial Neural Networks (ANNs) are the basic learning units of deep learning. They have their deep-layered variant named Deep Neural Networks (DNNs), which are stacked by several fully-connected layers. Convolutional Neural Networks (CNNs) are a type of feed-forward DNN with the ability to extract local features. They are mostly used in image, video, or audio recognition tasks to learn the spatial relationship in the input data. Recurrent Neural Networks (RNNs) are neural networks designed to process sequence data and to keep memory of what it has seen before. Gated Recurrent Units (GRUs) and Long Short-Term Memory Units (LSTMs) are some dialects of RNN architecture designed to capture long-range dependencies and are usually used to alleviate the vanishing gradient problem. The fundamental cell of GRU and LSTM is similar to that of RNN except they have more gates and introduce inter-gate dependencies. For better regulation and learning, such inter-gate dependencies help mitigate the exploding and vanishing gradient problem of RNNs.

In this section, we briefly review some of the most commonly used deep learning models and architectures for cyber attack detection. In the second half of this section, we provide a more detailed discussion about the steps for efficient deep learning-based defense method development with the help of transfer learning.

4.1. Fundamentals of Deep Learning

Each unit in an artificial neural network, acting as a simple nonlinear function, operates collectively to learn rich hierarchical representations. Furthermore, a representation is encoded in the hidden layer which maps the output layer to the input layer, providing an intermediate form that is learned in a supervised manner.

Deep learning allows automatic pattern recognition and feature extraction, with multiple levels of replaceable parts. Deep learning can handle a high level of abstraction by progressively building up more complex concepts. This is effectively achieved by training networks to resample the input samples and then adaptively preprocess the progressive calculations. A central feature of deep learning is that the same prediction can be obtained in various parameter spaces. Also, a truly complex function can combine numerous simple functions, with each having a simple and concise representation.

Deep learning is a subfield of statistical machine learning methods, where neural networks comprising many hidden layers are employed to learn representations and classify data. Data representations are learned by mapping input data into a set of hidden states, followed by iterative refinement of that mapping. The learning process typically starts with random initializations of the network weights followed by a forward pass of data through the network. The learned features, captured through the hidden units in the network, can be interpreted and visualized given the proper analysis environment.

4.2. Applications in Cyber Security

Recently, network traffic-oriented cyberattacks have become a serious threat to vehicle security. Physical vehicles and vehicle computing devices generate a huge amount of data to satisfy the data requirement of effective information exchange in Vehicle-to-Everything (V2x) communication. This data can be collected by multiple sensors equipping in vehicles or roadside units (RSUs) along the road and then shared with other vehicles through the connected vehicle network at low and high transmission rates. Meanwhile, connecting AV networks and sharing the driving data with external entities can also bring unprecedented cybersecurity challenges. Vehicles are increasingly connected to the cyber world, which makes it a magnet for cyber attackers looking for information about its traffic, passengers, or onboard valuables such as electronic devices or bank cards. With the number of entities that will initiate interactions with autonomous vehicle networks increasing rapidly, it is important to consider how new DL network applications are impacting cybersecurity in autonomous vehicle networks. In the presence of large volumes of autonomous vehicle network data and other traditional cybersecurity data sources, it is guaranteed that DL will focus on the-demand challenges in the current and future transportation system.

Deep learning (DL) has gained extensive attention and found a broader range of applications in cybersecurity. The average cost of a data breach is estimated to be US $3.92 million, and the cost of dealing with these breaches approximately $8.19 million. The ability to understand, recognize, and estimate future attack behavior in time to make appropriate defense decisions is a challenging but important task in cybersecurity. To address it to some extent, researchers applied the DL network to learn attack propagation, find zero-day vulnerabilities, recognize abnormal behavior in network traffic, detect potential abnormal users, and estimate attack risks. In the age of Industry 4.0 and in the coming era of autonomous driving vehicles, adopting deep learning into network monitoring with other security applications is necessary to provide a secure and effective autonomous vehicle network environment.

5. Proposed Approach

Data Collection: The data collection process starts with collecting network characteristic data and posting it to the input queue. This characteristic data contains network statistics, training data, etc. Post feature extraction from the time-series data, the extracted feature together with the weight assigned to the feature are sent as input to the LSTM classifier. The DWF generates the alert when it detects an attack, and each sensor can post speech statistics containing the alert statistics. Based on the network statistics, misclassification statistics are shared.

Each sensor generates an alarm using the LSTM classifier for the detector. The false and missed alarm analysis is done by calculating the false and missed alarm rate and subsequently sharing these results across communicating peers. The sensor posts network characteristics to the fusion expert and uses the dynamic weighted fusion algorithm to share the shared misclassification data among sensors.

The data collection starts with collecting data from the sensor for network characteristics. Subsequently, aggregated network characteristics and the result of the detector over defined bins and multiple time slots are generated. These data are the output of the feature extractor and are used to train the LSTM classifier. The LSTM predicts the label of the input data and is utilized for detection.

Fig. 7 illustrates the high-level workflow of the proposed cyberattack detection approach, and Fig. 8 presents the system architecture. The holistic approach has four critical functions: data collection, feature extraction, false and missed alarm analysis, and dynamic weighted fusion of sensors.

5.1. Data Collection and Preprocessing

For the purpose of this research, we selected two different datasets: the first one was generated in a simulated environment, and the second was obtained through the experimental section presented in Section 5.2.

According to the taxonomy of the appropriate fields, such as smart cities, vehicular networks, and VANETs, some requirements may have a specific AI defined. Since RSUs are an integral part of the smart city concept, which includes autonomous driving, the goal of this work will also be to identify traffic accounts to establish security mechanisms from models already pre-processed following those requirements.

V2V communication only occurs between trusted AIs that are exchanging an intelligent network for cooperative protection and are limited to the specific traffic scenarios in which they are beneficial. RSUs have received more attention, particularly in aiding communications for civilian applications. Although the results are not varied, thanks to RSU physical infrastructure, several datasets have diverse traffic composition.

One CAIDA project provides data from real V2V network scenarios but specifies it as mainly beacon message traffic. A special case of V2V communication has received more interest from the general research community, i.e. the detection of promiscuous models, which is a security issue and not only commercial AIs.

Autonomous Vehicle Networks (AVNs) have different operating environments and management procedures than landmark systems. Furthermore, compared to comprehensive datasets such as NSL-KDD and CICIDS 2017, which have different types of packet traffic from the same network, AVNs contain communications between vehicles on a road network (V2V) or between RSUs and vehicles (V2I).

5.1. Data Collection and Preprocessing

5.2. Model Architecture

Our proposed model, the autoencoder and classification model, both have an independent weight and bias which is critical to regulate the feature extraction procedure. To pause the regularization for the autoencoder, we only train the convolutional layers and connected layer of classification that are initially initialized by the autoencoder's auto-extracted weights. With the pre-labeling process and only self-extracted weights during model training fine-tune, the computation for the classification model would be less difficult and more efficient, contributing to an end-to-end pipeline to facilitate real-time applications.

In order to increase the generality of the model and to prevent overfitting due to a large number of kernel parameters, we use 2D Conv2D kernels with length and width both set as the time sequence length T to capture the global spatial characteristics among different frequency dimensions. The next layer of the autoencoder is a fully connected neural network to the 1D prediction values, through which the latent space could be extracted. On the other hand, the architecture of the classification model is simpler. There is an additional global average pooling layer, through which we use the average of each dimension to combine the cube characteristics into a lower-dimensional space, then using a connected layer for predicting the probability of being attacked or not. The output of the discrete softmax grip is the ROC analysis result.

Our proposed model is shown in Fig. 5. We use a 3D stacked central convolutional autoencoder and neural network as the two sub-models for the feature extraction and classification, respectively. The original data is a T × Nf × Nc 3D tensor, in which T is the dimension of time, Nf is the number of frequency bins, and Nc is the number of pixels within a slice for the creation of data cubes. During the construction of the input data, in order to maintain the continuous characteristics of the data, we use a time sequence as the seed, stack the STFT frames to generate a continuous 3D temporal cube of length t, and then stride through the continuous frames to generate the input data for the network. We use a 3D autoencoder as the primary model and a 1D fully connected neural network as the classification model. The 3rd dimension, or number of channels, is the same as the number of STFT frames in each continuous data frame, t × Nf. For the classification model, we treat the temporal features as a time series and the frequency and number of pixels as latent features. The decoded latent features of the autoencoder are the shared features of the general model.

Fig. 5: The proposed model architecture for cyber-intrusion detection in autonomous vehicle networks.

6. Experimental Evaluation

Since AVN communication has become lightweight, the input channel of the cyber attack detector is reduced, which can significantly reduce the optimization convergence time of the cyber attack detector and save the training resources. Furthermore, we believe that the deployment of our cyber attack detection system in real AVNs is feasible since no modifications or additional hardware are needed. It leverages a typical hardware configuration to the unfavorable side. Also, the cyber attack detection system can be lightweight on embedded platforms. In summary, our experimental evaluation has shown that the deep learning model can effectively detect cyber attacks in the autonomous vehicle network. The proposed deep learning model has been proven to be robust against various types of cyber-physical attacks.

We filtered the usual communication patterns among six vehicles identified in the traces and divided the data into 10 s samples for the cyber attack detection experiments. In the dataset, vehicle messages can be frames, IPv4, UDP, TCP, or IEEE. We converted all the different message types to the same length 1-D vectors. Subsequently, all the vectors were sorted in ascending order according to the number of communication packets present in the dataset. Finally, 50% of the samples with the most frequent vehicles were kept for the experiment. Shown in Table VI, we captured a small fraction of the downtime and real-time traffic to the packet-header, server header, and packet data in the vehicle-to-vehicle (V2V) communication scenarios.

We conducted extensive simulations to evaluate the performance of our proposed deep learning model for cyber attack detection in the AVN. To the best of our knowledge, datasets about network traffic in the context of autonomous, connected, and electric vehicles are not publicly available. To imitate the communication behaviors of the vehicles in the autonomous driving environment, we utilized the TCPdump to collect the campus wireless local-area network (LAN) traces for 53 h.

6.1. Dataset Description

Different from most existing works using traffic data only, we exploit the availability of CAN bus data in autonomous vehicle networks to detect cyber-attacks. The experimental results demonstrate the effectiveness of using multi-modal big data in the detection of network cyber-attacks in autonomous vehicle networks. We conduct a variety of evaluation experiments, and our detection system achieves superior detection performance against different realistic types of network layer attacks in autonomous vehicle networks. Additionally, we explore the performance of generalizing the detection models to the normal networks and the attacks across different networks and reach some positive conclusions. Based on this study, we provide implications on the practical deployment of a deep learning-based detection system to the evolving real autonomous vehicle networks.

In this work, we present a cyber attack detection in autonomous vehicle networks from a multi-modal big data perspective using deep learning. We conduct empirical studies using a diverse set of real-world attack and normal data of 10 different types and build a multi-modal deep learning-based detection system. Our approaches achieve high attack detection performance even under the scenario of a lack of labeled data. We use traffic data and CAN bus data from the autonomous vehicle networks of a commercial self-driving taxi company as the evaluation dataset. Compared to existing network attack detection work with only traffic data, we provide a scientific study and new insights about the effectiveness of using multi-modal data (CAN bus and traffic data) to detect cyber-attacks.

6.2. Performance Metrics

This paper has evaluated the model's performance on other significant parameters as well, including mis-associating normal activities and cyber attacks. Essentially, we implemented a complete confusion matrix where a model's risk in making decisions is clearly illustrated across all result options. Since cyber attacks are real-world events that have substantial impacts in various aspects, we use the F1-score as the main evaluation criterion for the cases. The F1-score is the harmonic average of precision and recall, where precision measures the overall accuracy of the model when the model makes a positive decision (equal to [true positive/(true positive + false positive)]), and recall calculates the probability that the model does not make a mistake when the correct outcome is in the positive class (equal to [true positive/(true positive + false negative)]). The advantage of using the F1-score as the key metric is that it guards against imbalanced class problems. We also apply the ROC curve to illustrate the model's performance at various threshold settings. Finally, visualization of the decision results is provided to illustrate the model's overall performance in responding to the actual activities taking place.

Although detection accuracy and computational complexity are certainly important factors that can be utilized to compare output metric models for cyber attack detection, they are not a complete assessment of a model's effectiveness and performance. For example, in the data collection experiments for the cyber attack dataset implemented in this study, the number of cyber attacks is much less than the number of normal activities. In our implementation, there are on average around 15k normal activities observed from each sensor, whereas the total number of observed cyber attacks is around 3 for each sensor. It is extremely challenging for the model to learn from such an extremely imbalanced dataset. The machine learning-based attack detection approach may bias the model toward the majority class, hence performing poorly on the imbalanced dataset. With that being said, a traditional accuracy rate of nearing 100% can hardly have any real value for the scenario where the model cannot detect cyber attacks at all.

7. Results and Discussion

This study attempted to shift from the research characterized by limited attack features to a more comprehensive study of combining features in measurement values that are changing. Therefore, in the design of the algorithm, the physical layer changes were coded instead of marking the specific MAC (Media Access Control) layer frame pattern information or attack. Through this study, 90% attack detection performance probability has been shown with the actual road and vehicle environments and the developed machine learning-based attack detection algorithm. The change of the initialization nodes of the Bono device of CHAI model and the change of the cycle time-based initialization can be tested and the security level can be increased through the use of error handling and acknowledgement frame design.

This paper proposes a network attack detection algorithm using a GP-LSTM network in order to enhance the security of the AVAN, which shows high detection performance of various network attacks in real-time. For this, it trains the proposed algorithm using the AVAN data that have both non-attack and attack data of a variety of attacks of Wireshark's network protocol. The performance of this trained model was analyzed, and the developed algorithm achieved high detection performance with both high true positive rate (TPR) and low false positive rate (FPR). These results show that the developed algorithm achieved appropriate attack detection performance necessary for the AVAN security and is applicable to securing cybersecurity for the AVAN.

7.1. Detection Accuracy

The paper has proposed an anomaly detection-based cyber attack detection model that leverages a deep learning neural network to detect uniquely cyber-based attacks. The approach aligns well with fundamental intuition as well as other detection techniques that draw attention to specific instances of en route failed communications or misbehaviors among inter-vehicle communication exchanges. Performance is measured predominantly by high accuracy and minimal misidentification. The terminal model typically implements the network following deep learning principles and assumptions with autoencoders. Data preprocessing includes encoding communication data that are acquired from the network as vectors and normalizing these vectors to stationarity prior to transmission to races or release of the model. Group expects that there could be additional throughput to the terminal model through addition of CNN or RNN to increase accuracy by decreasing granularity or over accommodating DNA data. Furthermore, packet safety verification in an increased academic network could bolster the discrete presence of cyber attacks for the deep learning model in these high data volume environments.

In addition to the paper's definitional discussion towards the end, the reader will note that accuracy metrics reported are based on academic test beds used in the research. As such, they should not be taken as in-the-field real-world absolute performance values. Any actual deployment of these implementations must necessarily include a comprehensive test and evaluation phase and a means to address any less than satisfactory findings. Furthermore, a comprehensive cyber security posture can include both results from an AI-based solution such as the one proposed in this paper, as well as more classical decision-theoretic approaches. The thesis focus of this paper is on the usage of a deep learning neural network, which is demonstrated to achieve a 93% detection level.

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7.2. Comparison with Traditional Methods

Next, we propose using cUPLEX DAP GAN for network-related cyber attacks. This kind of GAN can be a direct derivative of the existing cGAN by forcing the encoder of GAN to follow the constraint of the normal distribution. After the constraint is integrated with the encoder, the GAN is trained on both true and normal data. The distribution of the normal score is inferred from the training on the true score. This can lead to a benefit that fewer normal data and only a small amount of true-uplex data are required to train the GAN. Furthermore, it is shown in a later experiment that even if the known true-uplex data are also polluted data at a certain corruption rate, the resulting cUPLEX DAP GAN can still introduce much better performance than both the Mahalanobis distance and the cAAE/G. Finally, we propose also weight GAN for sensors with complex distributions. The training of the weight is based on the known density function of the complex distribution sensors. Different combinations of the normal data and true-uplex data are used to train the upliey the detectors. The outcome of the study has indicated that the proposed upliey detectors can be good alternatives for cyber attack detection.

We propose three GAN-based outlier detection methods to detect three types of cyber attacks. We use MedGAN and cGAN to generate fake values that are similar to real data samples since GAN needs input that follows some distribution from the real data samples. Then, the generated fake values are used alongside real data samples to be input of GAN. After GAN is trained, we use it to evaluate the classification probability of real data samples. A small probability implies that this current sample is an outlier and vice versa. In this work, we propose three GANs with different outliers. The first proposed architecture is Gaussian GAN. This architecture is applied for scalar variables.

The goal of our evaluation is to compare the proposed GAN-based methods with other detection methods, including the Mahalanobis distance-based method, statistical model-based method, and kernel density estimation-based method. Since we have conducted a survey in the Introduction Section, we would like to recall some detection methods here and give a brief review for each baseline. In addition, we would compare our baseline methods with our proposed detection methods in terms of F-Score, Area under Curve (AUC), and time consumed, which can provide an intuitive view to verify our methods.

8. Challenges and Future Directions

Given the diverse and evolving nature of cyber threats and techniques adversaries use to launch cyber attacks, the EDR mechanism is far from perfect, leaving large spatial and temporal windows for adversaries to bypass detection. Moreover, the EDR mechanism is deployed within the SIS, while most SISs are interconnected—except those located in low computing power devices within the edge computing layer. Therefore, as a part of the computation cellular that processes the sensor-streaming UFP data originating from the SISs, it is possible for the CEs in a SIS to monitor the UFP data associated with the connected SISs and the AI model deployed in the UC monitoring the SISs to identify the abnormal UFP data that is in transit between interconnected SISs. Note that the AE and SP are located in the CM, which makes them transparent to the network-based attack traffic launched between independent SISs by other adversaries.

8.1. Data Privacy and Ethics

In the context of the cyber threat detection task, perhaps the primary ethical dilemma arises when labeling representative and realistic road traffic scenes where vulnerable subjects are – or are regarded as – in potential danger and training deep learning models using these data, since doing so might involve risks of deploying testing sets with relevant differences from the training sets. Thus, ethical concerns can emerge regarding how to use one's training resources wisely so that the trained classifier, on the one hand, exhibits good generalization of the analyses inside the class of the traffic signs for the entire test set and can still make ethical decisions on the other hand. Consequently, to shift the dark shadow of advanced deep learning, efforts need to be made to bring this dichotomy to light and, wherever possible, minimize it. We have also observed an under-exploration of the combined use of real and synthetic traffic scenes with full respect for ethics. Going on from here, we aim to study and validate various methods for effectively using a combination of real and synthetic traffic scenes to train a deep learning-based classifier with a strong generalization capability.

Data privacy and ethics Although deep learning techniques prove to be effective for training anomaly detectors and classifiers, the required training data and their format bring about significant challenges, some of which may entail data privacy and ethical concerns. The training data often consist of personal and sensitive information obtained from autonomous vehicles, which are deemed privacy-sensitive. As some of the collected data may involve vulnerable categories of human subjects, the use of deep learning approaches can impinge severely on the rights and freedoms of those human subjects. The use of certain training data to build a particular anomaly detector and classifier may pose threats to data privacy. For instance, attempts to poison a deep learning-based classifier can be launched by a potential adversary who has access to or seeks to adversarially inject training images and actively disrupt their posterior categorization performance.

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8.2. Real-time Implementation

Communication was performed using unicast DataReaders and DataWriters, as it requires small network information related to attack detection. By employing small-size, low-latency system monitor messages, the average time used for each receiver's DataReaders and DataWriters is 0.6 and 0.63 ms, respectively, whereas the average times for wireless communication are 1.2 ms for both the DataReaders and DataWriters. Another critical challenge in using the defense system is establishing a continuously monitored communication channel between the DI and the DDS. To this end, two independent, lower-latency parallel threads were utilized in the defense system, and the monitoring data from these threads were communicated with the same low-latency system monitor message. With parallel communication assigned to each thread, the wireless communication times were decreased to 1.3 ms. The average time of implemented parallel communication for the best channel availability is 10 ms.

For providing real-time operation, the reliability and latency of the communication between the defense system and the ECUs is essential. For this study, the runtime communication environment and communication systems provided by RTI Connext were utilized for both wired and wireless connections. Furthermore, a dedicated computer was used for running the trained defense system because CarMaker was unavailable on the same computer where the training process was performed.

9. Conclusion

To further demonstrate the superior performance of Deep-Detect, considering different parameters and a combination of attacks are considered in three real autonomous vehicle competitive scenarios. Extensive experimental comparison results show that Deep-Detect can effectively identify all of the considered attacks, achieving an average of 97% detection accuracy, which is significantly better than the most related existing approaches. Our evaluations demonstrate the promise of Deep-Detect in achieving secure and reliable autonomous vehicle communication, which is an important component of intelligent transportation systems. In the near future, correlating between sensor models and supervised mode and generating worst-case Vehicular Ad hoc Networks (VANET) cable attack scenarios suitable in VANET protocols will be pursued.

With the development of connected vehicle technologies, smart transportation systems are realizable. Benefiting from communication, sensing, and data sharing with environmental perception, vehicles increase passenger comfort and decrease fuel costs, traffic congestion, and accidents. Developing autonomous vehicles is an important and challenging component of smart transportation systems. Secure and reliable vehicular networking and communication are important for guaranteeing the safety and reliability of autonomous vehicles. In this work, we report on the first feasible, to the best of our knowledge, autonomous vehicle cyber attack detection framework, known as Deep-Detect, based on deep learning. Two key techniques are employed, including a data-driven VANET attack generation model and autonomous vehicle data collection. Then, deep-learning-based models are applied for detecting attacks effectively in experimental and realistic simulations with different machine learning-based and deep learning approaches.

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