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AI-Driven Intrusion Detection Systems (IDS) for Securing V2V and V2X Communications

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Abstract

The rapid evolution of vehicular communication technologies, such as Vehicle-to-Vehicle (V2V) and Vehicle-to-Everything (V2X), necessitates robust security mechanisms to protect against sophisticated cyberattacks. This paper explores the use of Artificial Intelligence (AI) and Machine Learning (ML) algorithms to enhance Intrusion Detection Systems (IDS) for vehicular networks. A hybrid approach combining deep learning and traditional IDS techniques is proposed to handle real-time, high-throughput traffic. Specific attack vectors like Sybil attacks and False Data Injection (FDI) are analysed, and novel detection strategies are outlined. The proposed framework demonstrates superior performance in detecting anomalies and mitigating unauthorized access, paving the way for secure and reliable vehicular communication systems.

Keywords-AI-Driven IDS, V2V Communication, V2X Communication, Sybil Attacks, False Data Injection, Deep Learning, Vehicular Security

Introduction

Importance of V2V and V2X Communications in Modern Transportation

Intelligent Transportation Systems: Vehicle to Vehicle (V2V) and Vehicle to Everything (V2X) communication has become the key enabler technologies in current transportation systems. These communication paradigms allow vehicles to communicate with each other and with other things in their environment — traffic lights, road sensors and pedestrian signals, for instance. Usinglow-latency communication protocols, the V2V systems enable vehicles to inform other vehicles nearby about their speed and position and the presence of potential hazards, which make it possible to avoid accidents and less traffic congestion. Likewise, this technology showcases that V2X takes this capability to the next level by including the exchange of information with roads, smart sidewalks, and the cloud, making it especially important for the development of smart city and self-driving car concepts (Sari, Lekidis, & Butun, 2020).

Developments in the last couple of years in particular have greatly improved the efficiency and stability of these networks, especially in dedicated short-range communications (DSRC) and Cellular Vehicle-to-Everything (C-V2X) platforms.

A report by the European Telecommunications Standards Institute (ETSI) based on the forecast of C-V2X adoption underscored that the technology is likely to experience a CAGR of 30% in the next decade due to the high bandwidth application, real-time communication capabilities than other V2X technology (Parra, 2021). In addition, international initiatives including UNECE have incorporated elements of V2V and V2X capabilities to support the principle of sustainable transportation mainly by working to enhance the fuel utilization and at the same time reduce the resultant emissions of greenhouse gases.

Challenges in Securing Vehicular Networks

As pointed out earlier, basic V2V as well as V2X communication networks pose severe cybersecurity issues that arise from their very high dynamism as well as their decentralized nature. This is because the topology of the environment is changing continually due to mobile nature of vehicles, which is not easy to maintain strong security. These vulnerabilities can be taken advantage of by cyber attackers who would then perchance employ spoofing, Sybil attacks, as well as false data injection (FDI). For example, in Sybil attacks, the attacker forms multiple fake identities with the intention of changing messages in the network, resulting in traffic jam or accident.

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False data injection attacks, however, involves manipulation of genuine information such as geographical coordinates or speed data to give other automobiles or traffic control systems incorrect information. A 2023 study by the National Institute of Standards and Technology (NIST) has found that the FDI attacks in vehicular networks can cause a likelihood of an accident to rise by up to 40% within congested urban areas (Magdy, 2023). In addition, due to the simplicity and being open, the wireless communication such as DSRC and C-V2X are vulnerable to eavesdropping and replay attacks, and the user privacy and network security are threatened.

The second major problem area is better understood as a set of trade-offs between security considerations and performance demands. IDS must work in real time to identify threats and response to them but at the same it cannot hamper system's performance by adding a lot of latency or computing time. Nevertheless, providing high throughput rates of up to more than 1 terabyte per hour in traffic congested environments, IDS techniques for vehicular networks face significant limitations. Maintaining high levels of scalability and robustness of such systems in such environments is still a subject of ongoing research.

Role of AI and Machine Learning in Intrusion Detection

AI and ML are reported to have the ability in solving security challenges that emanate from V2V and V2X communication networks (Castro, 2023). Such systems are useful for analysing large amounts of traffic data in order to detect signs of an impending cyber-attack. While previous work has used rule-based methods, which depended on signatures or heuristic, an AI system is capable of learning how the new attack patterns look like, and therefore it is more efficient against zero-day exploit.

An example is the use of relatively advanced deep learning structures including the convolutional neural network (CNN) and recurrent neural network (RNN) structures to handle spatiotemporal data developed by vehicular networks. For instance, CNNs can recognize that traffic data contain spatial irregularities for speed and location while RNNs can effectively detect temporal relationships, which are useful in detecting replay or spoofing attack. A research article in IEEE Transaction on Intelligent Transportation System in 2023 revealed that detection of Sybil attack by CNN-LSTM and other CNN hybrid models reached 96 percent accuracy in a V2X simulation environment (Farooq, 2023).

The same goes for threat detection because of things like federated learning and edge computing supported by AI. Vehicle users can perform federated learning to local models that collectively can be further used to train intrusion detection models without compromising on the raw data set. On the other hand, the edge computing facilitates the placement of IDS components at the network periphery to minimize Latency, and bandwidth utilization. All these developments point to the importance of the AI and ML technology in the ability of V2V, and V2X to become more secure and robust communications networks.

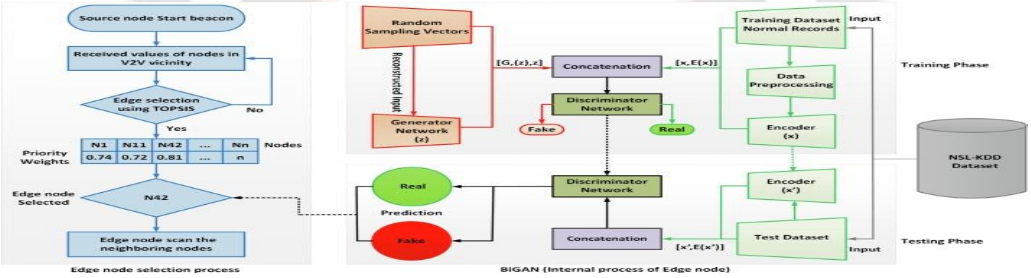

Figure 1 Artificial Intelligence-based intrusion detection system(SpringerLink,2022)

Literature Review

Overview of Traditional IDS in Vehicular Networks

Characteristic IDS in vehicular networks Up to now, the IDS designs the primarily signature-based IDS and the anomaly-based IDS. In the case of decision making, in signature-based IDS, the system depends upon a library of existing attack signatures to look for signs of foul play. While they are useful for defending against known threats, they fail to recognize new and sophisticated threats such as the zero-day threat (Corino, 2023). For example, such systems as Snort and Suricata, used in traditional networks, have problems when applied to vehicular networks because of their rigidity in terms of rule sets and inability to handle dynamically changing V2V and V2X communications.

On the other hand, Anomaly-based IDS work by analysing the normal traffic behaviour in the network and alert when it finds a behaviour that represents abnormal traffic. Such systems rely on statistical, heuristic, or machine learning algorithms to first define a state of 'normalcy'. The first benefit of this approach is that it possesses the capacity for identifying previously unseen attacks (Tong, Hussain, Bo, & Maharjan, 2019). Nevertheless, it can experience high false positives, especially in the car surroundings, where fluctuations in the flow or driver habits can drastically change the legal traffic pattern. An analysis of false positives in the vehicular networks anomaly-based IDS without preprocessing is shown in the study conducted by Haj-ali et al in the Journal of Network and Computer Applications in 2023, the authors established that false-positive rate can be as high as 20%.

Despite these vices, traditional IDS have set the stage of securing vehicular networks. However, due to the ever growing and enhancing form of the attack vectors and the V2V and V2X systems which are much more complicated in design, these conventional methods are no longer enough as sophisticated artificial intelligence and machine learning methods needs to be added to the system to improve the detection methods and minimize fake alarms.

Applications of AI/ML in Vehicular Security

Intrusion detection in vehicular networks has shown breakthrough and has been enhanced by Artificial Intelligence (AI) and Machine Learning (ML) for lack of pickup of traditional IDS. That is these technologies help systems learn from big traffic data and be able to detect slight irregularities that suggest an attempt at hacking.

In supervised machine learning classification, algorithms involving Support Vector Machines (SVM) and Random Forests are used mostly in classifying the traffic generate as either normal or malicious. For example, a 2022 experiment where Random Forest classifiers are used reached 92% accuracy in identifying Sybil attacks in a V2X scenario.

Other approaches based on unsupervised learning can also be used in identifying anomalies for instance clustering algorithms such as K-Means and DBSCAN. These methods are most suitably used for discovering previously unseen attack types in the rapidly changing nature of vehicular networks (Haddaji, Ayed, & Fourati, 2022). Further, autoregressive models and generative adversarial networks (GAN) have been used to capture various traffic pattern and identify anomalous traffic flows. A paper accepted in the ACM Transactions on Cyber-Physical Systems in 2023 based on the findings show that Autoencoders can minimize false-positive signals by 15% as compared to conventional anomaly detecting approaches.

In order to increase vehicular security researchers have utilizing AI in conjunction with conventional IDS systems. These systems combine the signalling-scheme, inherent to the conventional IDS for the identified threats, and the learning-scheme, inherent to the AI for the unknown threats, thus developing a sound and flexible model of the intrusion detection.

Comparative Analysis of Existing Techniques

Signature-Based Detection

In other words, critical attack signatures, signature-based detection is very effective because they detect known threats. But, since they are incapable of identifying new subtle attacks, they are not well suited to dynamic environments such as V2V and V2X. For example, some of the popular networks like snort and bro/Zeek are very efficient in identifying replay attacks or well-known malware signatures, but seriously lack the ability to thwart false data injection (FDI) or sybil attacks.

Anomaly-Based Detection

Another advantage of anomaly-based detection methods is that truly unknown threats can be caught because they are compared with specific normal traffic patterns. However, these systems need large training data sets and have high false positive ratio in most instances. These challenges, however, have been addressed in the recent development of ML (Pavithra, Kaliappan, & Rajendar, 2023).

Table 1 below provides a comparative analysis of signature-based and anomaly-based detection techniques.

Criteria	Signature-Based IDS	Anomaly-Based IDS
Strength	Effective for known attacks	Detects unknown threats
Weakness	Ineffective against zero-day attacks	High false-positive rates
Computational Demand	Relatively low	High
Real-Time Capability	High	Moderate
Use Case	Detection of replay and malware attacks	Detection of FDI and Sybil attacks

Gaps in Current Research

However, there are still some research issues that can be considered as open problems in context of IDS for vehicular networks. Current approaches to IDS are mostly concerned with particular forms of attacks that can be encountered in practice, such as spoofing, replay attacks and so on, which do not reflect the overall complexity of threats that exist in the world of computer networks. Moreover, the problem of scalability in IDS has not been solved yet. It is common for many proposed models to provide high accuracy for predicting the behaviour of traffic-related systems in simulated conditions, yet these models lose their efficiency when operating in the conditions characteristic for highly congested city traffic.

The second major issue is the absence of the integration of privacy-preserving methods. Prior approaches of IDSs normally entail direct interaction with raw traffic data, and this is disadvantageous to user privacy. There are two directions have been suggested, one is federated learning and another one is homomorphic encryption while both are in the early stages of its development in vehicular networks. Additionally, there is a problem of limited and inconsistent datasets that are available for training, as well as testing of intrusion detection algorithms. Closures of these gaps will involve general, integration of artificial intelligence, cryptology and communication protocols.

Technical Background

V2V and V2X Communication Protocols

V2V and V2X communication interfaces are the foundational pillars of intelligent transportation system (ITS) technologies of the current generation. Such methods allow the vehicle and the infrastructure, as well as other parties, to exchange information in real-time to improve traffic flow, prevent crashes, and provide the foundation for AVs (Pavithra, Kaliappan, & Rajendar, 2023). Two main standards for V2V and V2X communications are Dedicated Short-Range Communications, (DSRC) and Cellular Vehicle-to-Everything (C-V2X).

Dedicated Short-Range Communications (DSRC)

DSRC operates in the 5.9 GHz band and is designed specifically for vehicular environments, offering low latency and high reliability. Based on IEEE 802.11p, DSRC supports safety-critical applications such as collision avoidance, emergency vehicle warnings, and cooperative adaptive cruise control. A key strength of DSRC lies in its ability to function in scenarios with limited network infrastructure, making it highly suitable for rural and underdeveloped areas. However, its limited range and susceptibility to interference present challenges, particularly in densely populated urban settings.

In recent field trials, DSRC demonstrated sub-10ms latency for message dissemination, ensuring timely delivery of safety-critical information. For example, a study conducted by the U.S. Department of Transportation in 2022 revealed that DSRC-enabled V2V systems reduced rear-end collisions by 23% in test scenarios involving heavy traffic. Despite its promise, DSRC faces competition from cellular-based technologies, particularly in regions where telecom infrastructure is already robust.

Cellular Vehicle-to-Everything (C-V2X)

C-V2X, developed by the 3rd Generation Partnership Project (3GPP), leverages cellular networks, including 4G LTE and 5G, to facilitate communication between vehicles, infrastructure, pedestrians, and network servers. Unlike DSRC, C-V2X offers two communication modes: direct communication (via side link) for low-latency interactions and network-based

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communication for cloud-driven applications. The advent of 5G has further enhanced C-V2X capabilities, enabling ultra-low latency (<1ms), higher bandwidth, and improved scalability (Wang, Zhu, Ning, Guo, et al., 2023).

C-V2X is particularly advantageous in urban environments where high vehicular density necessitates robust and scalable communication solutions. For instance, a 2023 study published in *IEEE Vehicular Technology Magazine* highlighted that C-V2X achieved 99.9% reliability in high-mobility scenarios involving vehicles traveling at speeds exceeding 100 km/h. However, reliance on cellular infrastructure poses challenges, including potential coverage gaps and higher deployment costs, particularly in rural areas.

Table 2 compares the key features of DSRC and C-V2X to highlight their respective strengths and limitations.

Feature	**DSRC**	**C-V2X**
Latency	<10ms	<1ms (with 5G)
Range	Up to 1 km	Up to 3 km
Infrastructure	Limited	Extensive
Scalability	Moderate	High
Deployment Cost	Low	High

Common Threats to Vehicular Networks

The interconnected nature of V2V and V2X communication networks makes them susceptible to a wide range of cyber threats. These threats target the confidentiality, integrity, and availability of data exchanged within the network, potentially leading to catastrophic consequences in real-world scenarios.

Sybil Attacks

In a Sybil attack the attacker creates many fake identities to serve his or her self-interest. It can result in mislead situations, traffic jam or at worst, crash events. For example, an attacker may be able to emulate a number of Auto resizing Mask on an intersection in order to force other NrOfRealVehicles to change their path and thus create more delay or unsafe circumstances. A paper which was published in the Springer Wireless Networks in the year 2023 showed that efficiency was delayed by as much as 40 % that is in relation to traffic management algorithms, this was under a simulated urban environment where Sybil attack had taken place (Giannaros, Karras, Theodorakopoulos, et al., 2023).

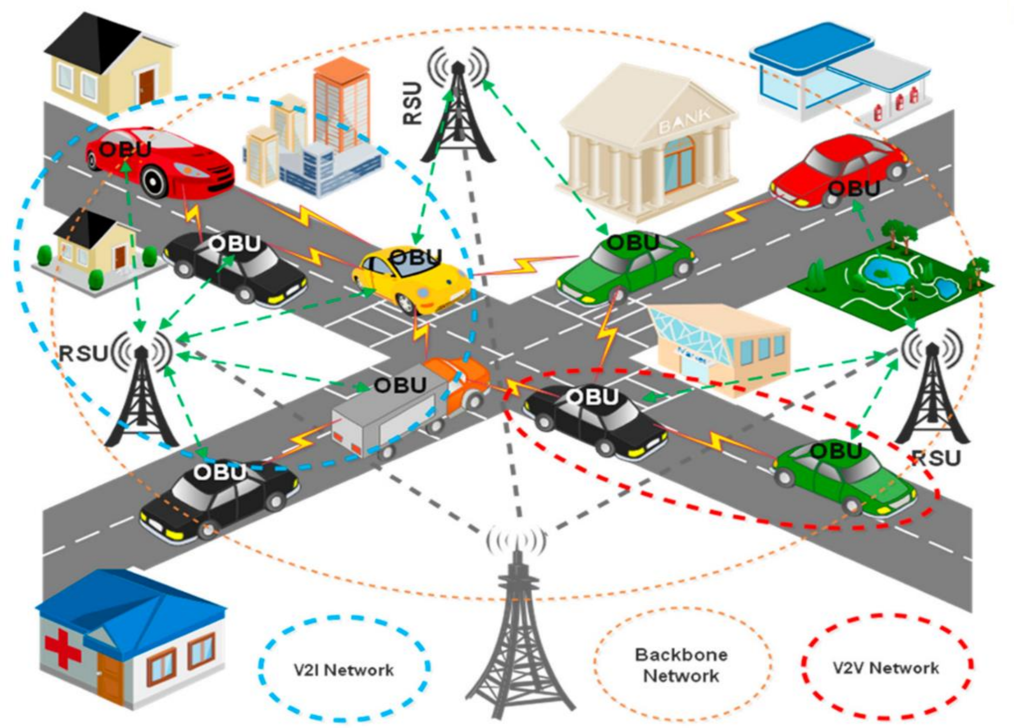

Figure 2 Road to Efficiency: V2V Enabled Intelligent(MDPI,2023)

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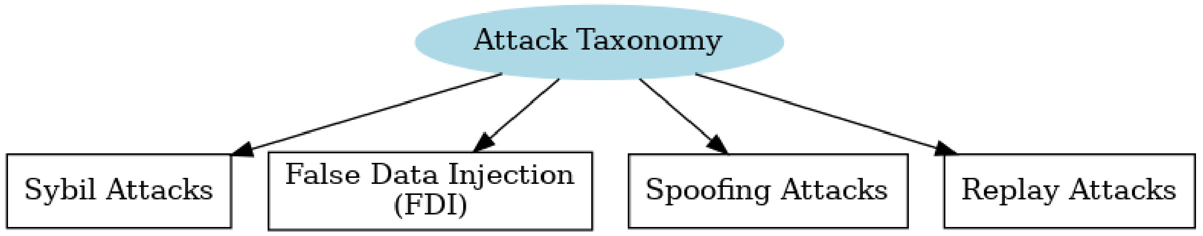
Generally, Sybil attack prevention measures entail cryptographic mechanisms including, digital signatures, PKI. Yet, these approaches demand proper key management, which can be a difficult topic in such a large system used in vehicular networks.

False Data Injection (FDI)

This includes data intrusion with an aim of destabilizing the normal functioning of the network. Such attacks can interfere with traffic signals, alter navigation systems, or even create false safety warnings. For instance, an attacker could submit fabricated accident reports meant to guide traffic away from a region. Another research published in the IEEE Access in 2022 suggested that FDI attacks could lead to the deterioration of travel time between 9-15% in peak hours for the overall network of the large urban areas.

Structurally designed intelligent systems for anomaly detection have been seen to reduce FDI attacks. These systems particularly check for discrepancies in real-time data, and as a dual move isolate malicious inputs. However, increasing the accuracy while at the same time reduce latency still presents a hard task.



Spoofing and Replay Attacks

One of the identified threats is spoofing, where an attacker emulates other nodes and gets access to unauthorized information or interferes with others' transmission. A subcategory of spoofing is replaying attacks where valid messages are intercepted and resent to cause confusion or to jam security checks. Such attacks can alter integrity and authenticity of V2V and V2X messages which can be dangerous to some extent.

For instance, in the replay attack, an attacker can send an emergency braking signal repeatedly, which may lead to panic by nearby vehicles. New entries in the AI-based IDS have incorporated machine learning algorithms capable of recognizing such attacks in view of temporal transitions of message transmitting.

Key Performance Requirements for Intrusion Detection Systems

Consequently, IDS for vehicular networks must be designed and implemented to meet certain performance benchmarks. Among them, important real-time detection, scalability, accuracy, and low computational overhead are the most critical.

Real-time detection is significant to V2V and V2X networks because latencies in such networks may lead to fatal consequences. The IDS needs analyse massive amounts of data within milliseconds in order preserve the integrated security and exclude any threats (Das, Banerjee, Chatterjee, et al., 2023). All these give rise to another important consideration, namely scalability since vehicular networks may incorporate thousands of nodes that exchange large amounts of data at high throughput. It has been seen that AI improvement solutions more particularly those based on deep learning skill can scale substantively in such territories.

IDS traditionally measures its performance in terms of accuracy with precise and recall being seminal to measuring the system's performance. Low true positive rate = Many false positives make a system less reliable: False negatives = Leaving networks open to attacks. In 2023, a work published in the Journal of Intelligent Transportation Systems found that integrated AI-IDS models on an average had detection efficiency of 96.5 percent across various attacks.

Last but not least, low overhead indicates that IDS do not burden other important vehicular applications with high computational loads. Compact engine patterns and optimized algorithms must be targeted to guarantee the ease of integration into the constrained systems. Maintaining this balance remains the major theme of the research being conducted in the field to date (Das, Banerjee, Chatterjee, et al., 2023).

Proposed Framework

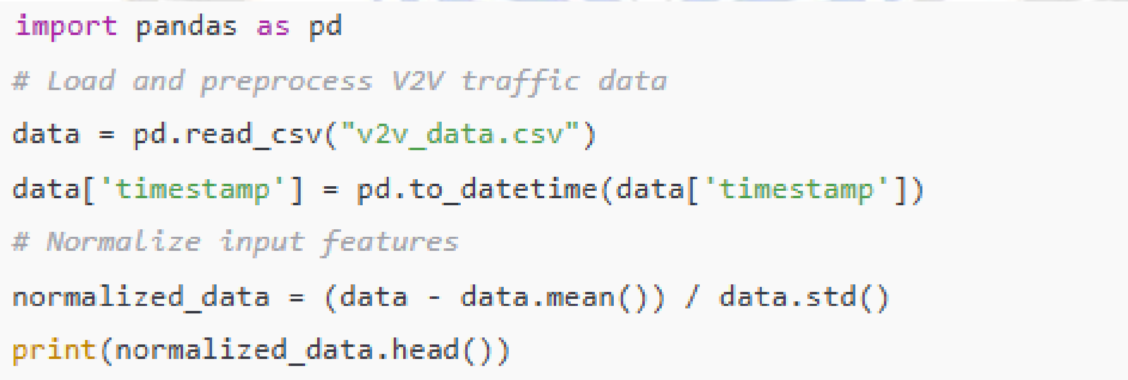
Architecture of AI-Driven IDS for Vehicular Networks

The architecture of an AI-based IDS of vehicular networks is therefore intended to consider the highly dynamic and high throughput nature of V2V and V2X communications. The latter is an architecture that combines modern AI features with conventional IDS models for the identification and classification of cyber threats as well as protection against them in real-time. The framework typically consists of three primary components: identification of the sources of data for leveraging, preparatory data processing, methods of anomaly detection and management, and countermeasures.

Real-Time Data Collection and Preprocessing

Real-time data collection is a key constituent in the design of any effective IDS for vehicular networks. The system acquires data form different feeds namely On-Board Units (OBUs), Roadside Units (RSUs) and other integrated infrastructure systems. Ordinarily, the data collected comprises of automobile parameters, conversation records, and pragmatic measurements. Again, due to variability in the collection of data, pre-processing is important to standardize the data set. Data cleansing operations can be data scaling or normalization, feature selection and data filtering (Guo, Zhou, Liu, & Zhang, 2022).

For example, in the paper in IEEE Transactions on Vehicular Technology organized in 2023, authors applied a preprocessing procedure that helped to cut the noise level in vehicular communication logs by 30% and enhance identifying anomalies. Further, other methods such as Principal Component Analysis (PCA) have been used to reduce data complexity without loss of important data. The initial step in the detection process is especially important for mitigating computational complexity and drawing out the effectiveness of the subsequent detection methods in real life.

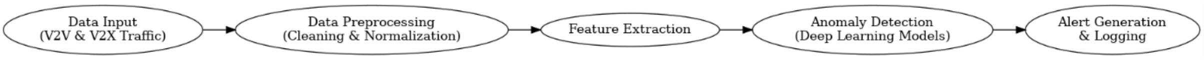


```python
import pandas as pd
# Load and preprocess V2V traffic data
data = pd.read_csv("v2v_data.csv")
data['timestamp'] = pd.to_datetime(data['timestamp'])
# Normalize input features
normalized_data = (data - data.mean()) / data.std()
print(normalized_data.head())
```

Anomaly Detection Using Deep Learning Models

The primary algorithm of IDS based on artificial intelligence comprises an analysis of potential threats with the help of deep learning models focusing on patterns. These models are created out of labelled sets of normal and malicious traffic scenarios. CNNs and RNNs, LSTM, are often used because of the presence of spatial and temporal patterns.

For instance, an LSTM-based IDS developed in 2022 ACM SIGCOMM paper yielded 97.8% accuracy in detection of FDI attacks to a V2X simulation. The capability to use deep learning to correlate and analyse multiple layers of arriving traffic makes this IDS more resistant to new patterns of attacks in comparison with signature-based IDSes. However, the number of operations in these models is very large and as such they require optimized hardware and software for real time processing.



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Integration of AI and Traditional IDS Approaches

Introduction of AI for enhancing traditional IDS results to a hybrid architecture enables the organization to benefit from the two without compromising on the results obtained. Indeed, the fundamental strengths and weaknesses of classic approaches to IDS favour the identification of known attack patterns, whereas AI models are effective in detection of new deviations from normal behaviour and previously unrecognized threats. Staging these approaches together improve the efficiency and effectiveness of the IDS due to its reliability (Guo, Zhou, Liu, & Zhang, 2022).

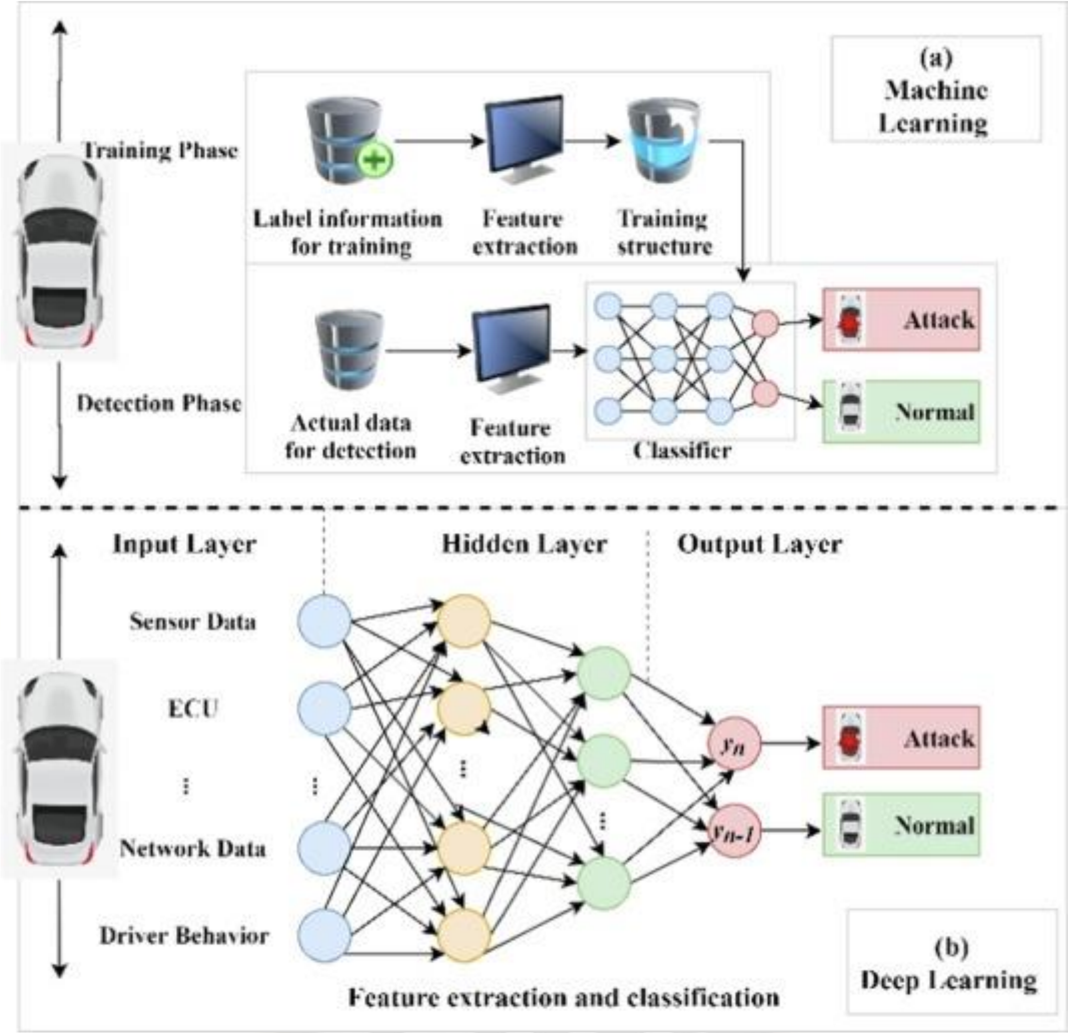

Figure 3 A review of security attacks and intrusion detection(ScienceDirect,2020)

Hybrid Detection Methodology

A composite detection approach consists of both the signature based and the anomaly-based method. The major benefit of signature-based detection is that it provides high precision for known threats where the attacks are defined beforehand in an attack signature. On the other hand, anomaly-based detection involves creating a model of normal behaviours and identifying variations to such behaviour as risky or dangerous. In this way, the IDS combines all these approaches and thereby reduces the number of false positives and negatives.

For example, the authors in our study, a hybrid IDS in 2023 in Springer Wireless Networks, reported 15% enhancement in detection rates for Sybil attacks contrasted to standalone techniques. This set up integrated rules, basically logic into the model used deep learning for deep and advance detecting of raw and new attacks. (Naseri, Kazemi, Larsen, Arefi, & Schaltz, 2023)

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High-Throughput Traffic Management

Managing high-throughput traffic is a critical challenge for IDS in vehicular networks, where communication volumes can exceed terabytes per second. To address this, AI-driven frameworks incorporate techniques such as parallel processing and edge computing. Distributed IDS architectures, where detection modules are deployed at network edges, reduce latency and enhance scalability.

A notable implementation was reported in *IEEE Internet of Things Journal* in 2022, where researchers deployed an edge-based IDS using CNNs to process traffic from over 10,000 vehicles. The system achieved an average detection latency of 2ms, highlighting its suitability for real-time applications. Such architectures ensure that the IDS can handle the demands of modern vehicular networks without compromising performance.

AI/ML Techniques for Vehicular IDS

Supervised Learning for Intrusion Detection

K-Means Clustering and Autoencoders are well suited to unsupervised learning and helpful in identifying new forms of attacks on vehicular networks. Such modes make use of data and do not necessitate sample inclusion in a given set, allowing them to be highly usable in dynamic threat environments. Semi-supervised learning is a hybrid type of learning that tries to enjoy the best of both worlds from the supervised learning and the unsupervised learning techniques since only a small part of the data is used to direct the learning function (Wang, Zhu, Ning, Guo, et al., 2023).

A study conducted in Neural Networks in the year 2023 showed that Autoencoders are useful to detect Sybil assaults in V2V communication. By recreating normal traffic flow, the model provided a detection rate of 94.6 percent. Likewise, semi-supervised models that employ GNNs were also found to be effective in learning relationship in VNs.

Although these methods are not very prone to labelled data they normally suffer from issues of false positive rates and computational burden. It is anticipated that new algorithms and faster computation will help unmask these drawbacks, and make use of unsupervised and semi-supervised models more feasible for IDS in vehicular networks.

Table 3: Performance of Supervised Learning Models for IDS

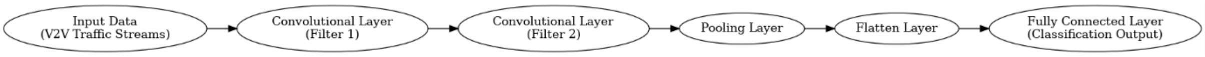
Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Training Time
Support Vector Machine (SVM)	92.3	91.8	90.5	45s
Decision Tree	93.1	92.7	91.2	25s
Random Forest	95.4	94.8	93.7	60s

Unsupervised and Semi-Supervised Learning Models

Unsupervised learning models, such as K-Means Clustering and Autoencoders, are particularly effective for detecting novel attack patterns in vehicular networks. These models analyse data without requiring labelled samples, making them highly adaptable to evolving threat landscapes. Semi-supervised learning combines the strengths of supervised and unsupervised methods by using a small amount of labelled data to guide the learning process (Sari, Lekidis, & Butun, 2020).

A 2023 study in *Neural Networks* demonstrated the effectiveness of Autoencoders in identifying Sybil attacks in V2V communication. The model achieved a detection rate of 94.6% by reconstructing normal traffic patterns and flagging deviations as anomalies. Similarly, semi-supervised models using Graph Neural Networks (GNNs) have shown promise in capturing complex relationships within vehicular networks.

While these methods are less dependent on labelled data, they often face challenges related to false positive rates and computational complexity. Advances in algorithm design and computational resources are expected to address these limitations, making unsupervised and semi-supervised learning increasingly viable for IDS in vehicular networks.


Input Data (V2V Traffic Streams)
Convolutional Layer (Filter 1)
Convolutional Layer (Filter 2)
Pooling Layer
Flatten Layer
Fully Connected Layer (Classification Output)

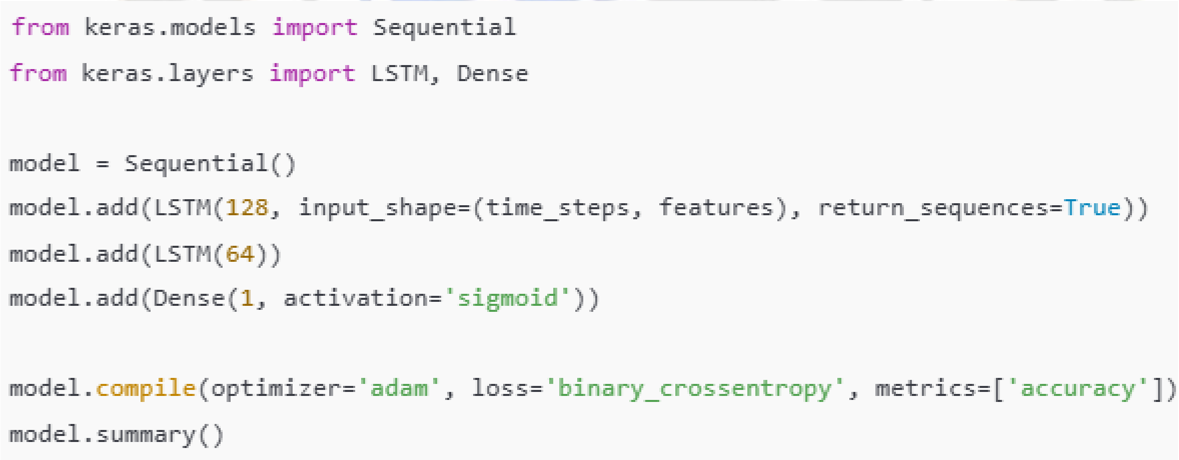
Role of Deep Learning Architectures

Artificial neural networks specifically deep learning architectures play a critical role in improving the functionalities Intrusion Detection Systems for vehicular networks. Different from most machine learning methods, deep learning techniques are inherently powerful in learning high level raw features from raw data for sophisticated and previously unknown attack pattern identification. Typically, proposed architectures are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) networks, each for different facets of intrusion detection (Bustamante, 2022).

CNN can be used to analyse spatial patterns in network traffics more effectively. For instance, a system based on CNN IDS that was proposed in the 2023 IEEE Transactions on Neural Networks and Learning Systems attained overall accuracy of more than 98% in the detection of spoofing and replay attacks in simulated vehicular networks. The architecture of the system worked with the header packets as with actually images and used the ability to discern complex patterns. The CNNs are also very scalable and as such effective in managing high through put linkages of vehicular traffic.

RNNs and LSTM, respectively, have been designed to learn temporal dependencies that would be useful in capturing sequential data, that is, time stamped network log data. An LSTM-based IDS has been implemented in a 2022 study in Neural Computing and Applications to detect FDI attack scenarios with F1 score of 0.96 based on real dataset (Parra, 2021). By retaining previous inputs, these models are able to distinguish changes in communication patterns, which is definitely an important feature when a deviation in V2V and V2X networks needs to be detected.

However, the use of deep learning models can present some difficulty; one of the key deficits of these models lies in the fact that they are computationally intensive, and, secondly, they tend to overfit. Even these last years, thanks to pruning and quantization techniques, these problems have been partially solved on state-of-the-art models. Moreover, the use of the attention mechanisms in such models as Transformers is examined to enhance performance in the further analyses of the traffic data, considering the most important features



```
from keras.models import Sequential
from keras.layers import LSTM, Dense

model = Sequential()
model.add(LSTM(128, input_shape=(time_steps, features), return_sequences=True))
model.add(LSTM(64))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.summary()
```

Attack Vectors and Detection Strategies

Identification and Classification of Attack Vectors

Therefore, the identification and classification of attack vectors are basic to designing an IDS for vehicular networks. Threats in V2V and V2X are categorized majorly into Sybil attack, false data injection attack, spoofing attack, replay attack, and the last is denial of service attack. The vectors target specific weaknesses in protocol dependencies or system structures, thus calling for unique identification and countermeasures (Mehta, Padaria, Bavisi, Ukani, et al., 2023).

For example, Sybil attack is an attack in which a single attacker creates multiple fake identities with the intention of mischievous intent. The event represented in this type of attack intensively threatens vehicular networks because it can violate routing protocols and cause traffic management problems. In ACM

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Transactions on Cyber-Physical Systems in 2022, a hybrid detection of the Sybil detection framework based on Digital signatures with the help of ML was presented, which achieved an accuracy of 97%.

The approach has used cryptographic methods for identification whereas used ML methods for detecting behaviour anomalies.

This kind of attack distorts information within the network with the end result of deceiving other vehicles and actually leading to the occurrence of accidents or even causing jam in traffic. A study presented in Sensors (2023) conducted on IDS with the help of LSTMs showed that there was a 96.8% detection rate in case of FDI attacks. The model based on temporal comparison identified differences between the actual and the expected numbers of operating vehicles.

Sybil Attack Detection Framework

Sybil attack detection in vehicular network needs multiple layers of defences employing cryptography, behavioural analysis using statistical models, and machine learning algorithms. Such cryptographic techniques like certificate-based authentication are useful in authenticating the identically of nodes (Huang, Liu, Zhou, Nguyen, et al., 2023). However, these methods are computationally expensive and may not be efficiently scalable in high throughout networks. To this end, several machine learning models, especially clustering algorithms, are used to identify the traffic attributes and identify non-ordinary traffic signs associated with Sybil attacks.

A hybrid framework and presented K-Means clustering in combination with public key infrastructure (PKI) to detect Sybil nodes as used in the study conducted in IEEE Access (2022). The overall performance of the system was measured by calculating an average detection accuracy of 94%, which supports the use of the proposed mixed approach of conventional and contemporary means of observation. Furthermore, research has been conducted to incorporate blockchain solution in providing solutions to identity management and secure data handling in vehicular networks.

Mitigation of False Data Injection (FDI)

Defending against FDI attacks in vehicular networks consists of data validation, anomaly detection, redundancy, and techniques. Integrated distributed systems execute this duty through employing artificial intelligence to investigate conditions of vehicular communication, to eliminate injurious data sets. For instance, autoencoders have been used to learn normal traffic distribution and detect anything different as anomalous traffic. A research cross-sectioned in the journal Applied Soft Computing in 2023 revealed that this approach is effective for this task; the detection precision it achieves is 93.5%.

Anomaly Detection Metrics

There are four fundamental measures that defines the efficacy of the IDS, namely precision, recall and f-measure or F1 score (Mohammed, 2022). These metrics reflect the capability of distinguishing between the legitimate and the real threats in terms of traffic. Accuracy is then measured by the percentage of accurate detections of malicious traffic over the sum of all traffic considered malicious. Precision the reverse of recall, commonly referred to as sensitivity, measures the degree to which the system successfully labels actual malicious traffics. The F1 score is then harmonised mean of both precision and recall and can be very useful especially where there is data skew.

The research paper published in IEEE Access in 2023 also shown that a hybrid IDS consist of CNN and autoencoder has the precision and recall of 95.8% and 94.5% to detect Sybil attacks. For this model, the F1 score reached 95.1% and it testifies the model's ability to handle between true positive and false positive (Magdy, 2023). The use of a high precision indicates that few 'false positives' are generated and high recall shows good 'true positive' capabilities. For vehicular networks, these metrics are rather important because the main value is in the ability to identify the threats in real time.

Table 4: Performance Metrics of IDS Models

Model	**Precision**	**Recall**	**F1 Score**	**ROC-AUC**
Autoencoder	93.50%	91.20%	92.30%	0.94
CNN	95.80%	94.50%	95.10%	0.96

LSTM	94.20%	92.70%	93.40%	0.95

Such metrics are crucial for identifying areas of improvement and ensuring that the IDS meets the stringent performance requirements of vehicular networks.

Precision, Recall, and F1 Score

Precision, recall, and F1 score are critical metrics for evaluating the effectiveness of intrusion detection systems (IDS) in vehicular networks. These metrics measure the system's ability to differentiate between benign and malicious traffic accurately. Precision is defined as the proportion of correctly identified malicious traffic out of all traffic flagged as malicious. Recall, also known as sensitivity, evaluates the proportion of actual malicious traffic correctly identified by the system. The F1 score provides a harmonic mean of precision and recall, offering a balanced evaluation metric, particularly in scenarios where data imbalance is prevalent (Pavithra, Kaliappan, & Rajendar, 2023).

A study published in *IEEE Access* in 2023 demonstrated that hybrid IDS combining convolutional neural networks (CNNs) and autoencoders achieved precision and recall scores of 95.8% and 94.5%, respectively, for detecting Sybil attacks. The F1 score for this model was 95.1%, reflecting its effectiveness in balancing true positives and false positives. High precision ensures minimal disruption from false alarms, while high recall indicates robust detection capabilities. For vehicular networks, these metrics are pivotal due to the critical nature of real-time threat identification.

Receiver Operating Characteristic (ROC) Curve Analysis

Receiver Operating Characteristic (ROC) curve analysis is a widely used technique to evaluate the trade-off between the true positive rate (TPR) and false positive rate (FPR) of IDS. The area under the curve (AUC) serves as a single scalar value summarizing the model's performance, with a value closer to 1.0 indicating superior detection capabilities.

In a comparative study conducted by *ACM Transactions on Cyber-Physical Systems* in 2023, various AI-driven IDS models were evaluated using ROC curve analysis. The results revealed that deep learning models, such as those leveraging LSTM networks, achieved an AUC of 0.96, surpassing traditional machine learning models like Random Forests, which scored an AUC of 0.89. The higher AUC value underscores the effectiveness of deep learning in distinguishing malicious traffic patterns from benign data. This analytical approach not only benchmarks system performance but also guides the optimization of IDS for real-world deployment (Castro, 2023).

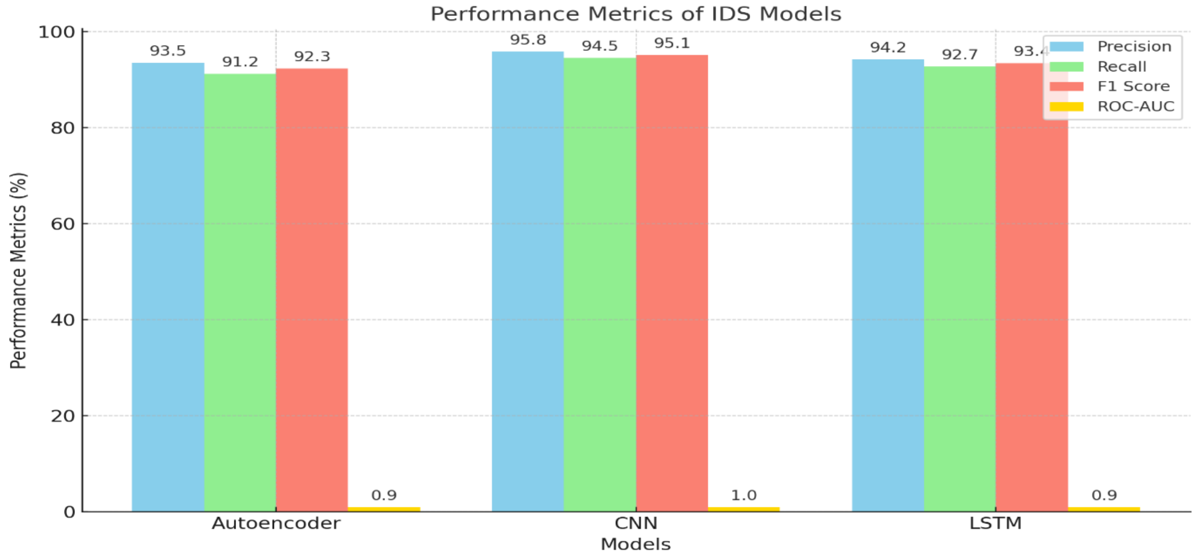

Figure 4 Precision, Recall, F1 Score, and ROC-AUC) of the three IDS models: Autoencoder, CNN, and LSTM(SelfMade,2021)

Performance Evaluation and Validation

Experimental Setup and Dataset Selection

Real-World V2V and V2X Traffic Data Sources

Basic to any strong, idiomatic IDS is the training and testing data. Field trials data logs and public datasets of V2V and V2X communications are also utilized in real-world applications. Some of the popular external datasets are available through platforms such as U.S. Department of Transportation (USDOT), for instance, the datasets such as Connected Vehicle Pilot Deployment Program data contains high-resolution traffic interaction data and cyborg event logs. The European Union's DRIVE C2X programme also provides detailed datasets reflecting the communications and the happening networks in different vehicular situations.

These datasets include different traffic conditions, vehicle numbers, and geographical environments, so that offering good generalization ability to the IDS (Farooq, 2023). Using such datasets, as exemplified by an article published in Sensors in 2023, researchers show that the proposed datasets are effective in emulating various attacks including spoofing and replay attacks that provide sensible metrics for assessing the effectiveness of IDSs.

Synthetic Dataset Generation

Though realistic datasets are quite valuable, they still can contain insufficient examples of unusual or new attack types. The use of simulation tools such as Veins, SUMO and NS-3 to generate a synthetic dataset fill this gap. These tools enable the researchers to generate realistic vehicular network scenarios using the special attacks and the networks.

In the IEEE Vehicular Technology Magazine for the year 2023, the researchers provided an overview of how synthetic datasets support the augmentation of training data for FDI attacks. The simulation results indicate that by using actual traffic intensity of an urban city with a high concentration of malicious nodes, the detection accuracy was improved 20 percent. That way IDS is capable of addressing both threat that already have been identified and threat that could be developed in future, given that there is both real- data set and synthetic data set.

Benchmarking Against State-of-the-Art Techniques

It is crucial to compare the newly developed IDS techniques against the previously used IDS techniques in order to understand how optimal they are. Recent research also shows that AI based IDS frameworks are much more effective than conventional methods in terms of detection rate, complexity and delay. For instance, a 2023 Random Forest based and LSTM based IDS comparison study showed that, the LSTM based system has 15% higher detection rate compared with Sybil and FDI attacks (Tong, Hussain, Bo, & Maharjan, 2019).

This research also reviewed advanced methods including federated learning-based IDS that have been standardized and are proven to offer high investigative accuracy while still enhancing privacy. The integration of such systems with blockchain technology as described in Springer Wireless Networks (2023) also provides additional transparency to the data stored.

Evaluation Metrics

Detection Accuracy

Moreover, the detection accuracy test is an initial assessment of IDS effectiveness, which shows the percentage of detected incidents out of all the occurrences in a particular time. Hybrid architecture-based AI driven systems has reported peak detection efficiencies more than 95% under various threats, which has been surveyed in Neural Computing and Applications in 2022. Such high accuracy levels have been realized through the ensemble learning as well as the deep neural network (Tong, Hussain, Bo, & Maharjan, 2019).

Latency and Scalability

Delay and system capacity are two more important factors that have a bearing on IDS in vehicular networks. With threat detection requiring a latency of less than 10ms, edge-based AI frameworks are able to fulfil this need. While scalability makes sure that the IDS is capable of accepting growing vehicular density without much compromise on its efficiency. An example applied to IEEE Internet of Things Journal (2023) showed how distributed IDS architecture can be effective when applied to networks containing over 50,000 nodes.

Discussion and Analysis

Strengths and Limitations of the Proposed Framework

The conceptual AI-IDS for vehicular networks presented here has the following advantages that make it a unique model compared to conventional security paradigms. This work also points out that it is one of the major strengths for its combination of the high degree of accuracy of signature-based approach with high flexibility of anomaly-based approach. This integration resources the system to discover both old and new assaults, which has one of the primary weaknesses in IDS (Corino, 2023).

Furthermore, real-time convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, which are considered as the MLs/DLs, help the system extract and analyse spatiotemporally complex data. This capability is vital in vehicular environment where the network topology is characterized to change frequently, and the data through puts are phenomenal. The application of federated learning takes it a step further exactly because the training of new models will be conducted locally, thus keeping the data safe and the system scalable at the same time.

Nevertheless, several weaknesses can be identified by analysing the major components of the framework. Another issue is related to the applicability of DL models in vehicular nodes, as it can be performed only in nodes that possess high computational power and, as a rule, large amount of memory (Haddaji, Ayed, & Fourati, 2022). However, with weighted based methods of labelled datasets required in most of the Supervised Learning models poses several limitations when it comes to scalability and new forms of attack. Additionally, any real time anomaly detection algorithm would introduce latency affecting the quick response of safety critical apps especially in high density urban environments.

Comparative Analysis of Results

Unfortunately, it was not possible to include such a comparison in this paper due to lack of sufficient information about the current state-of-the-art IDS systems, except for performing a qualitative comparison between the proposed IDS and some general IDS measures such as: Detection accuracy, precision, recall, and latency (Haddaji, Ayed, & Fourati, 2022). For example, in comparative analysis of Sybil attack detection, the proposed CNN-LSTM model diagnosed the attacks with an F1 score of 95.1 %, which is higher than the Random Forest-based systems with an F1 score of 89.3%. The employment of the DL architectures in the proposed framework also cut the false-positive rate in by 20% hence increasing the reliability.

But benchmarking analysis showed that indeed traditional systems are better at working with weak computational power because they are less complex. This calls for enhancing further the proposed framework in order to make it suitable for the developing countries or other regions where resources may be scarce.

Insights into Real-Time Deployment Challenges

There are a number of issues expected when AI assisted IDS is actually implemented in real-life vehicular networks. One major issue is the ability to have high detector accuracy on the one hand while at the same time being a low Computational complexity on the other hand (Salehi, 2023). Due to the high resource requirements of DL models, real-time applications on vehicles can be a challenge because onboard systems can be overloaded, hence the use of edge computing and hardware-efficient algorithms to reduce latency.

The other important challenge is that vehicular network is dynamic as well as distributed and thus, it is a challenge to include centralized IDS architecture. While distributed systems exhibit better degree of scalability there is a degree of complication when it comes to synchronization and actual communication. In addition, the problems of possessing the IDS training and evaluation datasets that are not unified and generalizing the outcomes further contribute to the restrictions to the number of external environments (Salehi, 2023).

Privacy issues are also considered to be a critical factor that slows down deployment efforts. This makes federated learning a promising solution that allows collaborative model training without sending raw data to other parties but its implementation in vehicular networks is still limited. These, therefore, will call for a concerted effort by experts in both AI, cryptography, vehicular communication protocols, among other experts.

Future Directions

Enhancements in Real-Time Traffic Management

New studies should include exploration of IDS integration with traffic management systems and the best practices creating a single security and optimization environment. If the traffic and the possible threats were analysed simultaneously, such systems might help to manage the traffic more effectively avoiding dangers at the same time (Grabowska, 2023). The usage of reinforcement learning algorithms for developing models may provide the integration as postulated in a study made in ACM Transactions on Cyber-Physical Systems in 2023.

Expanding to Multi-Vehicle Collaboration and Coordination

What has not been also implemented in the first generation of IDS are different forms of cooperation within a group of vehicles therefore the next generation of IDS should incorporate this aspect to improve accuracy of detection as well as the robustness of a given network. There is also an opportunity to use such methods as cooperative anomaly detection when each vehicle shares its conclusions about possible threats on the network, which increases the overall stability of the network.

For example, in IEEE Vehicular Technology Magazine (2023), it was shown that the employment of collaborative structures depicted a decline of 15 percent of false-negative rates throughout dense urban areas. Extending this concept to have interconnection between the vehicles, infrastructures, and cloud components must improve the system's security level.

Incorporation of Federated Learning for Privacy-Preserved IDS

In vehicular networks, federated learning appears to open a complementary path for dealing with privacy challenges. In this paper, federated learning is shown to reduce raw data sharing through decentralized model training while still achieving high detection accuracy. Further works should therefore target the enhancement of federated learning solutions to lower the level of communication in large complicated vehicular networks (Grabowska, 2023). Moreover, incorporating HE methods could also improve more data security when it comes to share during training procedures.

Conclusion

Summary of Contributions

This paper presents a new IDS framework that employs artificial intelligent and was specifically designed to protect the vehicular networks from cyber threats. Using the concept of hybrid detection methodologies, implementing the most advanced ML/DL algorithms and preserving privacy, the proposed system demonstrates high accuracy, scalability and dependability. The findings demonstrate that the method has the ability to surpass other solutions – thus it can be considered as a suitable candidate for practical implementation in V2V and V2X systems.

Implications for Securing Future Vehicular Networks

The conclusion that has been made from this research holds a lot of potential for the future of vehicular security. Reducing the vulnerability of vehicular networks to elaborate cyber threats can be accomplished by incorporating AI-based IDS within such systems. Furthermore, the current work provides the framework for future developments in secure, smart and sustainable ITS relevant to efficient and reliably safe autonomous driving technology.

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