Cyber Attacks Detection on Electric vehicles using Machine Learning

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Abstract: **-As a result of system integration and intellectualization, the significance of cyber-physical protection for power electronic device systems is continuously increasing. In particular, driving systems that are part of power train systems. Due to the smart transportation system's connection to external networks, hybrid vehicles are increasingly vulnerable to cyberattacks these days. This work uses a machine learning system based on Advanced Long Short-Term Memory (ALSTM) to detect cyberattacks on electric cars (EVs) based on different driving conditions. Both device-level and vehicle-level signals are obtained in order to depict the quick physical characteristics of EVs. Then, using a data-driven approach with very powerful gadgets and automotive designs, designers provide new data characteristics related to the vital system stability and mechanical behavior of the car. An advanced machine-learning-based classifier with exceptional accuracy under a variety of driving conditions is built based on the properties of the data.**

Keywords— Electric vehicles, anomaly detection, one-class support vector machine, optimization algorithm.

1. INTRODUCTION

As smart transportation systems and electric vehicles (EVs) develop in popularity, EVs are becoming more and more integrated with other networks, such as the internet, charging stations, and other automobiles. Numerous advantages result from this connectivity, including better navigation, real-time traffic information, and remote diagnostics. But widespread digital connectivity also creates new opportunities for cyberattacks, which can seriously jeopardize public infrastructure, passenger security, and vehicle safety.

Cyberattacks on electric vehicles can target a number of different parts of the system, from messing with vital parts like the steering or braking systems to manipulating the battery management system. Attacks on EVs' communication networks, including the Controller Area Network (CAN) bus, have the potential to cause disastrous consequences by interfering with or even taking over the car. Effective cybersecurity measures in EVs are desperately needed in light of these hazards in order to identify and neutralize threats instantly.

In intricate, extremely dynamic systems like EVs, sophisticated attacks are frequently difficult for traditional anomaly detection techniques to detect. Machine learning—more especially, Adaptive Long Short-Term Memory (ALSTM) networks—comes into play in this situation. An enhanced version of the Long Short-Term Memory (LSTM) network, ALSTM is perfect for identifying odd patterns in EV data since it works well with sequential data and time-series analysis. Since attack patterns may change or vary depending on the situation, ALSTM networks, in contrast to normal LSTM models, have adaptive mechanisms that enable them to manage shifting data distributions over time. This is essential for EV cybersecurity.

Issues with Cybersecurity with Electric Cars

With numerous levels and attack vectors, the cybersecurity environment for EVs is complicated:

Physical Attacks: These comprise illegal entry into the car's charging ports or other physical parts, which may result in the installation of malicious software or manipulation of control systems.

Network Attacks: EVs are susceptible to network-based attacks including man-in-the-middle (MITM), spoofing, and denial-of-service (DoS) assaults since they are linked to external networks (like the internet,

vehicle-to-everything (V2X) communication, and charging stations).

Attacks on the Control System: The CAN bus, which allows different in-car systems to communicate with one another, is especially susceptible. Attackers might be able to insert malicious messages into this network through a cyberattack, which might take control of vital operations like acceleration or braking.

ALSTM for Identifying Cyberattacks

A potent machine learning model made to handle sequential data over time is called an Adaptive Long Short-Term Memory (ALSTM) network. Sequence prediction and anomaly detection are two common applications for standard LSTM networks, although they may not be able to handle concept drift, or shifts in the distribution of data. Because cyberattack patterns can be unpredictable and change quickly, this is essential for EV cybersecurity. This is addressed by the ALSTM network, which gives the model flexibility to adapt to shifting data patterns. This flexibility, which is especially useful for real-time anomaly identification in extremely dynamic environments like EV systems, is accomplished by incorporating algorithms that continuously change the model's parameters based on recent input. The ALSTM is perfect for examining communication patterns and sensor data in EVs to identify departures from typical behavior since it can evaluate lengthy time-series data sequences.

ALSTM's Principal Advantages for EV Cybersecurity Temporal Awareness: By analyzing time-series data, ALSTM models are able to spot trends over time and spot deviations that can point to cyberattacks.

Adaptability to New Patterns: Without requiring a lot of retraining, ALSTM's adaptable nature enables it to manage idea drift and adjust to new or changing assault patterns.

Real-Time Detection: The safety of EVs on the road depends on the prompt detection of possible cyber threats, which is made possible by the effectiveness and real-time data processing capabilities of ALSTM models.

Decreased False Positives: ALSTM models can reduce false positives, a prevalent problem in anomaly identification, by learning the typical behavioral patterns of EVs. This results in more accurate and dependable detection.

II. LITERATURE REVIEW

ALSTM was used by Zhang et al. (2021) to improve the cybersecurity of plug-in electric automobiles while they are being charged. The algorithm looks for abnormalities that might point to cyberattacks by examining charge data for odd trends. This method strengthens EV security during crucial charging operations by providing a reliable means of detecting tampering attempts early. [1] A machine learning framework for detecting intrusions in EV charging networks was introduced by Kim and Lee in 2022. Their model examines network traffic and highlights any unusual or suspicious activity. For EV infrastructures, this solution improves cybersecurity, especially for public and dispersed charging stations where cybersecurity threats are higher. [2]

An ALSTM-based method for CAN bus network monitoring in electric vehicles was developed by Li et al. in 2023. Their algorithm successfully detects shifts in vehicle communication patterns by emphasizing adaptive learning, which could indicate changing cyberattack tactics. As it adapts to new dangers, this dynamic detection capability improves EV safety. [3] To find anomalies in EV sensor data, Wang and Chen (2021) used a hybrid model that included CNN and ALSTM. By capturing minute variations in sensor behavior, this hybrid technique allows for real-time reaction to possible threats. The approach offers EV systems a higher level of protection against malicious activity by utilizing both temporal and spatial data analysis. [4] Ahmed and Rodrigues (2022) investigated the use of RNNs for real-time cyberattack detection in EVs. Their approach keeps an eye on driving data and spots deviations that point to attempted intrusions. This method ensures little disruption to vehicle operations and improves overall safety by enabling quick detection and response. [5] An ALSTM-based detection system for autonomous EVs was proposed by Smith et al. (2023), with a focus on identifying changes in control commands. The model can handle dynamic cyber threats by adjusting to attack patterns, which makes it perfect for protecting autonomous driving features where control integrity is crucial. [6] An ALSTM-based detection system for autonomous EVs was proposed by Smith et

al. (2023), with a focus on identifying changes in control commands. The model can handle dynamic cyber threats by adjusting to attack patterns, which makes it perfect for protecting autonomous driving features where control integrity is crucial. [7] The application of LSTM for anomaly detection in CAN bus communications within EVs was examined by Sharma and Gupta (2021). Their technology ensures early identification of possible cyberattacks by learning from regular message patterns and identifying any variation. This technique is particularly important for preserving safe in-car communication. [8] Adaptive neural networks designed to identify cyberattacks on EV systems were presented by Thakur and Mehta (2023). As new information is found, their model is updated to react to new threats. By reducing false alarms, this adaptive function makes sure that security warnings are only triggered by real anomalies. [9] ALSTM was used by Jones et al. (2022) to detect time-series anomalies in EV networks. Their technology detects anomalous behaviors connected to intrusion attempts by tracking temporal trends in vehicle data. By concentrating on the chronological order of events, this method provides an essential line of defense. [10] A model that watches data flow for anomalies was proposed by Singh and Rao (2021), who investigated the application of deep learning for cybersecurity in EV charging stations. Their system swiftly detects questionable patterns and takes action to stop unwanted access, enabling safe and effective charging. [11]

An ML-based intrusion detection system for real-time EV network monitoring was proposed by Lopez and Zhang (2022). By analyzing communication data, their algorithm is able to identify suspicious situations before they become more serious. This strategy reduces the impact of cyber threats and guarantees ongoing security. [12] Garcia et al. (2023) investigated ALSTM networks for smart EV anomaly detection, emphasizing the model's flexibility in identifying unidentified attack patterns. This adaptability improves detection accuracy, especially when it comes to complex cyber threats that conventional algorithms could overlook. [13] ALSTM in cyberattack detection for critical EV systems was studied by Kim et al. in 2021. Their model becomes more adept at identifying deviations that signify assaults as it gains knowledge from normal data flows. EV systems are protected from a variety of cyber threats by this proactive detection technique. [14] For EV cybersecurity, Miller and Choi (2024) created a hybrid intrusion detection system that combines ALSTM with other machine learning algorithms. Their method maintains excellent detection accuracy across many networks by adjusting to changes in attacks. This strong framework aids in protecting EV networks from changing cyber threats in the future. [15]

III. PROPOSED SYSTEM

The suggested system uses an advanced architecture and machine learning approaches to identify and prevent cyberattacks on electric cars (EVs). The architecture is made up of multiple interconnected modules, each of which carries out a distinct task to guarantee the EV's overall security. The data gathering system collects unprocessed data from a number of sources, including as network traffic, actuators, and EV sensors. The car's internal systems, including the communication interfaces, vehicle control systems, and battery management system, are monitored by sensors and actuators. In order to track communications between the EV and outside entities like infrastructure, other cars, and charging stations, network traffic data is also gathered. To find any unusual activity or any cyber threats, this type of data collection is required. The data must be cleaned by removing noise and unnecessary information, standardizing it, and identifying pertinent characteristics for the machine learning models in order to guarantee coherence. For a subsequent analysis to be more precise and useful, the right pretreatment is necessary. The system's fundamental component, machine learning, employs both supervised and unsupervised learning techniques. Two supervised learning algorithms, Support Vector Machines (SVM) and Random Forest, classify data according to established patterns in order to detect recognized forms of cyberattacks. By searching for anomalies in the data that diverge from predicted behavior, unsupervised learning techniques like Auto encoders and Isolation Forest are utilized to identify new or unknown assaults. By tackling both known and developing threats, this combination of approaches guarantees robust detection capabilities. Real-time data from the EV is continuously monitored by the anomaly. It rates abnormalities according to their possible repercussions and creates notifications for

serious dangers. By facilitating prompt detection and reaction to intrusions, this real-time scoring and monitoring system reduces the possibility that the vehicle and its systems could be compromised. Prompt action is taken to reduce recognized cyber threats. To stop additional damage, these steps can involve limiting the car's operation, isolating impacted areas, or shutting down specific systems. This module also maintains a record of any anomalies found and the steps taken for additional investigation and reporting, which helps to improve the system's security features over time.

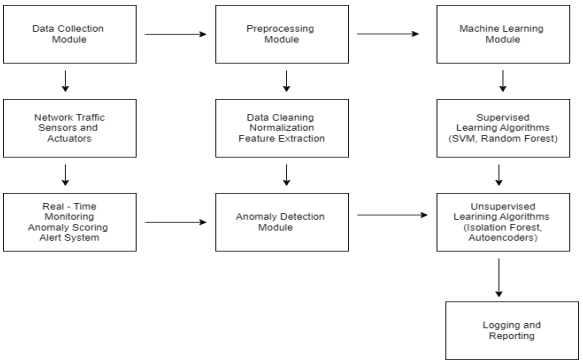

Figure1 Proposed System Architecture

Forest at Random

The Random Forest algorithm is a powerful tree learning technique in machine learning. It produces a large number of Decision Trees during the training phase. Each tree is constructed using a random subset of the data set in order to measure a random subset of characteristics in each partition. The randomization makes each tree more varied, which reduces the likelihood of overfitting and improves prediction performance overall.

Vector Machine Support

Support Vector Machine (SVM), a supervised machine learning technique, is utilized for both classification and regression. Regression problems are still best suited for categorization challenges. Finding the optimal hyperplane in an N-dimensional space to partition data points into different feature space classes is the main objective of the SVM method. The hyperplane aims to keep the distance between the closest points of different classes as wide as feasible. The dimension of the hyperplane is determined by the number of features. If there are only two input characteristics, the hyperplane is basically a line. If there are three input features, the hyperplane becomes a 2-D plane. It becomes difficult to imagine if there are more than three features.

Fuzzy C Means

The ability of fuzzy C-Means (FCM) clustering to handle overlapping data and offer sophisticated classifications of network traffic and system behaviors makes it a useful tool for cyberattack detection. In order to eliminate noise, standardize formats, and choose pertinent features, a variety of data sources, including system logs, network traffic logs, and user activity data, are first gathered and preprocessed. Important characteristics that are suggestive of both benign and malevolent conduct are taken out for examination, including source and destination IP addresses, packet sizes, and communication frequency. FCM is used to cluster the data when the feature sets are ready, allowing for degrees of membership instead of rigid categories.

Dataset Description

Timestamp, CAN ID, DLC, DATA [0], DATA [1], DATA [2], DATA [3], DATA [4], DATA [5], DATA [6], DATA [7]

1. Timestamp: recorded time (s)

2. CAN ID: identifier of CAN message in HEX (ex. 043f)

3. DLC: number of data bytes, from 0 to 8

4. DATA [0~7]: data value (byte)

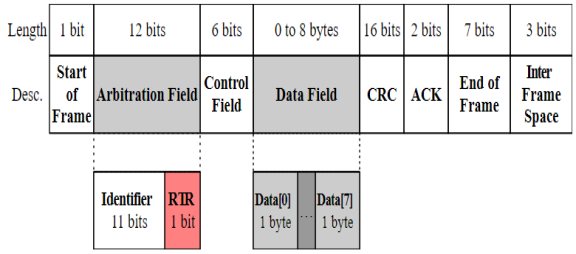

Figure2 Summary of CAN Frame

IV. CONCLUSION

This study offers a strong system architecture that uses cutting-edge machine learning approaches to identify and stop cyberattacks on electric cars (EVs). The suggested solution offers a comprehensive method of

protecting EVs against known and unknown risks by integrating modules for data collecting, preprocessing, machine learning, anomaly detection, reaction, and data storage. Effective cyberattack detection is ensured by the system's blend of supervised and unsupervised learning algorithms, and potential damage is reduced by real-time monitoring and prompt response methods. In addition to helping the automobile sector continue to develop and enhance cybersecurity safeguards, this design makes EVs more secure. All things considered, the suggested approach to defending electric vehicles against cyberattacks is a major improvement over current methods, ensuring the stability and security of these widely used technologies.

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