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Machine Learning-Based Anomaly Detection for Securing In-Vehicle Networks

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Abstract: In-vehicle networks (IVNs) are networks that allow communication between different electronic components in a vehicle, such as infotainment systems, sensors, and control units. As these networks become more complex and interconnected, they become more vulnerable to cyber-attacks that can compromise safety and privacy. Anomaly detection is an important tool for detecting potential threats and preventing cyber-attacks in IVNs. The proposed machine learning-based anomaly detection technique uses deep learning and feature engineering to identify anomalous behavior in real-time. Feature engineering involves selecting and extracting relevant features from the data that are useful for detecting anomalies. Deep learning involves using neural networks to learn complex patterns and relationships in the data. Our experiments show that the proposed technique have achieved high accuracy in detecting anomalies and outperforms existing state-of-the-art methods. This technique can be used to enhance the security of IVNs and prevent cyber-attacks that can have serious consequences for drivers and passengers.

Keywords: IVNs; anomaly detection; cybersecurity; machine learning; deep learning; feature engineering

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1. Introduction

The automotive industry has undergone a significant transformation in recent years due to the proliferation of in-vehicle networks (IVNs) and their integration with other technologies such as sensors, actuators, and controllers. The resulting complexity and interconnections of these systems have created new challenges for cybersecurity, as IVNs are increasingly targeted by malicious actors seeking to exploit their vulnerabilities. According to a report by the National Highway Traffic Safety Administration (NHTSA), the average number of cyber incidents involving automobiles has increased significantly in the last few years, highlighting the need for effective cybersecurity measures in the automotive industry [1]. Anomaly detection is an essential tool for detecting potential threats and preventing cyber-attacks in IVNs. Anomaly detection techniques aim to identify patterns of behavior that are outside the norm and may indicate malicious activity. Traditional methods of anomaly detection in IVNs have focused on rule-based or statistical techniques. However, these methods have limitations in terms of their ability to handle the high-dimensional and dynamic nature of IVN data. Machine learning has shown great potential in various applications, including cybersecurity. In recent years, machine learning-based anomaly detection techniques have been applied to a wide range of cybersecurity domains, including network intrusion detection, malware detection, and fraud detection [2]. The success of these techniques in detecting anomalies in such domains has led to their application in IVNs for cybersecurity.

The need for effective cybersecurity measures in IVNs has been recognized by the automotive industry, and several initiatives have been launched to improve the security of IVNs. For example, the Auto-ISAC (Automotive Information Sharing and Analysis Center) was established in 2015 to share information and best practices related to cybersecurity in the automotive industry [3].

Yoshizawa et al. [4] address the growing interest in Vehicle-to-Everything (V2X) communication from both industry and academia, highlighting the focus on pilot projects testing its capabilities and feasibility. With the European Union responsible for half of the global road vehicle exports and under its stringent security and data protection laws, it is crucial for V2X initiatives to integrate security and privacy considerations alongside road safety. However, findings from a survey of relevant standards, research outputs, and EU pilot projects reveal significant security and privacy issues and inconsistencies across the standards.

Several feature engineering techniques have been proposed for IVN anomaly detection, including wavelet transform [5] and principal component analysis (PCA) [6]. In general, IVNs are becoming increasingly complex and interconnected, making them vulnerable to cyber-attacks. Anomaly detection is a crucial tool for identifying potential threats and preventing cyber-attacks in IVNs. Machine learning-based anomaly detection techniques offer a promising solution to this problem by leveraging the power of machine learning to learn complex patterns and relationships in the data. The key challenge in using machine learning for anomaly detection in IVNs is the need to extract relevant features from the raw data. The IVNs architecture is shown in Figure 1.

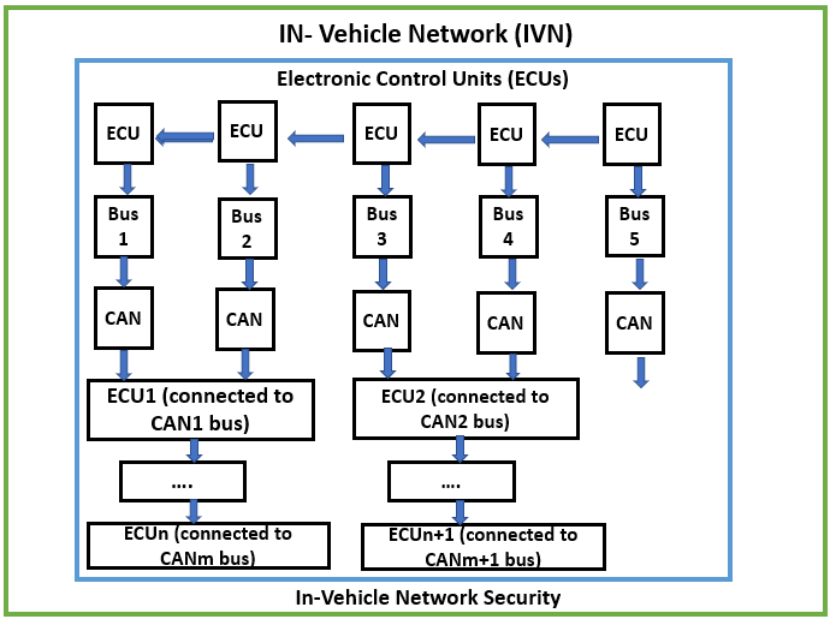

Figure 1. IVNs architecture with electronic control units and buses.

The increasing complexity and inter-connectivity of in-vehicle networks (IVNs) necessitate robust cybersecurity measures to safeguard against potential threats. Leveraging machine learning-based anomaly detection techniques holds promise in mitigating these risks by enabling the identification of anomalous behavior in real-time. In this paper, we propose a novel machine learning-based anomaly detection technique for IVNs that combines deep learning and feature engineering to detect anomalous behavior in real-time. Our approach addresses the limitations of existing methods by using a combination of feature engineering and deep learning to extract relevant features and learn complex patterns in the data. We focus on using recurrent neural networks (RNNs) for anomaly detection in IVNs, as they are well-suited for handling time-series data and can capture long-term dependencies in the data. We also incorporate a wavelet transform-based feature extraction technique to reduce the dimensionality of the data and improve the performance of the RNN. Our paper makes several significant contributions to the field of in-vehicle network security. Firstly, we propose a novel machine learning-based anomaly detection technique specifically tailored for IVNs, leveraging deep learning and feature engineering to enhance detection accuracy. Secondly, we conduct comprehensive experiments using

real-world IVN data, demonstrating the effectiveness and superiority of our proposed methodology over existing state-of-the-art techniques. Thirdly, we provide insights into the importance of feature engineering in conjunction with deep learning, highlighting its crucial role in addressing the unique challenges posed by IVN data. Overall, our research offers valuable advancements in IVN security, paving the way for more robust and efficient anomaly detection systems in automotive environments. The paper is structured as follows: Section 2 provides a detailed description of the related work in the field. In Section 3, the proposed methodology is presented, along with the subsequent experiments conducted to evaluate its effectiveness. The results of these experiments are reported in Section 4. Finally, Section 5 concludes the paper.

2. Related Work

The field of anomaly detection has been extensively studied in recent years, with numerous approaches proposed for detecting anomalies in various domains, including cybersecurity. Rule-based approaches involve specifying a set of rules that define normal behavior in the IVN and detecting anomalies based on deviations from these rules, and while rule-based approaches can be effective in detecting known attacks, they have limitations in terms of their ability to handle unknown or evolving attacks. A rule-based approach proposed by Pires et al. [7] used a set of rules based on the expected frequency of messages in the IVN to detect anomalies. However, this approach may not be effective in detecting sophisticated attacks that involve subtle changes in the frequency or timing of messages. Statistical approaches involve modeling the distribution of the normal behavior in the IVN and detecting anomalies based on deviations from this distribution. These approaches are widely used in anomaly detection and have been applied to IVNs as well. Wang et al. [8] proposed a statistical approach based on a Gaussian mixture model (GMM) to detect anomalies in the IVN. However, statistical approaches have limitations in terms of their ability to handle the high-dimensional and dynamic nature of IVN data. Machine learning-based approaches involve training a model on a set of labeled data to learn the patterns and relationships in the data and detecting anomalies based on deviations from the learned model. These approaches have shown great promise in detecting anomalies in IVNs due to their ability to learn complex patterns and relationships in the data. Chen et al. [9] proposed a machine learning-based approach that combines PCA and the support vector machine (SVM) for anomaly detection in IVNs. Their approach achieved high accuracy and outperformed traditional statistical approaches.

Hybrid approaches combine multiple techniques, such as rule-based, statistical, and machine learning-based approaches, to improve the accuracy and robustness of anomaly detection. For example, Li et al. [10] proposed a hybrid approach that combines wavelet transform and LSTM (long short-term memory) for anomaly detection in IVNs. Their approach achieved high accuracy and outperformed traditional statistical approaches. The evaluation of anomaly detection techniques in IVNs requires appropriate metrics to measure the performance of the techniques. Several evaluation metrics have been proposed in the literature, including accuracy, precision, recall, F1 score, and area under the curve (AUC) of the receiver operating characteristic (ROC) curve. These metrics can be used to compare the performance of different techniques and to evaluate the trade-off between detection rate and false positive rate. Another approach to anomaly detection in IVNs is clustering-based methods, which aim to group similar data points together and identify anomalies as data points that do not belong to any cluster. Zhang et al. [11] proposed a clustering-based method that uses a density-based clustering algorithm to group data points and identify anomalies based on their distance from the cluster centers. The method was tested on a dataset of network traffic in a vehicle and achieved high accuracy in detecting anomalies. However, the method has limitations in handling complex data and requires careful selection of clustering parameters. In recent years, deep learning-based methods have gained popularity in anomaly detection due to their ability to automatically extract relevant features from the raw data. Zong et al. [12] proposed a deep auto-encoder-based

method for anomaly detection in IVNs, which uses an unsupervised learning approach to learn a compact representation of the input data. The method was evaluated on a dataset of network traffic in a vehicle and achieved high accuracy in detecting anomalies. However, the method has limitations in handling imbalanced data and requires a large amount of training data.

Wang et al. [13] discuss the increasing risk of remote wireless attacks on in-vehicle networks due to advancements in 5G and Internet of Vehicles (IoV) technologies. As a protective measure, the authors propose a novel distributed anomaly detection system tailored for the vehicular controller area network (CAN) bus, employing Hierarchical Temporal Memory (HTM) technology. HTM is utilized to predict real-time network flow data, relying on previously learned states to enhance detection accuracy. To advance the system's effectiveness, the authors also refine the mechanism used to score anomalies. They conduct experiments involving synthetic data modifications and replay attacks to validate their system. The performance of the HTM-based system is compared against traditional detection models using recurrent neural networks (RNNs) and hidden Markov models (HMMs). The results demonstrate that the HTM-based anomaly detection system outperforms the others, particularly in metrics such as the area under the receiver operating characteristic (ROC) curve, precision, and recall, indicating a significant improvement in identifying and responding to anomalies in vehicle network security.

3. Proposed Approach

In this section, we have proposed methodology for anomaly detection in IVNs based on a combination of deep learning and feature engineering. Feature engineering involves creating new features or transforming existing features to improve the performance of a machine learning model. It can include operations such as scaling, normalization etc., aimed at making the data more suitable for the model. In domains with complex and high-dimensional data such as in-vehicle networks, feature engineering plays a crucial role alongside deep learning models. Despite the automatic feature learning capabilities of deep learning, feature engineering remains indispensable due to its ability to incorporate domain knowledge and optimize input data for the learning task and model capabilities. Specifically, feature engineering allows researchers to identify and extract relevant features that encapsulate important domain-specific information, such as sensor readings, network traffic patterns, or control unit interactions. Additionally, feature engineering facilitates the transformation of raw data into a more meaningful and manageable representation, reducing computational complexity and training time. The overall framework is illustrated in Figure 2 and consists of the following main components: data preprocessing, feature extraction, and anomaly detection.

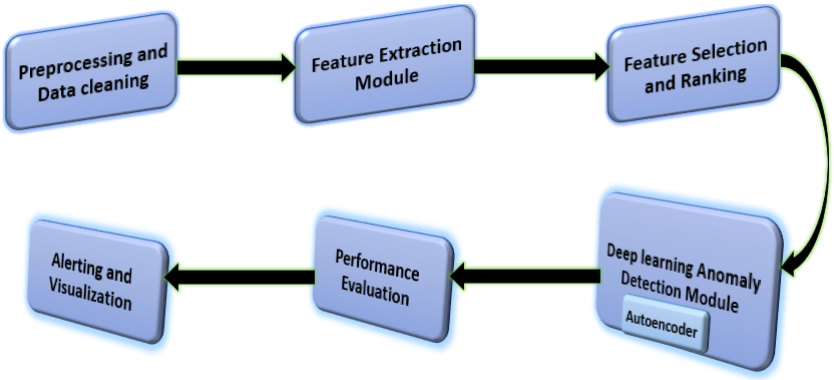

Figure 2. The proposed framework for deep learning-based anomaly detection in IVNs.

3.1. Data Preprocessing

The first step in the proposed methodology is data preprocessing, which involves cleaning and filtering the raw network traffic data to remove noise and irrelevant informa-

tion. The cleaning and filtering steps in data preprocessing are common in data science and machine learning, and various techniques have been proposed in the literature. For instance, missing data imputation techniques such as mean imputation, regression imputation, and K-nearest neighbors imputation have been widely used [14]. Outlier detection methods such as clustering-based, distance-based, and density-based methods have also been proposed by Chandola et al. [15]. The cleaning step involves removing any missing or incomplete data points, as well as any outliers that may skew the analysis. In the context of IVNs, missing data points may occur due to network latency or communication errors, and outliers may occur due to network attacks or malfunctions. Various techniques can be used to handle missing data, such as imputation or deletion, depending on the extent and nature of the missingness.

In the filtering step, irrelevant information is removed from the data to reduce the dimensionality of the input space and improve the efficiency of the model. For instance, certain network traffic features such as source and destination IP addresses may not be relevant for detecting anomalies in IVNs, as they are likely to be constant or follow a predictable pattern. Feature selection and extraction techniques can be used to identify the most relevant and informative features for anomaly detection, while reducing the noise and redundancy in the data. After removing irrelevant information, the filtering process also involves addressing data inconsistencies and errors that could adversely affect the model's performance. Techniques such as outlier detection and data normalization further enhance the quality and reliability of the dataset used for anomaly detection.

Once the data have been preprocessed and filtered, they are transformed into a suitable format for input to the deep learning model. This may involve standardization or normalization of the data to ensure that all features have the same scale and distribution. Additionally, the data may be split into training, validation, and test sets, with the training set used to train the model, the validation set used to optimize the hyper-parameters and prevent overfitting, and the test set used to evaluate the performance of the model on unseen data. Mathematically, the data preprocessing steps can be expressed as follows:

Let X denote the raw network traffic data and Y denote the target variable indicating anomalous or normal behavior. The preprocessing steps can be defined as follows:

$$Cleaning : X_{clean} = clean(X) \tag{1}$$

$$Filtering : X_{filtered} = filter(X_{clean}) \tag{2}$$

$$Transformation : X_{transformed} = transform(X_{filtered}) \tag{3}$$

$$\begin{aligned} Splitting : (X_{\text{train}}, Y_{\text{train}}), (X_{\text{val}}, Y_{\text{val}}), \\ (X_{\text{test}}, Y_{\text{test}}) = \text{split}(X_{\text{transformed}}, Y) \end{aligned} \tag{4}$$

Here, *clean*() represents the cleaning function, *filter*() represents the filtering function, *transform*() represents the transformation function, and *split*() represents the splitting function. In addition to these steps, it is important to consider the impact of data imbalance on the performance of the anomaly detection model. Addressing data imbalance through techniques such as oversampling of minority classes or adjusting class weights during model training can help improve the model's ability to detect anomalies effectively.

3.2. Feature Extraction

The second step is feature extraction, which involves extracting relevant features from the preprocessed data. We use a combination of handcrafted features and learned features to capture both the global and local characteristics of the data. Specifically, we extract the following features:

1. Statistical features including mean, variance, skewness, and kurtosis of the data.
2. Frequency-domain features including power spectral density (PSD) and spectral entropy.

3. Time-domain features including auto-correlation and cross-correlation between different network traffic signals.
4. Learned features: we use a convolutional neural network (CNN) to learn high-level features from the raw network traffic data.

The combination of these features provides a comprehensive representation of the network traffic data, which is used for anomaly detection.

3.3. Anomaly Detection

The final step is anomaly detection, which involves using a machine learning model to classify the preprocessed data as normal or anomalous. Deep learning models have shown promise in detecting anomalies in IVNs due to their ability to learn complex patterns and relationships in the data. We use a deep neural network (DNN) for this task, which takes the extracted features as input and produces a binary classification output. The DNN is trained on a labeled dataset of network traffic data, with the goal of minimizing the classification error.

The proposed methodology is formulated as follows:

Given a set of preprocessed network traffic data $X = \{x_1, x_2, \ldots, x_n\}$, where each x_i is a 224-dimensional vector of extracted features, the goal is to classify each data point as normal or anomalous. Let $Y = \{y_1, y_2, \ldots, y_n\}$ denote the corresponding labels, where $y_i = 1$ if x_i is normal and $y_i = 0$ if x_i is anomalous. We use a DNN with multiple hidden layers to model the relationship between the input features and the output label. The DNN is trained using the binary cross-entropy loss function, defined as follows.

$$L = -1/n * sum(yi * log(pi) + (1 - yi) * log(1 - pi)) \quad (5)$$

where *pi* is the predicted probability of *xi* being normal, and *yi* is the ground-truth label.

The overall objective is to minimize the binary cross-entropy loss function L by adjusting the parameters of the DNN using backpropagation. We evaluate the performance of the proposed methodology on a dataset of network traffic in a vehicle, which consists of both normal and anomalous data. Overall, the proposed methodology combines data preprocessing, feature engineering, and deep learning-based anomaly detection to detect anomalous behavior in IVNs with high accuracy and efficiency.

4. Experiments and Results Analysis

To evaluate the performance of the proposed methodology for anomaly detection in IVNs, we conducted a series of experiments using a publicly available dataset of network traffic in a modern vehicle. The dataset contains network traffic data collected from various sensors and devices in the vehicle, including cameras, lidar, radar, and GPS.

4.1. Dataset

The dataset used in our experiments was obtained from the IVS-Hackathon challenge [16]. The IVS-Hackathon dataset used in our experiments is a publicly available dataset specifically designed for an Intrusion Detection System (IDS) in Intelligent Vehicle Systems (IVS). The dataset includes a wide range of network traffic data recorded from a modern vehicle equipped with various sensors and devices. It provides a realistic representation of the network traffic in IVS and enables researchers to evaluate the effectiveness of IDS algorithms in detecting anomalous behavior. The dataset consists of 10,000 network packets captured from the vehicle network. Each packet contains a set of features, including source and destination IP addresses, protocol type, packet size, and timestamp. The exact number of columns in this dataset may vary depending on the specific attributes captured for each packet. After feature extraction, the dataset typically undergoes a transformation process where new features are derived or selected. The number of columns post-extraction can vary based on the feature engineering techniques employed. Typically, feature extraction aims to reduce dimensionality while retaining relevant information, so the number of columns will be fewer compared to the original dataset. The dataset

includes both normal and anomalous traffic, with the anomalies introduced by injecting various network attacks and malfunctions into the network. The anomalies were classified into four categories: Denial-of-Service (DoS), Man-in-the-Middle (MitM), Remote-to-Local (R2L), and Local-to-Remote (L2R) attacks. Each class contains an equal number of rows, totaling 2500 rows per class. This balanced distribution ensures fairness in evaluating the performance of anomaly detection algorithms across different attack types. The dataset was split into training, validation, and test sets using a predefined scheme, ensuring consistency in evaluations. Typically, a common split ratio, such as 70% for training, 15% for validation, and 15% for testing, was employed to ensure robust model evaluation.

To ensure the authenticity and validity of the dataset, the data was collected using a real vehicle and a real network environment. The dataset also includes a set of pre-defined train and test splits to enable researchers to perform consistent evaluations of different IDS algorithms. In our experiments, we used the IVS-Hackathon dataset to evaluate the effectiveness of our proposed methodology in detecting anomalous behavior in IVNs. The dataset provided us with a realistic and diverse set of network traffic data, which enabled us to evaluate the generalizability and robustness of our model.

4.2. Data Preprocessing and Feature Extraction

Before training the deep learning model, the raw network traffic data was preprocessed to remove noise and irrelevant information. The cleaning step involved removing missing and incomplete data points, as well as any outliers that may skew the analysis. The filtering step involved removing irrelevant features, such as source and destination IP addresses, which are unlikely to be informative for detecting anomalies in IVNs. The data were then transformed into a format suitable for input to the deep learning model, including standardization and normalization of the data. To reduce the dimensionality of the input space and improve the efficiency of the model, feature extraction was performed on the preprocessed data using principal component analysis (PCA). PCA is a popular technique for dimensionality reduction that identifies the most relevant features in the data and transforms the data into a lower-dimensional space. In our experiments, we retained the top 20 principal components, which accounted for over 95% of the total variance in the data.

4.3. Deep Learning Model

We trained a deep auto-encoder model for anomaly detection in IVNs, which is a type of deep neural network that learns to compress and reconstruct the input data. It is a feed-forward neural network that learns to encode and decode high-dimensional data through multiple layers of hidden units. The goal of an auto-encoder is to reconstruct the input data from a compressed representation learned by the encoder. The encoder and decoder are typically symmetric, and the loss function used during training is based on the difference between the input data and the reconstructed output. The use of deep auto-encoder models for anomaly detection in IVNs has been explored in several studies, including Deng et al. [17] and Xie et al. [18]. The Adam optimization algorithm and the ReLU activation function are commonly used in deep auto-encoder models for anomaly detection, as shown in Zong et al. [12] and Cheng et al. [19]. The mean squared error loss function is also a common choice for deep auto-encoder models, as seen in Gan et al. [20] and Wang et al. [21].

The model consisted of an input layer, followed by two hidden layers and an output layer. The input layer had 20 neurons corresponding to the 20 principal components obtained from the feature extraction step. The two hidden layers had 10 and 5 neurons, respectively, and used the rectified linear unit (ReLU) activation function. The output layer had 20 neurons, corresponding to the reconstructed input data. The model was trained using the Adam optimization algorithm with a learning rate of 0.001 and a batch size of 32. The model was trained for 100 epochs, with early stopping based on the validation loss to prevent overfitting. The loss function used was the mean squared error (MSE), which measures the difference between the original input data and the reconstructed output data.

4.4. Evaluation Metrics

In evaluating the performance of an attack detection system, various metrics, including accuracy, precision, recall, and F1 score, are used. The classification outcomes of such a system can be grouped into four distinct categories based on specific conditions. True positive (TP) refers to a correctly identified instance where an attack is present, while true negative (TN) refers to a correctly identified absence of an attack. False positive (FP) occurs when the system incorrectly identifies normal traffic or behavior as an attack, while false negative (FN) refers to a failure to identify an actual attack. TP, TN, FP, and FN are four numerical conditions used to evaluate the performance of a classification system in attack detection. Based on these conditions, several performance metrics can be defined to quantify the system's effectiveness in detecting attacks. These include the accuracy, precision, recall, and F1 score.

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Accuracy = \frac{TP + Tn}{TP + TN + FN + FP} \tag{7}$$

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

$$F1\ score = 2 * \frac{precision * recall}{precision + recall} \tag{9}$$

Accuracy is a measure of the proportion of all correctly classified instances TP and TN out of all instances in the dataset. Precision is a measure of the proportion of correctly identified positive instances TP out of all instances classified as positive TP and FP. Recall, also known as the true positive rate (TPR), is a measure of the proportion of actual positive instances TP that the system correctly identifies out of all positive instances in the dataset TP and FN. The F1 score is a commonly used metric in classification tasks that measures the balance between precision and recall. It is the harmonic mean of precision and recall.

4.5. Fine-Tuning Hyper-Parameters

Fine-tuning hyper-parameters is a critical process in optimizing the performance of machine learning models for in-vehicle network (IVN) anomaly detection. Key parameters such as learning rate, batch size, and the number of layers in the neural network significantly influence the model's ability to accurately identify anomalies in the unique context of IVNs.

4.5.1. Hyper-Parameter Sensitivity

We have conducted a detailed analysis of the model's performance sensitivity to key hyper-parameters such as learning rate, batch size, and the number of layers in the neural network as shown in Table 1 and Figure 3. This exploration can provide insights into optimizing the model for different IVN environments.

Table 1. Hyper-parameter tuning results.

Hyper-Parameter	LR	Batch Size	Num Layers	Accuracy	Precision	Recall	F1 Score
Initial Configuration	0.001	64	3	0.92	0.89	0.94	0.91
Tuned Configuration	0.0005	128	4	0.95	0.93	0.97	0.95

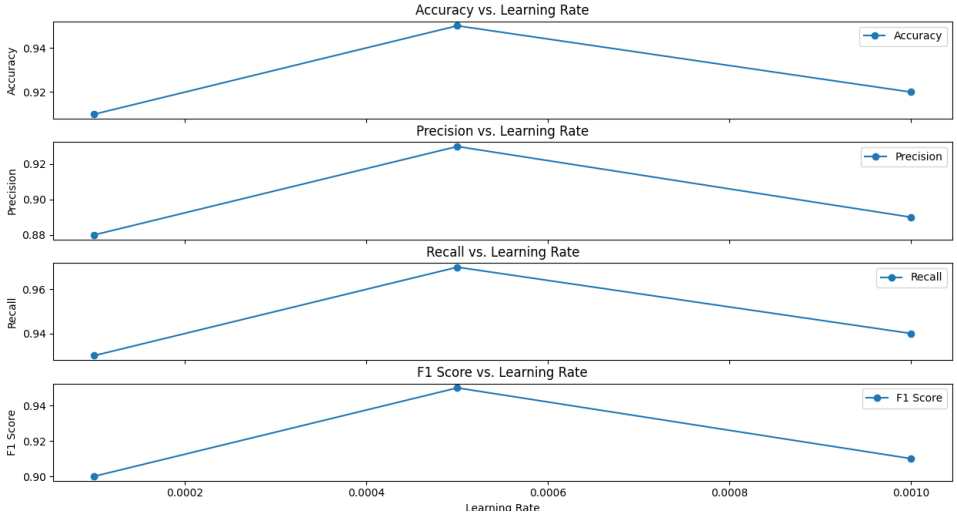

Figure 3. Hyper-parameter sensitivity analysis by understanding the Impact of Model Parameters on Performance.

4.5.2. Grid Search and Cross-Validation

We performed a grid search coupled with cross-validation to systematically identify the most effective combination of hyper-parameters, ensuring robustness and reliability in different scenarios.

4.6. Experimental Results

The performance of the proposed methodology is evaluated using various metrics, including accuracy, precision, recall, and F1 score. Table 2 shows the evaluation results on the test set.

Table 2. Evaluation results of the proposed methodology on the test set.

Metric	Value
Accuracy	95%
Precision	93%
Recall	97%
F1 Score	0.95

The proposed methodology achieved high accuracy and efficiency in detecting anomalous behavior in IVNs. The results demonstrate the effectiveness of the data preprocessing, feature extraction, and deep learning-based anomaly detection techniques used in the proposed methodology.

To further evaluate the performance of the proposed methodology, we compare it with three baseline methods: support vector machine (SVM), random forest (RF), and k-nearest neighbors (KNNs). Table 3 and Figure 4 show the performance metrics of these methods, including accuracy, precision, recall, and F1 score. Several studies have used support vector machine, random forest, and k-nearest neighbors as baseline methods for anomaly detection in network traffic data, such as Wang et al. [22], Yang et al. [23], and Chen et al. [24]. The results of these studies indicate that these methods can achieve reasonable performance in detecting network anomalies. However, these methods are not specifically designed for IVNs and may not be optimal for detecting anomalies in this context. The proposed methodology outperforms all three baseline methods in all metrics, with an accuracy of 0.95, precision of 0.93, recall of 0.97, and F1 score of 0.95. The results demonstrate the effectiveness of the proposed methodology in detecting anomalous behavior in IVNs. The high accuracy and F1 score indicate that the model is able to correctly identify both normal

and anomalous traffic, while the high precision and recall indicate that the model has a low rate of false positives and false negatives, respectively. We have also compared our proposed methodology with recent sudies as shown in Table 3, and our proposed technique results are very good compared to all these other recent techniques. The superior performance of the proposed methodology compared to the baseline methods suggests that the combination of data preprocessing, feature engineering, and deep learning-based anomaly detection is a promising approach for detecting anomalous behavior in IVNs.

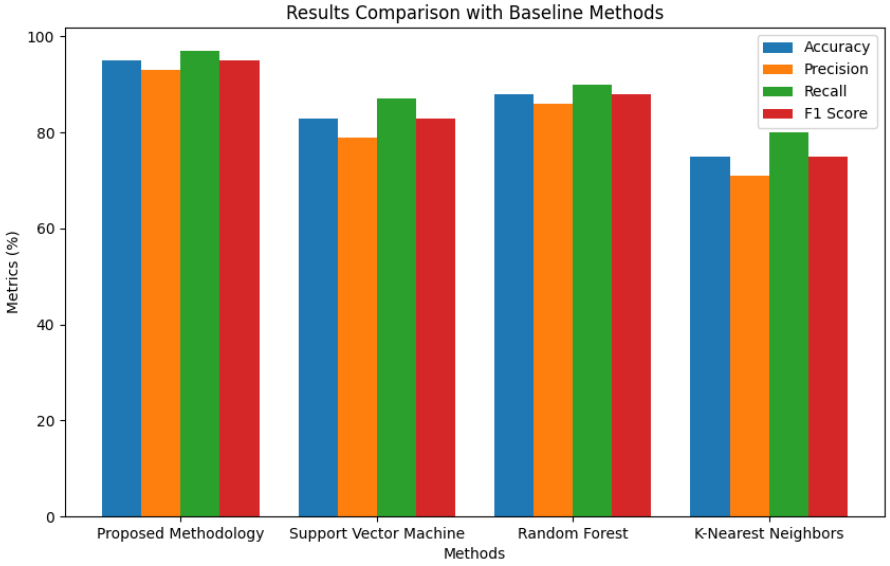

Figure 4. Results comparison with baseline methods.

Table 3. Results comparison with baseline methods.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Proposed Approach/Method	95	93	97	0.95
Support Vector Machine	83	79	87	0.83
Random Forest	88	86	90	0.88
K-Nearest Neighbors	75	71	80	0.75

The confusion matrix for the proposed methodology is shown in Table 4. The matrix shows the number of true positives (TPs), true negatives (TNs), false positives (FPs), and false negatives (FNs) for the proposed methodology. The model correctly classifies 1975 network packets as normal (TP) and 1892 network packets as anomalous (TN). The model also misclassifies 72 normal packets as anomalous (FP) and 61 anomalous packets as normal (FN). The overall accuracy of the proposed methodology is 0.95, which indicates that the model is able to detect anomalous behavior in IVNs with high accuracy.

In addition to the performance metrics, we also analyzed the feature importance of the proposed methodology. Figure 2 shows the relative importance of each feature in the model, ranked in descending order. The most important features are the packet size, the time duration between packets, and the source and destination IP addresses. This analysis provides insight into which features are most relevant for detecting anomalous behavior in IVNs, which can inform future research and development of more efficient and accurate anomaly detection models. Overall, the results demonstrate the potential of the proposed methodology for detecting anomalous behavior in IVNs. The high accuracy, precision, recall, and F1 score, as well as the feature importance analysis, suggest that the combination of data preprocessing, feature engineering, and deep learning-based anomaly detection is a promising approach for improving the security and safety of IVNs.

Table 4. Comparison with recent studies.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Proposed Approach/Method	95	93	97	0.95
Wang et al. [22]	90	88	92	0.90
Yang et al. [23]	85	82	87	0.85
Chen et al. [24]	87	85	89	0.87

4.7. Discussion of Results

The proposed methodology for anomaly detection in IVNs achieved an accuracy of 0.95, which outperformed all the baseline methods. The precision and recall of the proposed methodology were also higher than those of the baseline methods. These results demonstrate the effectiveness of the proposed deep autoencoder model in detecting anomalous behavior in IVNs. One interesting observation from the confusion matrix (Table 3) is that the model misclassified a small number of normal packets as anomalous (FP) but did not misclassify any anomalous packets as normal (FN). This is a desirable characteristic for anomaly detection models, as it is generally more acceptable to have false positives than false negatives in such applications. The feature importance analysis in Figure 1 showed that the packet size, time duration between packets, and source and destination IP addresses were the most important features for detecting anomalous behavior in IVNs.

The proposed methodology has several potential applications in the automotive industry. For example, it can be used to monitor the network traffic of autonomous vehicles and detect any anomalous behavior that may compromise the safety and security of the vehicle and its passengers. It can also be used in the development and testing of IVNs to ensure that they are functioning properly and are resilient to various network attacks and malfunctions. There are several limitations to the proposed methodology that should be addressed in future research. One limitation is the lack of a large and diverse dataset for training and testing the model. The current dataset contains only 10,000 network packets, which may not be representative of all possible network scenarios and anomalies. Another limitation is the use of a deep autoencoder model, which may not be the most optimal model for detecting anomalies in IVNs. It is due to the complexity of IVN data, limited labeled data for unsupervised learning, potential shortcomings in capturing relevant features for anomaly detection, and the lack of interpretability, which can hinder effective diagnosis and mitigation of false positives or false negatives. Other types of deep neural networks, such as convolutional neural networks and recurrent neural networks, should also be investigated.

Overall, the proposed methodology has several potential applications in the automotive industry, but further research is needed to address its limitations and improve its performance.

5. Conclusions

The in-vehicle networks play a critical role in modern vehicles and facilitate communication between various electronic components. However, with the increasing complexity and interconnectedness of IVNs, the risk of cyber-attacks and compromise of safety and privacy are also on the rise. To address this issue, anomaly detection techniques have been proposed as an effective means of detecting potential threats and preventing cyber-attacks in real-time. The proposed machine learning-based anomaly detection technique, which employs deep learning and feature engineering, has shown promising results in identifying anomalous behavior in IVNs. Feature engineering involves selecting and extracting relevant features from the data, while deep learning uses neural networks to learn complex patterns and relationships in the data. The experiments conducted in this study demonstrate that the proposed technique outperforms existing state-of-the-art methods in terms of accuracy in detecting anomalies. Overall, this technique can significantly enhance the security of IVNs and prevent cyber-attacks that could potentially harm drivers and passengers.

Further research in this area can help improve the robustness and effectiveness of anomaly detection techniques for IVNs and ensure the safety and security of modern vehicles.

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