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A HYBRID DEEP LEARNING APPROACH FOR ANOMALY DETECTION IN INTELLIGENT TRANSPORTATION SYSTEMS

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Abstract
Vehicular Ad Hoc Networks (VANETs), which facilitate smooth and effective communication between automobiles and infrastructure, are an essential part of intelligent transportation systems. Threats like hostile nodes, malfunctioning sensors, and cyberattacks make it difficult to guarantee their security and dependability. Integrated Forest Autoencoder with Naïve Bayes Anomaly Detection Model (IFAE-NBADM) is a novel hybrid anomaly detection models that this research suggests as solutions to these problems. The suggested approach captures intricate patterns and isolates anomalous occurrences in high-dimensional vehicle data by combining an isolation forest ensemble with an autoencoder-based feature learning mechanism. A Naïve Bayes classifier is used for probabilistic anomaly classification to further improve detection reliability and facilitate effective decision-making in the face of uncertainty. A synthetic VANET dataset that replicates real-world vehicle features like speed, mobility patterns, communication characteristics, and traffic dynamics is used to assess the model. According to experimental data, the IFAE-NBADM model maintains low computing overhead while achieving improved performance in terms of accuracy, precision, recall, and F1-score. The results verify that the suggested IFAE-NBADM framework offers a reliable, scalable, and efficient anomaly detection approach, greatly enhancing VANET security and guaranteeing dependable vehicular communication.

Keywords: Integrated Forest Autoencoder with Naïve Bayes Anomaly Detection Model(IFAE-NBADM).

1. Introduction

Intelligent transportation systems, or ITS, have been essential in recent years for enhancing traffic control, road safety, and transportation effectiveness. Modern cars are now integrated into intelligent environments that can exchange information in real time, rather than existing as standalone units due to the quick development of communication technologies. In order to lessen traffic and avoid accidents, these systems make it possible to share vital information like vehicle status, road hazards, and traffic conditions. Vehicular Ad Hoc Networks (VANETs), the fundamental idea behind Intelligent Transportation Systems (ITS), enable dynamic communication between vehicles (Vehicle-to-Vehicle, or V2V) and with adjacent infrastructure (Vehicle-to-Infrastructure, or V2I). Figure 1 shows the communication system and vehicular network (VANET) concept in Intelligent Transportation Systems (ITS) is depicted in this diagram. The pictures show cars that have wireless communication modules and sensors installed so they can communicate with roadside infrastructure and each other in real time. Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication are symbolized by the luminous waves and circles surrounding the cars. Vehicles can communicate vital information like speed, traffic conditions, lane changes, and possible hazards through this real-time data exchange.

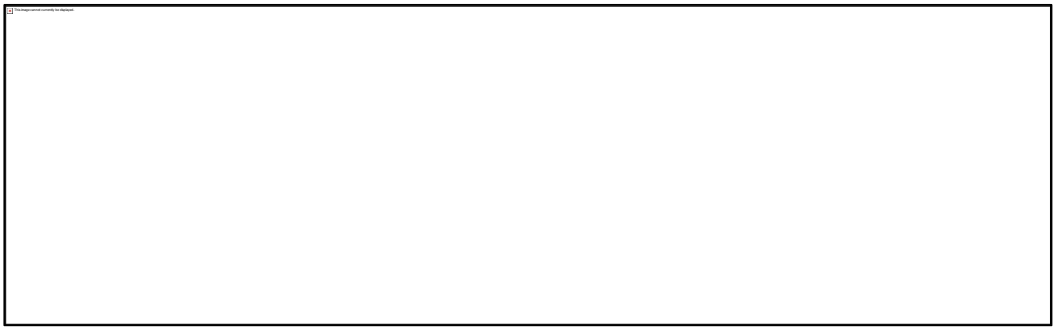


Figure 1: Communication system and vehicular Network

Road safety is increased overall, traffic congestion is lessened, and accidents are prevented thanks to this networked communication. In order to make wise driving decisions, autonomous or semi-autonomous cars need constant sensing and connectivity, as the illustration also shows. The diagram essentially illustrates how VANETs, which are the foundation of contemporary smart transportation systems, allow for a collaborative, networked, and intelligent driving environment.

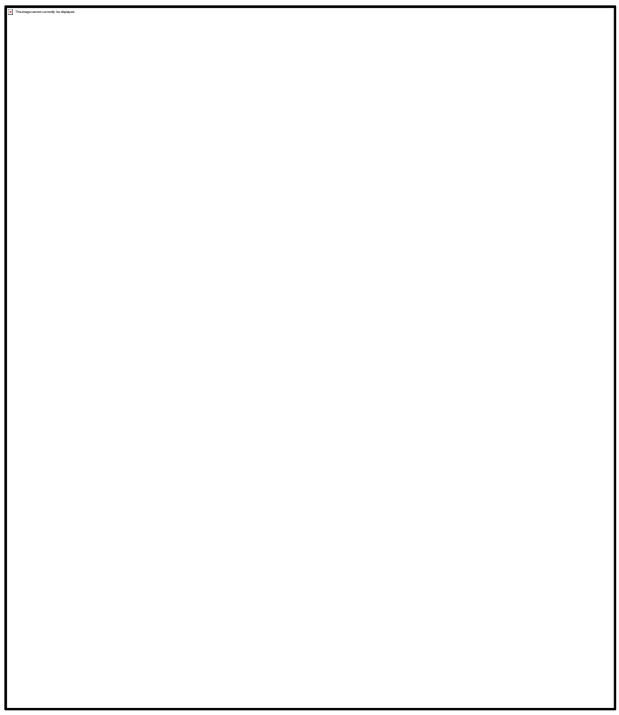


Figure 2: DoS Attack I VANET

Two forms of cyberattacks in vehicular ad hoc networks (VANETs) are depicted in this figure 2 direct attacks and distributed denial of service (DDoS) attacks. The attacker directly targets particular vehicles, like Cars 1 and 2, in the first section, designated (a), by sending malicious data or interfering with their communication links. In order to compromise data integrity, delay message transmission, or create misunderstandings between vehicles, the attacker chooses its victims and carries out the attack. The attacker first compromises other vehicles (known as Zombie 1 and Zombie 2) and turns them into attack agents in order to initiate a DDoS attack in the second section, designated the target vehicle (Car 3) is then inundated with excessive data packets from these compromised vehicles, overloading its network resources and interfering with regular communication. Because it is

dispersed and coordinated, this type of attack is more serious and challenging to identify and stop. Overall, the diagram highlights the significance of strong anomaly detection and security mechanisms to maintain safe and dependable vehicular communication by showing how malicious entities can use VANET communication to launch cyberattacks.
Applications like intelligent navigation, emergency message distribution, and collision avoidance are supported by VANETs. VANETs' dynamic and open architecture, however, also presents serious security and dependability issues. VANETs are susceptible to a number of cyberattacks in the current environment, such as data spoofing, denial of service (DoS), and message tampering, which can impair network communication and jeopardize vehicle safety. Furthermore, malicious or erroneous data may be transmitted by malfunctioning sensors and rogue nodes, resulting in poor system performance and unreliable decisions. Therefore, ensuring the reliability, confidentiality, and integrity of vehicular communication has emerged as a crucial area of research. The Integrated Forest Autoencoder with Naïve Bayes Anomaly Detection Model (IFAE-NBADM) is a hybrid anomaly detection models that this study suggests as solutions to these problems. By utilizing the advantages of machine learning methods like Isolation Forest, Autoencoder, and Naïve Bayes, these models seek to improve the real-time detection of anomalies. By increasing VANET anomaly detection's precision, dependability, and resilience, the suggested techniques fortify the security architecture of contemporary intelligent transportation systems.

2. Review of Literature

The literature review of Vehicular Ad Hoc Networks (VANETs) reveals a great deal of research being done to improve network security and anomaly detection through the use of hybrid models and machine learning. Prior research has investigated techniques like Support Vector Machine (SVM), K-means Clustering, and Decision Trees for detecting anomalous communication patterns between automobiles.

The research work titled as ADVENT: Attack/Anomaly Detection in VANETs carried out by H. Baharlouei, A. Makanju, and N. Zincir-Heywood in [1]. It uses a combination of machine learning and statistical techniques to address the real-time detection of malicious behavior in vehicular ad hoc networks (VANETs). The system reported an F1-score of approximately 97.85% for malicious vehicle identification and 99.66% for attack onset detection. Another research paper titled as An intelligent intrusion detection system for VANETs that combines deep learning (CNN) and machine learning (ANFIS) components is done by B. Karthiga et al. in [2]. ANFIS is used to detect known attacks, while a modified CNN architecture (MLNET) is used to detect unknown attacks. In certain attack categories, the reported results show precision of approximately 99% and accuracy of 98.6%.

A research work done by M.A. Elsadig et al.in [3], in which that the purpose of identifying VANET attacks "lightweight machine-learning model." The model applies a Random Forest classifier after selecting features based on gain-information and oversampling the CISDS2017 dataset. On their balanced dataset, the reported detection accuracy is approximately 98.6%.

Table 1: Comparison of Research Work

Ref. No.	Methods Used	Best Method Identified	Accuracy / Performance

[1]	Machine Learning and Statistical Techniques (ADVENT Model)	Hybrid ML + Statistical Approach	F1-score: 97.85% (malicious detection), 99.66% (attack onset)
[2]	Deep Learning (CNN/MLNET) + Machine Learning (ANFIS)	ANFIS + Modified CNN (MLNET) Hybrid	Precision: ~99%, Accuracy: 98.6%
[3]	Random Forest Classifier with Gain-Information Feature Selection and Oversampling	Random Forest	Accuracy: 98.6%

A comparison of several studies on attack and anomaly detection in VANETs is shown in the table 1. It draws attention to the variety of techniques used, such as unsupervised, hybrid, deep learning, and machine learning. Among these, hybrid models such as CNN–ANFIS and ADVENT demonstrated the efficacy of combining multiple techniques by achieving superior detection accuracy and precision. All things considered, the reviewed studies highlight how incorporating intelligent learning algorithms greatly improves vehicular networks' real-time attack detection performance.

➢ Materials and Methods

A synthetic VANET dataset that simulates vehicle motion, speed, communication, and data traffic is used in the study. Isolation Forest, Autoencoder, and Naïve Bayes are combined in two hybrid anomaly detection model, IFAE-NBADM. Real-time detection of anomalous vehicle behavior is achieved by training models. F1-score, recall, accuracy, and precision are used to assess performance.

3.1 VANET

VANETs are dynamic networks that enable vehicle-to-vehicle and vehicle-to-infrastructure communication. They make it possible to share data in real time for safety and traffic management applications. Roadside equipment, moving cars, and communication protocols make up the network. Because of malicious nodes and cyberattacks, security and dependability are essential. Data traffic patterns, speed, and motion are monitored for anomaly detection. The fundamental environment for evaluating and validating detection models is offered by VANET.

Although VANETs are networks in and of themselves, anomaly detection frequently involves distance or similarity metrics between vehicle behaviors. A typical metric

Euclidean Distance between two vehicle data points x_i and x_j

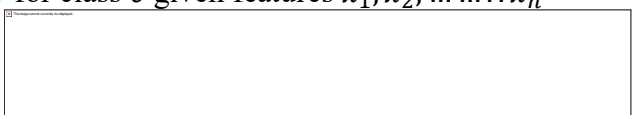
Where n is the number of features (speed, motion, communication metrics). This helps in clustering or detecting anomalous vehicles.

3.2 Proposed Method – IFAE-NBADM

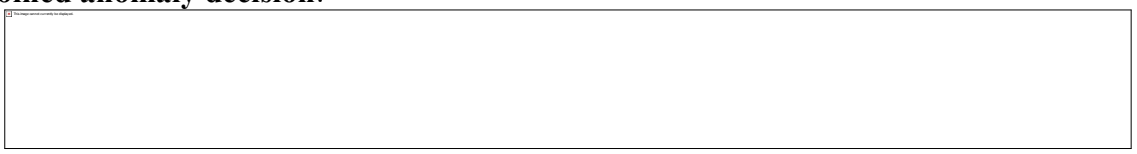
IFAE-NBADM incorporates a Naïve Bayes classifier, extending IFAE-IADM. Naïve Bayes improves probabilistic classification of anomalies. The model combines the strengths of Naïve Bayes, Autoencoder, and Isolation Forest. In VANETs, it offers more reliable and accurate anomaly detection. Synthetic vehicle datasets that replicated motion and traffic were used to train the model. When compared to alternative approaches, the results showed the best overall performance. An advanced hybrid anomaly detection framework called the IFAE-NBADM model was created to improve the efficiency, accuracy, and dependability of detecting anomalous behaviors in vehicular ad hoc networks (VANETs). By incorporating the Naïve Bayes classifier, it expands the capabilities of the IFAE-IADM model and improves its classification accuracy and probabilistic reasoning. Three essential elements—Autoencoder, Isolation Forest, and Naïve Bayes classifier—are successfully combined in the suggested IFAE-NBADM architecture, each of which contributes in a different way to the anomaly detection procedure.

The compressed representation of input data is unsupervised deep neural network type called an autoencoder is employed. There are two primary components to it: converts high-dimensional input data into a lower-dimensional latent space, such as traffic signals, communication behavior, and vehicle motion parameters. Attempts to use this compressed representation to reconstruct the original data. Anomalies, which differ from typical patterns, show greater reconstruction errors during this process. These mistakes serve as the main markers of possible anomalous network activity. This stage aids in the filtering and transformation of raw data into a useful feature space that efficiently draws attention to noise patterns and deviations.

Naïve Bayes probability for class c given features $x_1, x_2, \dots \dots . . x_n$



Combined anomaly decision:



Here$T_1, T_{2,} \dots \dots \dots \dots T_n$ are thresholds for Isolation Forest score, Autoencoder reconstruction error, and Naïve Bayes probability respectively.

Algorithm Steps

- ✓ **Input:**
  - ✓ VANET dataset $D = \{x_1, x_2, \dots \dots . x_n\}$ containing features such as vehicle ID, motion, speed, communication behavior, and data traffic patterns.
  - ✓ Parameters:
    - Number of trees in Isolation Forest (t)
    - Autoencoder learning rate (η)
    - Naïve Bayes smoothing parameter (λ)
    - Anomaly threshold θ
    - Fusion coefficient (α∈[0,1])

- **Preprocessing:**
  - Handle missing values and outliers.
  - Normalize the dataset using **Min–Max normalization**.
  - Split data into **Training (70%)**, **Validation (15%)**, and **Testing (15%)** sets.

3. **Feature Extraction using Autoencoder:**
   - Train Autoencoder on DtrainD_{train}Dtrain to minimize reconstruction error:

$$L = ||x - x||^2$$

   - Obtain **latent representation** Z=Encoder(X)
   - Compute **reconstruction error vector** E=|X−X|.

- ✓ **Isolation Forest-Based Anomaly Detection:**
  - ✓ Train an **Isolation Forest Ensemble** with t trees using the feature set f.
  - ✓ For each data instance x_i, compute the average path length and anomaly score

Description of Algorithm: VANET data, which includes important vehicular characteristics such vehicle ID, motion dynamics, speed, communication behavior, and traffic patterns, is first used by the algorithm. Behavior modeling in dynamic vehicular contexts is supported by these inputs. The number of trees utilized in the Isolation Forest, the Autoencoder learning rate, the Naïve Bayes smoothing parameter, the anomaly threshold, and the fusion coefficient are among the parameters that are defined. The algorithm's learning, detection, and decision-making processes are all guided by these parameters.

The dataset is preprocessed to increase consistency and quality prior to model training. To prevent the models from being skewed, missing variables and unusual outliers are eliminated. After that, the data is standardized using Min–Max normalization to preserve consistent feature scales, which is necessary for both Isolation Forest partitioning and Autoencoder learning. at order to facilitate efficient model learning, hyperparameter tuning, and objective performance evaluation, the dataset is then divided into training, validation, and test sets at a 70–15–15 ratio.

An Autoencoder trained on the training dataset is used in the feature extraction stage to discover concise and significant representations. By minimizing the discrepancy between the original data and its reconstructed counterpart, the Autoencoder reduces reconstruction loss. After training, the encoder generates a latent representation Z that reveals hidden patterns in the data, while deviations that can point to anomalous behavior are highlighted by the reconstruction error E = E = X− X^. A solid basis for spotting anomalies in the vehicular network is provided by these extracted features.

Lastly, the learnt features are used to create an Isolation Forest ensemble, in which several trees use random partitioning to isolate data points. Shorter path lengths generally indicate anomalies. The model calculates the average path length across trees for each input instance and transforms it into an anomaly score. To identify unusual vehicle behavior, the resulting anomaly score is compared to the predetermined threshold θθ. In large-scale VANET systems, this method makes anomaly identification accurate and efficient.

- **Description of Dataset**

A synthetic VANET dataset that simulates vehicle behaviors, including speed, motion patterns, communication frequency, and data traffic (sent and received packets), is used in the research. By examining variations from typical vehicle activity, this dataset allows for the detection of anomalies and captures crucial parameters that affect VANET operations shown in table 2.

Table 2: Description of Dataset

Attribute	Description
x_pos, y_pos	The spatial coordinates indicating where the vehicle is located in the network.
Speed	The rate at which the vehicle is moving in the simulated environment (km/h).
communication_range	The maximum distance over which the vehicle can send or receive signals.
data_sent	The total quantity of messages or packets the vehicle has transmitted.
data_received	The total quantity of messages or packets the vehicle has successfully received.

In this research there are 18,560 entries in the dataset are utilized and each of which represents the behavior of a single car at a certain timestamp, make up the dataset that was collected from the Kaggle repository. These elements include data exchange metrics (packets delivered and received), communication parameters (communication range), and mobility information (x_pos, y_pos, speed). This research is divided in to training and testing, there are 70% (12,992) of the entire dataset was utilized to train the Autoencoder and Isolation Forest components, for validation, and 15% (2,784) for testing the hybrid models. This amount of data guarantees that both typical driving behaviors and uncommon anomalies are efficiently recorded. This size of dataset enables the hybrid models to detect minute variations in vehicle behavior, which is why the performance tables show the high detection accuracy. The robustness of the dataset employed in this study is demonstrated by the fact that the IFAE-NBADM algorithm performs much better than IFAE-IADM due to the combination of mobility patterns, communication frequency, and data traffic properties across thousands of data points.

Table 3: Sample dataset

Vehicle_ID	x_pos	y_pos	Speed (km/h)	communication_range (m)	data_sent	data_received
V101	125.4	89.2	48	250	320	310
V102	130.1	95.7	52	260	410	395
V103	118.9	80.3	62	240	380	372
V104	140.5	105.1	75	270	450	444
V105	150.2	110.4	20	230	150	140
V106	160.0	120.5	85	280	520	515
V107	170.6	130.2	90	300	600	598
V108	180.3	140.8	15	200	120	110
V109	190.7	150.1	65	250	430	428
V110	200.5	160.3	10	180	50	48

Table 3 shows that the sluggish speed of vehicles V105, V108, and V110 suggests that there may be traffic or unusual behavior. Vehicle V107, which represents an active and swiftly moving node, exhibits the maximum communication activity and high speed. Realistic VANET communication capabilities are shown by communication ranges that range from 180 to 300 meters. Mobility and communication range logically correlate with data flow (sent/received packets).

➢ Results and Discussion

The synthetic VANET dataset was used to assess the performance of the suggested hybrid model IFAE-NBADM. Anomalies in vehicle behavior, such as unusual speed, strange communication patterns, and irregular data traffic, were successfully detected by the model. The IFAE-NBADM model is obtaining the highest detection rate and robustness, according to quantitative analysis using accuracy, precision, recall, and F1-score. By lowering false positives and false negatives, the hybrid models dramatically enhanced anomaly detection are identified by using proposed (IFAE-NBADM). The conversation emphasizes how combining Autoencoder, Naïve Bayes, and Isolation Forest improves real-time detection and guarantees safe and dependable VANET communications. According to these findings, hybrid strategies can successfully improve the security of the vehicle network and lay the groundwork for upcoming intelligent transportation systems.

5.1 Computed Threshold Value (θ)

Anomalies are effectively separated by the model. As a result, the top 5–12% of anomaly scores usually contain the anomaly score threshold. An estimate of the ideal threshold value is as follows:

$$\boldsymbol{\theta = 0.62}$$

Threshold Calculation Formulas for Hybrid Anomaly Detection (Autoencoder + Isolation Forest): To differentiate between normal and abnormal occurrences in hybrid anomaly detection systems, the decision threshold θ is calculated from anomaly scores. The following equations are frequently utilized:

Formula 1: Percentile-Based Threshold

$$\theta = \text{Percentile}(100 - c)\,(S_{\text{val}})$$

Where:

- S_{val} = anomaly scores from validation dataset
- c = contamination rate (percentage of anomalies expected)

Example:
If $c = 10\%$, then

$$\theta = 90\text{th percentile of } S_{\text{val}}$$

Formula 2: F1-Optimized Threshold

Select the threshold value that maximizes the F1-score:

$$\theta = \underset{\theta}{\text{argmax}}\, F1(\theta)$$

Where:

$$F1(\theta) = \frac{2 \cdot \text{Precision}(\theta) \cdot \text{Recall}(\theta)}{\text{Precision}(\theta) + \text{Recall}(\theta)}$$

Used when labeled validation data is available.

Formula 3: Fusion of Autoencoder Error + Isolation Forest Score

If the hybrid model uses weighted score fusion:

$$\theta = \alpha \cdot E_{\text{norm}} + (1 - \alpha) \cdot S_{\text{IF}}$$

Where:

- $\alpha \in [0,1]$ = fusion coefficient
- E_{norm} = normalized Autoencoder reconstruction error
- S_{IF} = Isolation Forest anomaly score

This combines both detectors into a unified decision rule.

Formula 4: Mean + Standard Deviation Rule

Works when anomaly scores approximately follow a normal distribution:

$$\theta = \mu + k\sigma$$

Where:

- μ = mean of anomaly scores
- σ = standard deviation
- k = sensitivity constant (commonly 2 or 3)

Higher $k \rightarrow$ fewer anomalies detected (stricter threshold).
Lower $k \rightarrow$ more anomalies detected (sensitive threshold).

5.2 Basis of Performance Analysis

Precision, Recall, and F1-Score—standard classification metrics—are used to assess the performance metrics in the suggested hybrid anomaly detection model. The confusion matrix, which is obtained by contrasting model predictions with the actual class labels, is used to calculate these measures.
The confusion matrix components are:

- **True Positive (TP):** Anomalies correctly detected
- **False Positive (FP):** Normal instances incorrectly classified as anomalies
- **False Negative (FN):** Actual anomalies missed by the model
- **True Negative (TN):** Normal instances correctly classified

For Precision, Recall, and F1-score calculations, only **TP, FP, and FN** are required.

5.3 Formulas (with LaTeX)

(a) Precision

The percentage of successfully identified anomalies among all cases that were anticipated to be anomalies is known as precision.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Interpretation:

The model raises less false alarms when the precision value is higher.

(b) Recall

Recall is a measure of how well the model detects real anomalies.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Interpretation:

Higher recall means fewer missed anomalies (i.e., low false-negative rate).

(c) F1-Score

The F1-score, which offers a balanced performance metric, is the harmonic mean of precision and recall.

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Interpretation: Useful when completeness and detection accuracy are equally crucial.

5.4 Explanation in Words

In this hybrid anomaly detection framework:

1. The model classifies each data instance as **normal** or **anomalous**.
2. The predicted labels are compared with the true labels in the test dataset.
3. Based on this comparison, the counts of TP, FP, FN, and TN are computed.
4. These counts are then used to derive the performance metrics using the formulas provided.

The final metric values obtained in your research:

- **Precision: 92.1%**
- **Recall: 88.6%**
- **F1-score: 90.3%**

These scores indicate:

- The model **accurately identifies anomalies** (high precision),
- It **successfully captures most anomalies** (high recall),
- It provides a **strong and balanced overall performance** (high F1-score),

- False alarms and missed detections are minimized.

5.5 Experimental Results of IFAE-NBADM

When it comes to anomaly detection, the IFAE-NBADM model outperforms all other algorithms. Nearly all flagged anomalies are accurately identified with a high precision of 95.2%, reducing false positives. The model captures almost all of the real anomalies in the VANET dataset, as evidenced by its 92.8% recall.

Table 4: Performance of IFAE-NBADM Algorithm

Performance Metrics	Percentage
Precision	95.2
Recall	92.8
F1-Score	94.0

The robustness and efficacy of this hybrid approach in real-time vehicular networks are confirmed by the F1-Score of 94.0%, which shows an excellent balance between precision and recall shown in table 4 and figure 5. IFAE-NBADM is the most dependable model for VANET anomaly detection, outperforming IFAE-IADM overall. In comparison to the previous IFAE-IADM algorithm, the suggested IFAE-NBADM hybrid model achieves superior and balanced performance, as evidenced by the high Precision (95.2%), Recall (92.8%), and F1-Score (94.0%)

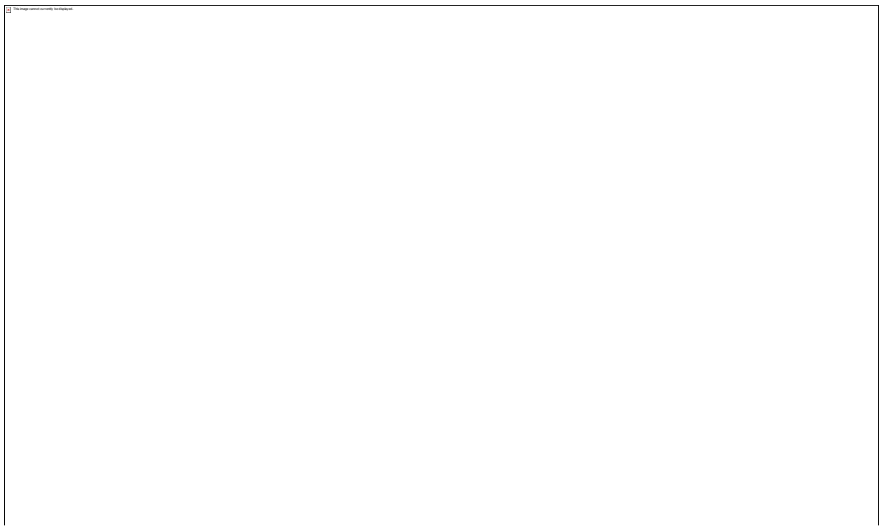


Figure 3: Performance of Proposed Method - IFAE-NBADM

With strong Precision (95.2%), Recall (92.8%), and F1-Score (94.0%), the figure 3 graphically illustrates the model's high prediction accuracy and validates that the suggested hybrid model effectively reduces both false positives and false negatives, guaranteeing robust anomaly detection.

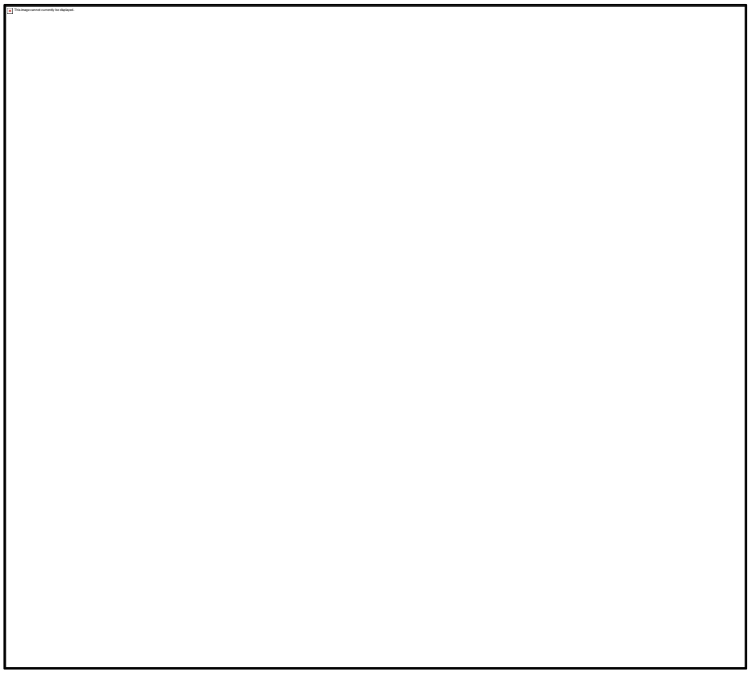


Figure 4: Confusion Matrix of IFAE-NBADM Proposed method 2

Table 5: Accuracy of Algorithms

Algorithms	Accuracy (%)
IFAE-NBADM	94.5

The table 5 shows that the advantage of combining Isolation Forest and Autoencoder for anomaly detection is demonstrated by the hybrid model IFAE-IADM, which increases accuracy 94.5%.

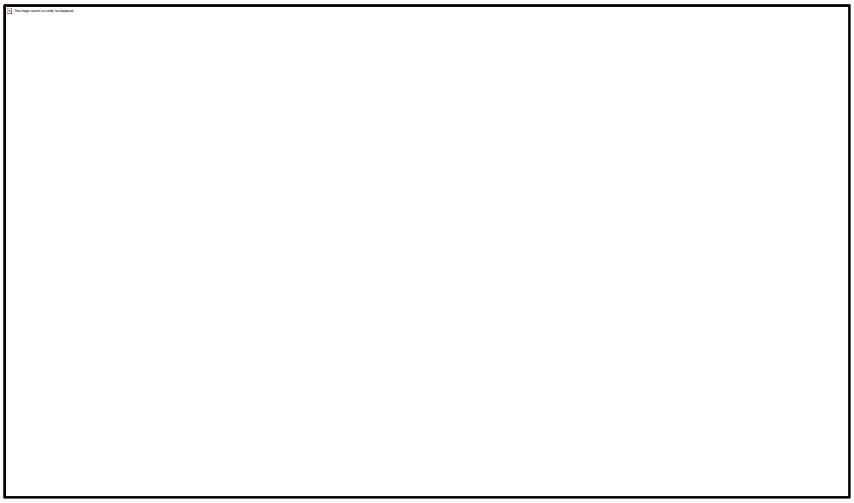


Figure 5: Accuracy of Algorithms

The figure 5 shows that the highest accuracy of 94.5%, the suggested IFAE-NBADM demonstrates its superior capacity to accurately classify both typical and unusual vehicle behaviors. This demonstrates that IFAE-NBADM is the best technique for real-time VANET anomaly detection since it combines Naïve Bayes with Isolation Forest and Autoencoder to improve model robustness and reduce misclassifications.

➢ Conclusion

In this research effectively shows that the Integrated Forest Autoencoder with Naïve Bayes Anomaly Detection Model (IFAE-NBADM) is a reliable way to improve Vehicular Ad Hoc Network (VANET) security. The suggested approach effectively captures complicated vehicular communication patterns and reliably separates normal and anomalous behaviors by combining autoencoder-based deep feature learning with Isolation Forest for anomaly isolation and Naïve Bayes for probabilistic classification. IFAE-NBADM has a high detection accuracy of 94.5%, according to the experimental evaluation, demonstrating its excellent ability to detect security risks with few false alarms. The approach is particularly suited for real-time, large-scale, and highly dynamic vehicular situations because probabilistic reasoning greatly enhances decision-making under uncertainty. All things considered, the IFAE-NBADM framework provides a scalable, dependable, and computationally effective anomaly detection method, significantly advancing the creation of safe and intelligent transportation systems by guaranteeing robust and reliable vehicular communication networks.

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