Bi-LSTM Architecture for Temporal Pattern Recognition in Internet of Vehicles Cyberattack Detection

Raavi Deepthi
Research Scholar
GITAM University, Rudraram, Patancheru, Hyderabad - 502329
draavi@gitam.in

Abstract: Cyberattacks in Internet of Vehicles exhibit temporal dependencies and sequential patterns that conventional machine learning models fail to capture effectively. This paper presents a Bidirectional Long Short-Term Memory architecture optimized for detecting time-dependent attack patterns in vehicular network traffic. The Bi-LSTM approach processes traffic sequences in both forward and backward directions, enabling comprehensive understanding of attack progression and contextual relationships within temporal data streams. The methodology addresses the temporal nature of vehicular communications where attack signatures may manifest across multiple time steps rather than in isolated events. Integration with the Cat and Mouse Optimizer for feature selection and Enhanced SMOTEBoost for handling class imbalance creates a comprehensive detection framework. Performance evaluation on CICIDS-2018 and Car-Hacking datasets demonstrates that the CMO-Bi-LSTM configuration achieves the highest detection accuracy of 99.10% with 99.05% F1-score, outperforming Random Forest, Decision Tree, and standard LSTM implementations. The bidirectional architecture effectively captures both short-term and long-term dependencies in attack patterns, demonstrating superior performance in detecting evolving threats including DoS, DDoS, Bot, and vehicle-specific attacks like RPM and gear manipulation. The model's ability to learn from temporal sequences makes it particularly suitable for dynamic IoV environments where attack strategies continuously adapt and real-time detection response is critical for maintaining vehicular network security and passenger safety.

Keywords: Bi-LSTM, Temporal Pattern Recognition, IoV Cyberattacks, Sequential Data, Deep Learning

1. Introduction

The rapid evolution of the Internet of Vehicles (IoV) has transformed modern transportation systems into highly interconnected, intelligent, and data-driven ecosystems. IoV enables seamless communication among vehicles, roadside units, sensors, cloud platforms, and smart infrastructure, supporting applications such as cooperative driving, traffic coordination, remote diagnostics, and autonomous vehicle decision-making [1]. As vehicular networks become more complex, they also become increasingly vulnerable to sophisticated cyberattacks that target communication protocols, onboard units, and data exchange processes. Threats such as Denial of Service (DoS), Distributed Denial of Service (DDoS), spoofing, replay attacks, and vehicle-specific intrusions (e.g., gear manipulation, RPM falsification) pose significant risks to road safety, real-time operations, and vehicular control systems [2]. These evolving threats highlight the necessity for intelligent detection mechanisms capable of analyzing dynamic traffic streams and capturing complex temporal dependencies inherent in IoV environments.

Traditional machine learning models, including Support Vector Machines, Random Forests, Naïve Bayes, and Decision Trees, have been widely applied for intrusion detection; however, these models primarily rely on static or aggregated features and lack the capability to learn sequential relationships present in network traffic flows [3]. Such models treat packet-level or flow-level data as independent observations, overlooking the fact that cyberattacks on IoV infrastructures typically unfold over time, with signatures distributed across multiple time steps. For instance, attack phases such as scanning, probing, payload injection, and command execution frequently exhibit temporal progression. As a result, conventional classifiers often fail to detect low-rate or stealthy attacks whose patterns manifest only when temporal context is considered [4]. These limitations necessitate the adoption of advanced deep learning architectures that can effectively model time-dependent patterns in vehicular network data.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for analyzing sequential data due to their ability to capture long-range dependencies, memory retention, and dynamic temporal transitions [5]. Despite their promising

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capabilities, standard LSTM architectures process sequences only in a forward direction, limiting their ability to fully capture dependencies that may appear later in the sequence. Temporal attack patterns in IoV, however, often require understanding both past and future contextual signals. To address this challenge, Bidirectional LSTM (Bi-LSTM) networks extend traditional LSTM models by processing input sequences in both forward and backward directions, thereby enhancing the model's representation of temporal patterns and improving detection of complex cyberattack sequences [6]. Bi-LSTM architectures provide a more comprehensive temporal representation, enabling the detection of early indicators, hidden transitions, and evolving attack features that might otherwise be overlooked.

In addition to temporal modeling, IoV intrusion detection systems face two major challenges: high-dimensional features and severe class imbalance. Vehicular datasets often contain hundreds of traffic-level and protocol-level attributes, many of which are redundant or irrelevant. High-dimensional feature spaces can lead to increased computational cost, slower training, and reduced generalization. Furthermore, typical IoV datasets exhibit significant imbalance, where legitimate traffic dominates, and attack samples—especially emerging or rare attack types—are underrepresented. This imbalance results in biased classifiers that achieve high accuracy but poor recall for minority attack classes, ultimately undermining the system's real-world reliability [7].

To address these challenges, this research integrates the **Cat and Mouse Optimization (CMO)** algorithm for optimal feature selection and **Enhanced SMOTEBoost** for balancing skewed datasets. CMO, a nature-inspired metaheuristic algorithm, effectively identifies the most informative feature subsets by optimizing interactions between exploration and exploitation. This ensures that the Bi-LSTM model receives reduced yet highly relevant features, improving both training efficiency and detection accuracy. Enhanced SMOTEBoost, a hybrid of SMOTE oversampling and boosting mechanisms, generates synthetic minority samples while iteratively focusing on misclassified instances. This process alleviates class imbalance and improves recall for rare cyberattack categories, making the detection framework more robust against underrepresented threats.

The proposed **CMO-Bi-LSTM framework** harnesses temporal modeling, feature optimization, and imbalance correction to create a comprehensive intrusion detection system tailored for IoV. By learning dynamic attack signatures from sequential traffic patterns, Bi-LSTM enables the model to distinguish between benign fluctuations and malicious behavior with high precision. The bidirectional nature of the architecture strengthens its capability to extract contextual dependencies that appear both before and after attack initiation. Performance evaluation using benchmark datasets such as **CICIDS-2018** and **Car-Hacking** demonstrates that the proposed framework significantly outperforms baseline models including Random Forest, Decision Tree, and standard LSTM classifiers. Achieving a detection accuracy of **99.10%** and an F1-score of **99.05%**, the CMO-Bi-LSTM architecture exhibits superior detection performance for both network-level and vehicle-specific attacks.

The relevance of this work is further amplified by the nature of IoV networks, where latency constraints, real-time decision-making, and continuously changing attack strategies demand accurate and fast detection. Since physical safety is directly linked to cybersecurity in autonomous and connected vehicles, delays or misclassifications in detection can result in catastrophic failures. Therefore, efficient temporal modeling is not only beneficial but essential for maintaining operational integrity and passenger safety in IoV systems. The proposed approach contributes to advancing state-of-the-art detection systems by showing how sequence-aware deep learning, combined with evolutionary optimization and adaptive resampling, can effectively capture emerging attack vectors in a highly dynamic vehicular environment.

Overall, this study underscores the importance of adopting temporal deep learning models for cyberattack detection in IoV networks. It demonstrates that Bi-LSTM, supported by intelligent feature selection and imbalance-aware learning, provides a scalable and effective solution for monitoring distributed vehicular communication systems. The findings not only highlight the robust performance of the proposed model but also contribute to establishing a methodological foundation for future research focused on real-time, sequence-aware intrusion detection in intelligent transportation systems.

2. Literature Review

Recent years have witnessed substantial progress in intrusion detection mechanisms for the Internet of Vehicles (IoV), with researchers increasingly exploring deep learning and temporal sequence modeling to address evolving cyberattack patterns. Early studies primarily relied on classical machine learning classifiers such as Support Vector Machines, K-Nearest Neighbors, and Decision Trees. While effective for structural pattern recognition, these models failed to capture

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sequential relationships intrinsic to vehicular communication data [8]. IoV traffic carries dynamic temporal correlations, and ignoring this sequence-level dependency often leads to poor detection of stealthy and evolving attacks.

Subsequent research introduced deep neural networks to overcome the limitations of static classifiers. Convolutional Neural Networks (CNNs) were initially applied to intrusion detection due to their strong feature extraction capabilities; however, CNNs inherently focus on spatial representations and lack the memory components required for modeling temporal dependencies across multiple time steps [9]. As a result, they perform sub-optimally in detecting progressive attacks such as DDoS bursts, replay injections, and remote command sequences, which require temporal pattern learning.

To address this, researchers began adopting Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures. LSTM-based IDS solutions demonstrated improved performance as they effectively retained historical information and modeled long-term dependencies in network flows [10]. Nevertheless, traditional unidirectional LSTM models process data only in a forward direction, limiting their ability to fully comprehend attack signatures occurring later in the traffic sequence. This restriction is critical in IoV environments where future states can influence the interpretation of past behaviors, such as sudden RPM anomalies during an ongoing spoofing sequence.

To overcome this limitation, Bidirectional LSTMs (Bi-LSTMs) gained traction, enabling simultaneous forward and backward sequence processing. Studies highlighted that Bi-LSTM architectures outperform traditional LSTMs in temporal classification tasks and anomaly detection due to their enhanced context learning capabilities [11]. Research in vehicular intrusion detection confirmed that Bi-LSTMs could detect early indicators of cyberattacks more effectively by capturing future contextual information—particularly useful for slow-building, multi-stage attacks.

Parallel to advancements in temporal modeling, several works focused on addressing issues related to high-dimensionality and poor feature representation in IoV datasets. Feature selection algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) were utilized to optimize data preprocessing pipelines [12]. These metaheuristic algorithms demonstrated promising results but exhibited slow convergence and occasional stagnation in local minima. More recent research emphasized the value of using evolutionary and nature-inspired optimizers to select compact and discriminative feature subsets for deep learning-based IDS systems.

Another major challenge identified in The literature is the severe class imbalance commonly observed in vehicular datasets, where normal traffic heavily outweighs attack traffic. This imbalance leads to biased training and suboptimal performance in minority-class detection. Traditional oversampling methods such as SMOTE and ADASYN provided moderate improvements but often produced noisy synthetic samples that degraded classifier quality [13]. Boosting-based resampling frameworks attempted to address this by iteratively refining misclassified samples, but limitations persisted in creating balanced and realistic attack distributions.

Enhanced hybrid ensemble methods, combining oversampling with boosting mechanisms, were introduced as a more robust solution. Researchers demonstrated that SMOTEBoost variants significantly improved minority-class recall in highly skewed IoV and CAN-bus datasets [14]. These hybrid solutions provided a foundation for integrating temporal deep learning models with balanced data augmentation strategies, leading to more reliable detection outcomes.

Furthermore, several studies examined IDS integration on specialized vehicular datasets such as CICIDS-2018, UNSW-NB15, and Car-Hacking (CAN-intrusion). They underscored that cyberattacks on in-vehicle networks (e.g., gear manipulation, RPM spoofing, brake injection) exhibit unique time-correlated patterns distinct from conventional IP-based attacks [15]. As IoV threats evolve into multi-stage intrusion chains that manipulate both network-level and vehicle-control-level components, the need for advanced temporal sequence models becomes increasingly critical. The literature supports the conclusion that a combination of optimized feature selection, imbalance handling, and bidirectional sequence learning creates a robust foundation for next-generation IoV intrusion detection systems.

Collectively, prior studies affirm the necessity of combining temporal deep learning models with intelligent preprocessing strategies to address the challenges posed by dynamic IoV environments. Motivated by these findings, the present research proposes an integrated CMO-Bi-LSTM framework capable of extracting temporal patterns, selecting optimal features, and correcting class imbalance to

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deliver high-performance cyberattack detection across diverse vehicular datasets.

3. Methodology

The proposed methodology integrates three major components:
(1) **Enhanced data preprocessing** to address imbalance and temporal structuring,
(2) **Cat and Mouse Optimization (CMO)** for feature selection, and
(3) **Bidirectional Long Short-Term Memory (Bi-LSTM)** architecture for temporal attack pattern recognition.

The framework ensures that both forward and backward dependencies in IoV traffic sequences are captured while reducing dimensionality and improving minority-class detection.

3.1 Data Preprocessing and Temporal Structuring

IoV traffic from CICIDS-2018 and Car-Hacking datasets is first normalized using Min–Max scaling to retain dynamic variations in temporal flows. Oversampling is then performed using **Enhanced SMOTEBoost**, generating synthetic samples iteratively while penalizing misclassified attack instances.

Each traffic flow is segmented into fixed-length sequences:

$$X = \{x_1, x_2, \ldots, x_T\}$$

where TTT represents the number of time steps per sequence. This conversion ensures the model processes the temporal evolution of each attack pattern.

3.2 Cat and Mouse Optimization for Feature Selection

The CMO algorithm models interactions between "cats" (explorers) and "mice" (optimal solutions). Feature subsets are encoded as binary vectors, and the fitness function is computed as:

Equation (1): Fitness Function for Feature Subset

$$F(\mathbf{S}) = \alpha \cdot \mathrm{Acc}(\mathbf{S}) - \beta \cdot \frac{|\mathbf{S}|}{N}$$

Where:

- S\mathbf{S}S = selected feature subset
- Acc(S)\text{Acc}(\mathbf{S})Acc(S) = classifier accuracy using subset S\mathbf{S}S
- |S|\mathbf{S}||S| = number of selected features
- NNN = total available features
- α,β\alpha, \betaα,β = weighting coefficients

This function maximizes classification performance while minimizing redundant features.

3.3 Bidirectional LSTM Architecture

The Bi-LSTM model processes input sequences in both forward and backward directions:

Equation (2): Forward and Backward Hidden States

$$\overrightarrow{h_t} = \mathrm{LSTM}_f(x_t, \overrightarrow{h_{t-1}}), \qquad \overleftarrow{h_t} = \mathrm{LSTM}_b(x_t, \overleftarrow{h_{t+1}})$$

The final representation merges both directional states:

$$h_t = [\overrightarrow{h_t} \,||\, \overleftarrow{h_t}]$$

This allows the model to capture complete temporal dependencies critical for detecting slow-evolving and multi-stage IoV attacks.

3.4 Softmax Classification Layer

The concatenated Bi-LSTM output is passed into a dense classification layer to compute attack category probabilities.

Equation (3): Softmax Output Layer

$$P(y = k \mid h_t) = \frac{e^{W_k h_t + b_k}}{\sum_{j=1}^{K} e^{W_j h_t + b_j}}$$

Where:

- K = number of attack classes
- Wk,bk = trainable weights and biases
- P(y=k) = probability of class k

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The predicted class corresponds to the maximum posterior probability

4. Results and Discussion

The performance of the proposed **CMO-Bi-LSTM** model is evaluated using CICIDS-2018 and Car-Hacking datasets. The results are compared with three baseline models: Random Forest (RF), Decision Tree (DT), and standard LSTM. Evaluation metrics include Accuracy, Precision, Recall, F1-Score, and Detection Rate. The findings demonstrate that integrating **Cat and Mouse Optimization (CMO)** for feature selection and **Enhanced SMOTEBoost** for imbalance correction significantly improves the detection capability of the temporal deep learning architecture.

4.1 Quantitative Results

Table 1. Performance Comparison Across Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree (DT)	94.80	94.10	94.30	94.20
Random Forest (RF)	96.50	96.30	96.00	96.10
LSTM	97.20	97.00	97.10	97.00
CMO-Bi-LSTM (Proposed)	**99.10**	**99.15**	**99.00**	**99.05**

Discussion:
Results in Table 1 indicate that the proposed model outperforms traditional classifiers and even the standard LSTM. The bidirectional processing enables the network to identify forward and backward temporal dependencies in vehicular traffic, leading to a substantial improvement in accuracy and F1-Score. The use of CMO optimally reduces redundant features, contributing to faster training and performance stability. Enhancing minority class representation through SMOTEBoost further increases recall values by improving detection rates of rare attacks such as RPM spoofing and gear manipulation.

4.2 Attack-Specific Detection Performance

Table 2. Class-Level Performance for IoV Attack Types

Attack Type	Precision (%)	Recall (%)	F1-Score (%)
DoS Slowloris	99.20	98.90	99.05
DDoS	99.30	99.10	99.20
Bot Attack	98.80	98.50	98.65
CAN RPM Spoofing	99.00	98.80	98.90
Gear Position Injection	99.10	98.70	98.90
Overall (CMO-Bi-LSTM)	**99.15**	**99.00**	**99.05**

Discussion:
Table 2 shows that the model maintains consistently high precision and recall across all attack categories. Complex vehicular-network attacks such as RPM spoofing and gear position manipulation exhibit strong detection due to the model's capability to learn long-term and short-term sequential patterns. Most vehicle-specific cyberattacks unfold over multiple time steps; thus the bidirectional memory mechanism effectively extracts temporal correlations that conventional models miss.

4.3 Interpretation of Results

1. **Temporal Learning Advantage:** With Bi-LSTM processing both past and future context, the system accurately captures multi-stage attacks that evolve over time.
2. **Feature Optimization:** CMO reduces input dimensionality by removing irrelevant or redundant features, improving training efficiency and preventing overfitting.
3. **Improved Minority Class Detection:** Enhanced SMOTEBoost addresses skewed distributions, especially beneficial for infrequent CAN-bus attacks.
4. **Superior Balance of Metrics:** The proposed model achieves simultaneously high precision, recall, and F1-scores, which are essential for real-time vehicular security.

4.4 Overall Discussion

The combined effect of **temporal modeling**, **feature optimization**, and **class balancing** leads to a highly effective intrusion detection system for IoV environments. The proposed CMO-Bi-LSTM demonstrates a **significant performance gain of**

Doi:10.48047/ijiee.2025.15.1.3

1.9–4.3% over existing deep learning models and **3–5% over classical machine learning approaches**. Such improvements are crucial in IoV environments where delayed detection can compromise vehicle safety and passenger lives.

Conclusion

This study proposed a comprehensive cyberattack detection framework for Internet of Vehicles by integrating Cat and Mouse Optimization, Enhanced SMOTEBoost, and a Bidirectional LSTM architecture. Experimental evaluation on CICIDS-2018 and Car-Hacking datasets demonstrated that the proposed CMO-Bi-LSTM model effectively captures both short-term and long-term temporal dependencies in vehicular traffic sequences, achieving a highest accuracy of 99.10% and F1-score of 99.05%. The bidirectional learning mechanism enhances the model's ability to detect multi-stage and time-correlated attacks, while CMO-driven feature selection reduces dimensionality and computational overhead. Enhanced SMOTEBoost further ensures robust minority-class recognition, improving detection of rare yet critical in-vehicle attacks such as RPM spoofing and gear manipulation. Overall, the results confirm that the proposed approach significantly outperforms traditional machine learning models and standard LSTM architectures, making it a highly suitable solution for real-time, adaptive, and secure IoV environments.

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