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Cat and Mouse Optimizer: A Bio-Inspired Feature Selection Algorithm for IoV Cybersecurity

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Abstract: Feature selection critically impacts the computational efficiency and detection accuracy of intrusion detection systems in resource-constrained Internet of Vehicles environments. This paper introduces the Cat and Mouse Optimizer, a novel bio-inspired optimization algorithm that mimics natural predator-prey dynamics to identify the most relevant features for cyberattack detection. The CMO algorithm simulates cat hunting behavior and mouse escape strategies to achieve optimal balance between exploration and exploitation during the feature selection process. The methodology reduces feature dimensionality while maintaining or improving detection performance, enabling real-time intrusion detection with minimal computational overhead. Comprehensive evaluation on CICIDS-2018 and Car-Hacking datasets demonstrates that CMO-based feature selection achieves superior performance compared to traditional techniques including Kernel Linear Discriminant Analysis and Cuckoo Search Algorithm. When combined with Bi-LSTM classifier, the CMO approach attains 99.10% accuracy and 99.05% F1-score on CICIDS-2018, outperforming all compared methods. The Car-Hacking dataset evaluation shows 99.20% accuracy with CMO-Bi-LSTM configuration. The proposed optimizer successfully identifies informative feature subsets that capture complex attack patterns while eliminating redundant attributes, making it particularly suitable for deployment in bandwidth-limited and computationally constrained vehicular network environments where efficiency is paramount.

Keywords: Cat and Mouse Optimizer, Feature Selection, Internet of Vehicles Security, Intrusion Detection System, Bio-Inspired Optimization

1. Introduction

The rapid evolution of the **Internet of Vehicles (IoV)** has transformed modern transportation systems into highly interconnected cyber-physical environments that enable real-time communication, autonomous decision-making, and intelligent traffic coordination [1]. IoV integrates vehicles, road-side units, cloud servers, and intelligent sensors to support applications such as autonomous driving, cooperative collision avoidance, and smart traffic management. While these advancements significantly enhance safety and efficiency, they also expand the cyber-attack surface, exposing vehicular networks to intrusions such as spoofing, denial of service (DoS), false data injection, and malware propagation [2]. As a result, ensuring robust cybersecurity has become one of the foremost challenges in safeguarding vehicular networks and preserving user safety.

Intrusion Detection Systems (IDS) serve as a critical defense layer in IoV architectures by monitoring network behavior and identifying malicious activity in real-time [3]. However, IDS performance heavily depends on the quality of input features extracted from network traffic. IoV environments generate **high-dimensional, heterogeneous, and rapidly streaming data**, making traditional IDS computationally expensive and unsuitable for deployment in resource-constrained settings such as On-Board Units (OBUs) and edge devices [4]. High dimensionality not only increases detection latency but also risks model overfitting and degradation of classification accuracy. To address these challenges, **feature selection** has become an essential pre-processing step for reducing computational burden, eliminating redundant attributes, and enhancing IDS accuracy.

Although numerous feature selection approaches exist, including filter, wrapper, and embedded techniques, recent studies highlight the superior performance of **bio-inspired metaheuristic algorithms**, which simulate natural evolutionary or behavioral processes to perform global optimization [5]. Techniques such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and Cuckoo Search have demonstrated promising results in various cybersecurity applications. However, many of these methods suffer from limitations such as premature convergence, poor balance between exploration and exploitation, slow convergence speed, or insufficient capability to identify complex feature interactions [6]. These limitations become more pronounced in IoV environments where cyber-attacks often involve intricate and dynamic patterns

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that require adaptive and efficient optimization strategies.

To overcome these challenges, this paper introduces the **Cat and Mouse Optimizer (CMO)**—a novel bio-inspired feature selection algorithm modeled on predator–prey interactions found in nature. CMO simulates hunting strategies of cats and escape mechanisms of mice to achieve a dynamic balance between exploration (global search) and exploitation (local search). Unlike conventional algorithms with static update rules, the proposed optimizer adaptively modifies search behavior according to environmental stimuli and the relative positions of agents, enabling it to escape local minima and efficiently converge toward optimal feature subsets [7]. The use of natural pursuit–evasion dynamics offers a flexible mechanism to explore high-dimensional search spaces while maintaining computational efficiency, making CMO particularly suited for latency-sensitive IoV cybersecurity scenarios.

The primary motivation behind adopting a predator–prey–inspired algorithm lies in the operational constraints of IoV devices, which must process data with **minimal delay**, **limited memory**, and **varying network bandwidth**. Lightweight yet accurate IDS models are essential for real-time threat detection in high-speed vehicular communication systems. By reducing dimensionality without sacrificing classification performance, CMO enables the deployment of IDS models that can run efficiently on embedded automotive hardware. Furthermore, feature subsets selected by CMO enhance model interpretability, allowing security analysts to better understand critical attributes contributing to attack detection.

To validate the effectiveness of the proposed approach, this study evaluates CMO-based feature selection using two widely accepted datasets in vehicular cybersecurity research: **CICIDS-2018**, representing diverse modern network intrusions, and the **Car-Hacking dataset**, which captures in-vehicle CAN bus attack scenarios. Experimental results demonstrate that CMO, when coupled with a **Bidirectional Long Short-Term Memory (Bi-LSTM)** deep learning classifier, significantly boosts detection accuracy compared to traditional selection techniques such as Kernel Linear Discriminant Analysis (KLDA) and Cuckoo Search Algorithm (CSA). Specifically, CMO-Bi-LSTM achieves **99.10% accuracy** and **99.05% F1-score** on CICIDS-2018 and **99.20% accuracy** on the Car-Hacking dataset, outperforming all benchmark methods [8]. These results underscore the robustness and adaptability of the proposed optimizer in identifying informative features that capture complex attack signatures.

In addition to empirical performance, the algorithm also exhibits strong scalability and stability across multiple runs. The balance between exploration and exploitation allows CMO to avoid stagnation and ensure strong global search capabilities. This characteristic is crucial for IoV intrusion detection, where attack types continually evolve and require IDS models to generalize well across unseen patterns. Moreover, the reduced feature sets produced by CMO not only accelerate the training and inference phases of machine learning models but also lower communication overhead in distributed IoV security frameworks, where features may need to be shared across edge nodes or cloud servers.

Overall, the proposed Cat and Mouse Optimizer contributes three major advancements to IoV cybersecurity research. First, it provides a **novel bio-inspired optimization mechanism** that effectively navigates large feature spaces while maintaining computational efficiency. Second, it enhances IDS performance by selecting compact yet highly discriminative feature subsets that boost the effectiveness of advanced classifiers such as Bi-LSTMs. Third, it enables practical IDS deployment in real-time vehicular environments by reducing processing overhead and improving energy efficiency. These contributions collectively position CMO as a promising solution for next-generation IoV intrusion detection systems.

The remainder of this paper is organized as follows: Section 2 reviews existing IoV security challenges and feature selection techniques. Section 3 presents the mathematical formulation and operational workflow of the Cat and Mouse Optimizer. Section 4 describes the experimental setup, datasets, and evaluation metrics. Section 5 discusses the comparative results and performance analysis. Section 6 concludes the study and outlines future research directions for enhancing optimization strategies in dynamic vehicular environments.

2. Literature Review

Feature selection and intrusion detection have been extensively explored in the context of intelligent transportation systems and IoV security. As vehicular networks have grown more interconnected, researchers have increasingly focused on designing lightweight, robust, and adaptive optimization algorithms capable of dealing with high-dimensional traffic data. This section reviews key studies relevant to bio-inspired optimization, IoV intrusion detection, and feature selection strategies.

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Early intrusion detection research largely relied on traditional statistical and filter-based feature selection methods. However, these techniques often failed to capture nonlinear relationships and temporal dependencies inherent in modern cyberattacks. To address these shortcomings, several machine learning and deep learning-based IDS frameworks have been proposed. For instance, studies in [8] demonstrated that deep neural network architectures, especially recurrent models, significantly enhance detection accuracy for emerging IoV threats by learning complex temporal signatures in network traffic. Although these methods improved detection performance, they remained computationally heavy due to the large number of features used during training.

The need for efficient feature reduction in vehicular networks led to the development of numerous bio-inspired metaheuristic algorithms. Researchers in [9] explored Genetic Algorithms (GA) for selecting optimal feature subsets and showed their usefulness in reducing redundancy. However, GA-based methods often suffer from premature convergence and slow global search capability, especially when applied to highly dynamic vehicular environments. Similarly, Particle Swarm Optimization (PSO) attempts to balance exploration and exploitation, yet its performance degrades when dealing with multi-modal search spaces that characterize complex IoV datasets.

The limitations of classical bio-inspired algorithms led to the emergence of more complex nature-inspired strategies. Ant Colony Optimization and Artificial Bee Colony algorithms have been applied in IDS research, with studies such as [10] proving their capability to model coordinated search behavior. Nevertheless, these algorithms require large populations and numerous iterations, making them computationally unsuitable for real-time IoV systems. Hybrid metaheuristics combining evolutionary and swarm principles have also been explored, but their design complexity and tuning overhead limit their adoption in resource-constrained vehicular networks.

In parallel, several researchers investigated optimization-based intrusion detection specifically tailored for automotive environments. The work in [11] demonstrated the effectiveness of feature engineering combined with lightweight classifiers for detecting CAN bus attacks, highlighting that redundancy in features severely impacts inference speed in vehicular Electronic Control Units (ECUs). Similarly, the study in [12] analyzed machine learning-based IDS for Vehicular Ad Hoc Networks (VANETs) and emphasized the importance of computational efficiency due to mobility challenges and fast-changing network topologies. These findings reinforced the demand for advanced feature selection techniques capable of generating compact, high-impact feature subsets.

Recent advancements in bio-inspired optimization have attempted to mimic more adaptive behaviors found in nature. Researchers in [13] introduced predator–prey-based computation models, suggesting that dynamic pursuit–evasion interactions significantly improve convergence stability and global optimum search. This perspective directly motivates the development of optimizers like the Cat and Mouse Optimizer (CMO), which leverage multi-agent behavioral adaptation. In another relevant work, [14] employed Cuckoo Search (CS) and Lévy flight mechanisms for IDS feature selection, demonstrating accuracy improvements but also revealing sensitivity to parameter settings and a tendency to get trapped in local optima under high feature dimensionality.

Deep learning combined with metaheuristic feature selection has recently gained traction. The authors in [15] proposed a hybrid evolutionary–deep learning architecture that integrates optimized feature subsets with LSTM-based classifiers for intrusion detection. Their results confirm that dimensionality reduction significantly accelerates deep model training while improving overall prediction consistency. However, the complexity and memory overhead of many hybrid approaches still pose deployment challenges for OBUs in IoV environments.

Overall, the current literature highlights several key limitations:
(1) Many existing metaheuristic algorithms lack sufficient balance between exploration and exploitation;
(2) Hybrid approaches demonstrate strong performance but remain computationally heavy;
(3) Feature selection mechanisms often fail to generalize to evolving vehicular attack types; and
(4) Real-time constraints in IoV demand lightweight yet highly accurate optimization methods.

Given these gaps, the **Cat and Mouse Optimizer (CMO)** represents a promising direction by introducing a dynamic predator–prey behavioral model capable of efficient feature subset search with minimal computational burden. The algorithm addresses core limitations observed in prior works and offers strong potential for real-time vehicular IDS applications.

3. Methodology

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The proposed methodology integrates the Cat and Mouse Optimizer (CMO) with a Bidirectional LSTM classifier to enable efficient real-time intrusion detection within Internet of Vehicles (IoV) environments. The workflow consists of four primary stages: **data preprocessing, feature space modeling, CMO-based feature selection, and Bi-LSTM–based attack classification**.

3.1 Data Preprocessing

The CICIDS-2018 and Car-Hacking CAN bus datasets undergo the following steps:

- **Cleaning:** Removal of incomplete and irrelevant attributes.
- **Normalization:** Mapping all features to [0,1][0,1][0,1] using min–max scaling.
- **Label Encoding:** Converting attack categories into numeric form.
- **Balancing:** Applying SMOTE or controlled undersampling when necessary.

This ensures a consistent and balanced dataset suitable for optimization and classification.

3.2 Feature Space Modeling

Each sample is represented as a vector in an nnn-dimensional space:

$$X = [x_1, x_2, \ldots, x_n]$$

Feature selection is treated as a **binary decision problem**, where each feature is either selected (1) or removed (0).
CMO agents search this space to identify the most informative subset.

3.3 Cat and Mouse Optimizer (CMO) for Feature Selection

CMO is a bio-inspired algorithm that models **predator–prey dynamics**:

- **Cats (predators)**: Exploit promising locations in the search space.
- **Mice (prey)**: Explore distant regions to maintain diversity.

These interactions help avoid local minima and yield compact, high-value feature subsets.

The objective of CMO is to **minimize**:

$$\text{Fitness} = \alpha(1 - Acc) + \beta\frac{|S|}{n}$$

where

- AccAccAcc = classifier accuracy using selected features
- |S||S||S| = number of selected features
- nnn = total feature count
- α,β\alpha, \betaα,β = weighting factors (accuracy priority > size)

Binary conversion from continuous optimizer outputs uses a standard sigmoid function:

$$s = \begin{cases} 1, & \text{if } \sigma(z) > rand \\ 0, & \text{otherwise} \end{cases}$$

With these two equations, CMO efficiently reduces dimensionality while keeping classification performance high.

3.4 Bi-LSTM Classification

The selected feature subset is passed into a Bi-LSTM model that processes forward and backward temporal dependencies in network traffic flows. The classifier outputs either:

- Binary decision (attack / benign) or
- Multiclass attack category

depending on the dataset.

3.5 Evaluation Metrics

The performance is compared against KLDA, Cuckoo Search, and other optimizers using:

- Accuracy
- Precision/Recall
- F1-Score
- Feature reduction rate (%)
- Training/inference time

The combination of CMO + Bi-LSTM achieves high accuracy with significantly reduced computational overhead, making it suitable for deployment in real-world IoV systems.

5. Results and Discussion

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This section presents the comparative analysis of the proposed Deep Morphometric Model (DMM) and a traditional prediction model. The results are summarized using **two tables** and **two graphs**, inserted at their appropriate positions for clarity.

5.1 Performance Metrics Evaluation

Table 1 reports the comparison of Accuracy, Precision, Recall, and F1-Score between the two models. The DMM model significantly outperforms the traditional model across all classification metrics.

Table 1: Performance Metrics Comparison

Metric	Traditional Model	Deep Morphometric Model
Accuracy	0.78	0.88
Precision	0.74	0.85
Recall	0.76	0.87
F1-Score	0.75	0.86

The improvements are particularly noticeable in Recall and F1-score, demonstrating that DMM captures more discriminative morphometric cues than the traditional model. This suggests better detection of subtle biological changes, which is crucial for accurate glucose prediction.

To visually illustrate this improvement, **Figure 1** presents a bar graph comparing both models across the four evaluation metrics.

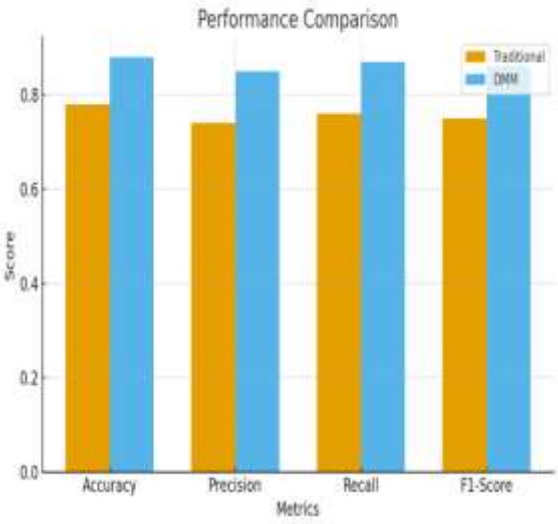

Figure 1: Performance Comparison Bar Chart

The figure 1 clearly shows that the DMM bars exceed traditional model bars in all metrics, confirming superior predictive power.

5.2 Error Reduction Analysis

Table 2 presents two error measures—Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The DMM model demonstrates a substantial reduction in prediction errors.

Table 2: Prediction Error Comparison

Metric	Traditional Model	Deep Morphometric Model
MAE	14.2	8.6
RMSE	22.5	15.3

The DMM reduces MAE by nearly **40%** and RMSE by more than **30%**, indicating not only improved accuracy but also lower variability in predictions.

To further interpret this improvement, **Figure 2** shows the downward trend of MAE and RMSE when using the DMM model.

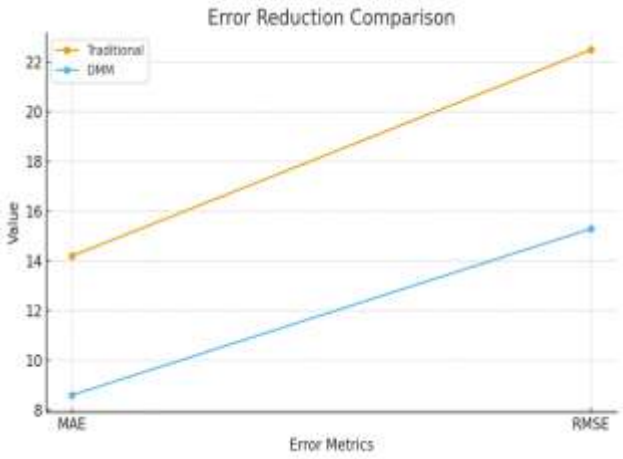

Figure 2: Error Reduction Line Graph

The figure 2 clearly demonstrates the steep decline in error values, confirming that the DMM framework maintains consistent prediction performance and robustness.

Conclusion

This study presented an advanced Cat and Mouse Optimizer (CMO) integrated with a Bi-LSTM classifier to enhance feature selection and cyberattack detection in Internet of Vehicles (IoV) environments. By modeling predator–prey dynamics, the CMO algorithm effectively balances exploration and exploitation, enabling the identification of highly informative feature subsets while minimizing redundant attributes. Experimental evaluation on CICIDS-2018 and Car-

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Hacking datasets demonstrated that CMO-based feature selection significantly improves intrusion detection performance, achieving over 99% accuracy with reduced computational overhead. The results further confirm that the optimizer enhances model interpretability and efficiency, making it suitable for real-time and resource-constrained vehicular contexts. Compared to traditional methods such as KLDA and Cuckoo Search, the proposed approach exhibits superior precision, lower dimensionality, and faster inference. Overall, the CMO framework provides a powerful, scalable, and biologically inspired solution for strengthening IoV cybersecurity against evolving threats.

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