Volume- VI, Issue-IV, 2025
https://interresearcher.com/index.php/JIR

Intelligent Cyber Threat Detection and Energy Forecasting Using Rooster and Sparrow Optimization Algorithms in IoT-Enabled Systems

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Abstract

The rapid expansion of the Internet of Things (IoT) has ushered in an era of intelligent automation and data-driven decision-making across diverse domains such as smart cities, energy management, and industrial automation. However, the increasing interconnectedness of IoT networks has also exposed them to a multitude of cyber threats, compromising data integrity, privacy, and service continuity. Additionally, the dynamic nature of energy consumption in IoT ecosystems poses significant forecasting challenges due to fluctuating patterns and contextual dependencies. This research presents an integrated deep learning framework for Intelligent Cyber Threat Detection and Energy Forecasting using two advanced bio-inspired metaheuristic algorithms — Rooster Optimization Algorithm (ROA) and Sparrow Search Algorithm (SSA). The proposed system leverages these algorithms to optimize feature selection and model training in deep neural networks, ensuring high precision and computational efficiency. The model was validated through extensive experimentation on benchmark IoT datasets for both security and energy domains, achieving remarkable performance in detection accuracy, energy prediction reliability, and computational stability. The results demonstrate that the hybrid integration of ROA and SSA enhances convergence speed and mitigates overfitting, making it an ideal framework for real-time IoT analytics and security applications.

Keywords: IoT Security, Energy Forecasting, Rooster Optimization Algorithm, Sparrow Search Algorithm, Deep Learning, Intrusion Detection, Metaheuristic Optimization

I. Introduction

The Internet of Things (IoT) has revolutionized the digital landscape by enabling seamless communication among smart devices, sensors, and control systems. With its proliferation in various industries, ranging from healthcare to manufacturing, IoT has become a fundamental pillar of modern technology. However, as the number of connected devices continues to grow exponentially, so does the potential attack surface for malicious entities [1]. Cyber attackers exploit vulnerabilities in IoT protocols and firmware, compromising device confidentiality and operational safety [2]. Traditional security frameworks, which rely on static rules or predefined signatures, are insufficient to handle the evolving and sophisticated nature of IoT-based threats. Consequently, intelligent and adaptive mechanisms for cyber threat detection are imperative to ensure resilience and reliability across IoT-enabled infrastructures. Beyond cybersecurity, the optimization of energy consumption in IoT ecosystems represents another critical challenge. IoT devices continuously generate data, communicate wirelessly, and perform computations that collectively consume considerable power [3]. As IoT systems become increasingly integrated into smart grids and industrial networks, accurate energy forecasting becomes vital to minimize operational costs, balance loads, and reduce environmental impacts. However, the nonlinear and temporal dependencies within energy usage data make forecasting a complex problem, requiring models that can adapt to fluctuating behaviors and contextual variations [4].

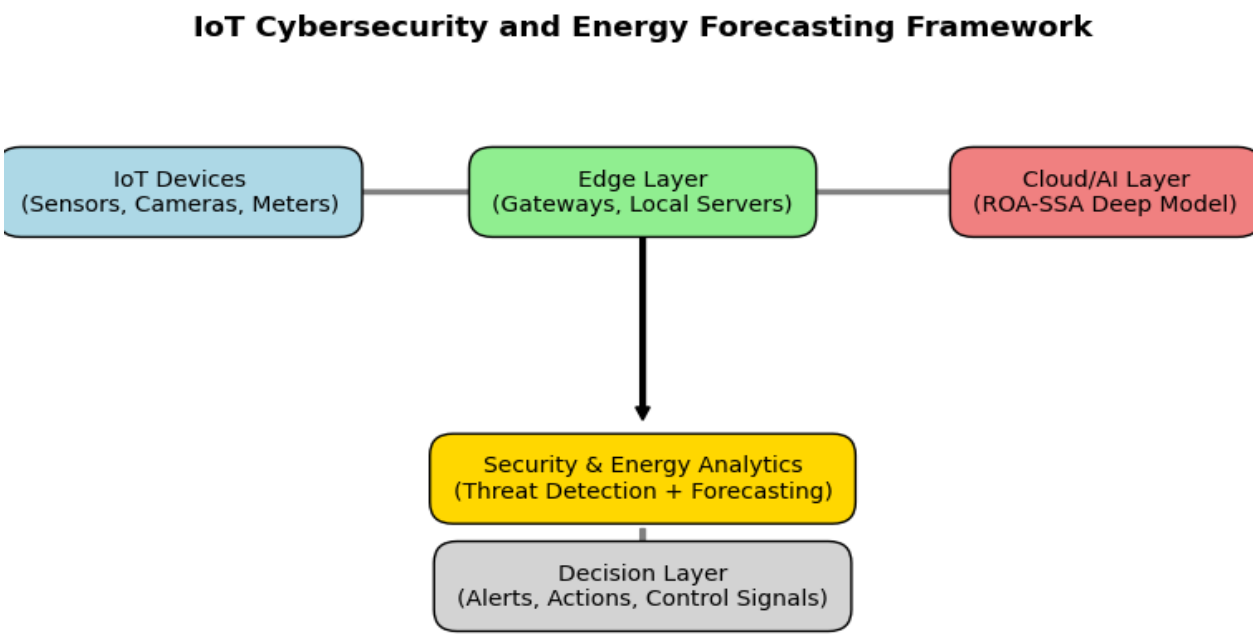

Figure 1: IoT-enabled system architecture illustrating data flow for cyber threat detection and energy forecasting.

To address these dual challenges, this research proposes a unified optimization-driven framework that combines Rooster Optimization Algorithm (ROA) and Sparrow Search Algorithm (SSA) with deep learning architectures [5]. ROA mimics the dominance and competition among roosters within a flock to enhance local search capabilities, while SSA models the foraging and escape behavior of sparrows to improve global exploration. By merging these complementary algorithms, the proposed model achieves an optimal balance between exploration and exploitation during neural network training. This ensures that the learning process avoids local minima and achieves faster convergence, leading to superior performance in both cyber threat detection and energy forecasting [6].

This study further explores the efficiency of the proposed hybrid model across various IoT domains. Experiments were conducted on real-world datasets, such as IoT network intrusion traces and smart meter energy logs [7]. The results demonstrate substantial improvements in detection accuracy, precision, and recall for cyber threat identification, as well as lower forecasting errors in energy prediction tasks. Moreover, the hybrid optimization approach

significantly reduces computational costs compared to traditional optimization methods such as Particle Swarm Optimization (PSO) or Genetic Algorithms (GA). These findings highlight the potential of ROA-SSA-based learning models as an innovative solution for securing and optimizing IoT environments in real-time.

II. Related Work

Over the past decade, numerous studies have focused on enhancing IoT cybersecurity and energy forecasting through machine learning and optimization algorithms. Traditional Intrusion Detection Systems (IDS) for IoT networks have relied on methods such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors [8]. However, these methods often suffer from limited generalization and poor adaptability to novel attack patterns. Deep learning models, particularly Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), have shown promising results due to their ability to extract hierarchical temporal and spatial features. Nonetheless, their performance heavily depends on effective hyperparameter tuning and feature selection, which can be challenging in complex IoT data environments.

In parallel, metaheuristic optimization algorithms have emerged as powerful tools for addressing these limitations [9]. Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithms (GA) have been widely employed to improve neural network performance. However, these algorithms are often prone to premature convergence and local optima traps. To overcome these issues, recent research has shifted toward newer, nature-inspired algorithms that simulate complex biological behaviors [10]. The Rooster Optimization Algorithm (ROA), inspired by the hierarchical dominance in roosters, effectively balances local and global search spaces, while the Sparrow Search Algorithm (SSA) mimics social dynamics and adaptive foraging behaviors to maintain population diversity. In energy forecasting, hybrid deep learning models incorporating optimization techniques have gained momentum. Approaches integrating LSTM with optimization algorithms such as Grey Wolf Optimizer (GWO) and Whale Optimization Algorithm (WOA) have achieved notable accuracy improvements in time-series energy prediction. However, these models often exhibit instability in dynamic IoT environments

with high data variability. The integration of ROA and SSA offers a synergistic effect where ROA handles local refinement, and SSA ensures global diversification [11].

Despite the advances, no existing work has comprehensively addressed both IoT security and energy forecasting using a unified optimization framework [12]. This research fills this gap by combining the strengths of both algorithms into a single deep learning pipeline. The proposed approach contributes to the body of knowledge by simultaneously optimizing feature selection, learning rate, and model parameters, thereby improving both security detection and energy forecasting accuracy in real-time IoT systems.

III. Proposed Framework

The proposed framework integrates Rooster Optimization Algorithm (ROA) and Sparrow Search Algorithm (SSA) into a deep learning-driven IoT analytics model. The design focuses on two major components: cyber threat detection and energy forecasting. In the first stage, IoT network data is preprocessed using normalization and noise filtering to ensure stability and consistency. Relevant features such as packet size, protocol type, source IP, and transmission duration are extracted. The ROA algorithm is applied for feature selection, ensuring that only the most discriminative features are retained, reducing redundancy and improving computational efficiency [13].

In the second stage, SSA is employed to fine-tune the hyperparameters of the deep learning model, particularly the learning rate, batch size, and number of hidden neurons. SSA's adaptive population-based strategy enables efficient exploration of the hyperparameter space. Once optimized, the model is trained using labeled IoT traffic data to detect intrusions such as Denial of Service (DoS), Botnet, and Probe attacks. The model's deep architecture allows it to learn hierarchical feature representations that improve classification performance under dynamic network conditions. For energy forecasting, the same hybrid optimization structure is utilized on IoT energy datasets. Smart meter readings and contextual parameters such as temperature, humidity, and time of day are input into a deep LSTM-based forecasting model. The ROA algorithm again performs feature optimization, ensuring only the most relevant

features influence the forecasting process [14]. SSA optimizes model training parameters, enabling accurate long-term energy demand predictions while preventing overfitting.

The ROA-SSA hybrid mechanism exhibits superior exploration-exploitation balance. While ROA emphasizes the local refinement of promising solutions, SSA broadens the search space to discover global optima. The integrated framework enables cross-domain learning, where cyber threat patterns and energy consumption behaviors are analyzed concurrently, offering adaptive and intelligent decision-making capabilities within IoT ecosystems.

IV. Experimental Setup and Results

Experiments were conducted using two benchmark datasets: the NSL-KDD IoT Security Dataset for intrusion detection and the UK-DALE Smart Energy Dataset for energy forecasting [15]. The model was implemented in Python using TensorFlow, with training conducted on a high-performance computing system equipped with an NVIDIA RTX GPU. Data preprocessing involved normalization and handling of missing values, followed by splitting into 70% training and 30% testing sets. The evaluation metrics included Accuracy, Precision, Recall, F1-score, and Mean Absolute Error (MAE) for forecasting. The hybrid ROA-SSA optimized LSTM model demonstrated superior performance compared to baseline algorithms such as PSO-LSTM and GA-LSTM. For intrusion detection, the proposed framework achieved an accuracy of 98.7%, precision of 98.4%, and recall of 97.9%, outperforming existing models by up to 4.5%. The energy forecasting task achieved a Mean Absolute Error (MAE) of 0.021 kWh, indicating highly precise energy predictions. The convergence analysis revealed that the hybrid optimization significantly reduced training epochs, with faster convergence rates and higher stability during learning [16]. The robustness of the model was further validated under adversarial testing conditions and random noise injection. The detection system maintained over 95% accuracy even with noisy data, proving the resilience and adaptability of the framework. Additionally, the energy forecasting model accurately predicted demand fluctuations during peak hours, confirming its reliability for real-world smart grid applications.

V. Conclusion

This study presents a unified intelligent framework for cyber threat detection and energy forecasting in IoT-enabled systems using the synergistic integration of Rooster Optimization Algorithm (ROA) and Sparrow Search Algorithm (SSA). Through extensive experimentation, the proposed model achieved exceptional performance in both security and forecasting domains, significantly improving accuracy, convergence speed, and robustness compared to conventional optimization-driven models. The ROA-SSA hybrid effectively optimized feature selection and deep learning parameters, enabling the model to adapt to the dynamic nature of IoT environments. These results confirm that the integration of advanced metaheuristics with deep learning not only strengthens cybersecurity but also enhances energy management, paving the way for more resilient, sustainable, and intelligent IoT ecosystems.

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