

# Towards Explainable and Lightweight AI for Real-Time Cyber Threat Hunting in Edge Networks

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## Abstract

As cyber threats continue to evolve, securing edge networks has become increasingly challenging due to their distributed nature and resource limitations. Many AI-driven threat detection systems rely on complex deep learning models, which, despite their high accuracy, suffer from two major drawbacks: lack of interpretability and high computational cost. Black-box AI models make it difficult for security analysts to understand the reasoning behind their predictions, limiting their practical deployment. Moreover, conventional deep learning techniques demand significant computational resources, rendering them unsuitable for edge devices with limited processing power. To address these issues, this study introduces an Explainable and Lightweight AI (ELAI) framework designed for real-time cyber threat detection in edge networks. Our approach integrates interpretable machine learning algorithms with optimized lightweight deep learning techniques, ensuring both transparency and computational efficiency. The proposed system leverages decision trees, attention-based deep learning, and federated learning to enhance detection accuracy while maintaining explainability. We evaluate ELAI using benchmark cybersecurity datasets, such as CICIDS and UNSW-NB15, assessing its performance across diverse cyberattack scenarios. Experimental results demonstrate that the proposed framework achieves high detection rates with minimal false positives, all while significantly reducing computational demands compared to traditional deep learning methods. The key contributions of this work include: (1) a novel interpretable AI-based cybersecurity model tailored for edge computing environments, (2) an optimized lightweight deep learning approach for real-time cyber threat detection, and (3) a comprehensive analysis of explainability techniques in AI-driven cybersecurity applications. By bridging the gap between model transparency and computational efficiency, this research enhances the practicality and reliability of AI-based security solutions for edge networks.

**Keywords:** *Explainable Artificial Intelligence (XAI); Cyber Threat Hunting; Lightweight Deep Learning; Edge Computing Security; Federated Learning; Intrusion Detection Systems (IDS); Real-Time Threat Detection.*

## 1. Introduction

### 1.1 Background and Motivation

The rapid expansion of edge computing has enabled real-time data processing closer to end devices, reducing latency and improving efficiency in fields such as smart cities, industrial automation, healthcare, and autonomous systems. However, the decentralized and resource-constrained nature of edge networks makes them particularly vulnerable to cyber threats. Unlike traditional cloud-based security solutions that rely on centralized control, edge devices operate in distributed environments, which introduces significant security challenges and makes them prime targets for malicious activities.

To address these security concerns, Artificial Intelligence (AI) and Machine Learning (ML) algorithms have been widely adopted in Intrusion Detection Systems (IDS) and Threat Intelligence Platforms. These AI-driven approaches

enhance the ability to detect, analyze, and respond to cyber threats in real time. However, despite their advantages, existing AI-based cybersecurity systems suffer from two major limitations:

1. **Lack of Model Interpretability:** Most AI-powered security models function as black-box systems, providing accurate threat detection but failing to explain their decision-making process. This lack of transparency hinders security analysts from understanding the reasoning behind AI-generated alerts.
2. **High Computational Demand:** Deep learning-based cybersecurity models are typically designed for high-performance computing environments and require significant processing power. This makes their deployment impractical for edge networks, where devices operate with limited resources.

Given these challenges, there is a growing need for Explainable and Lightweight AI (ELAI) models that can detect cyber threats in real time while maintaining computational efficiency and providing transparency in decision-making.

## 1.2 Problem Statement

Although AI-based threat detection has made significant advancements, current solutions prioritize accuracy over explainability and efficiency. Many existing Intrusion Detection Systems (IDS) and anomaly detection models rely on deep learning architectures that, while effective, demand high computational power and fail to provide interpretable results. These limitations create significant barriers to deploying such models in resource-constrained edge computing environments.

Several key research gaps persist:

- **Inefficient AI Models for Edge Networks:** The majority of cybersecurity models are developed for cloud-based infrastructures and are not optimized for edge computing environments.
- **Lack of Explainability in AI-Based Security Models:** Deep learning methods often lack interpretability, making it difficult for cybersecurity professionals to validate alerts and diagnose security breaches.
- **Inability to Address Zero-Day Attacks Effectively:** Many existing solutions rely on predefined attack patterns, making them less effective at detecting novel or zero-day threats.

This study aims to bridge these gaps by developing a novel Explainable and Lightweight AI (ELAI) framework that enhances real-time cyber threat detection in edge networks while reducing computational overhead and improving transparency.

## 1.3 Research Objectives

This study proposes the development of an Explainable and Lightweight AI (ELAI) framework designed to enhance cybersecurity in edge networks. The primary objectives are:

- To create an optimized AI model that can function efficiently in edge environments while maintaining high detection accuracy.
- To incorporate explainability techniques such as SHAP (Shapley Additive Explanations), attention-based deep learning, and decision trees into the cybersecurity framework, ensuring transparency in threat detection.
- To evaluate the proposed model using benchmark datasets such as CICIDS 2017, UNSW-NB15, and N-BaIoT, analyzing its performance in detecting real-world cyber threats.
- To develop an adaptive cyber threat hunting approach capable of dynamically adjusting its detection strategies to identify emerging attack patterns, including zero-day exploits.

By achieving these goals, this research will contribute to improving AI-driven cybersecurity solutions for edge networks, ensuring both efficiency and interpretability.

## 1.4 Contributions of This Study

This research introduces several key contributions:

1. A novel AI-powered cybersecurity framework that integrates explainable AI techniques with lightweight deep learning for efficient real-time threat detection in edge networks.
2. A computationally efficient deep learning model tailored for edge environments, minimizing resource consumption while maintaining robust cybersecurity capabilities.
3. An in-depth evaluation of explainability techniques within AI-driven cybersecurity applications, addressing the urgent need for transparent security models.
4. An adaptive cyber threat hunting system capable of detecting and mitigating emerging security threats using AI-driven techniques.
5. A comparative analysis of the proposed framework against existing cybersecurity models using established benchmark datasets, demonstrating its superiority in performance and efficiency.

By integrating explainability and computational efficiency, this study contributes to the advancement of next-generation AI-driven cybersecurity solutions designed for real-world deployment in edge computing environments.

## 2. Related Work

### 2.1 Introduction to AI-Driven Cybersecurity

With the increasing complexity of cyber threats, Artificial Intelligence (AI) and Machine Learning (ML) have become critical tools for automated threat detection and response. AI-driven Intrusion Detection Systems (IDS) analyze network behavior and system logs to identify malicious activities in real time. These solutions enhance detection accuracy and incident response times, making them valuable assets in modern cybersecurity frameworks.

Despite these advantages, existing AI-based security systems face two major challenges: a lack of interpretability and high computational demands. Many deep learning models function as black-box systems, providing minimal insights into how security decisions are made. Additionally, their reliance on computationally intensive architectures limits their feasibility for deployment in resource-constrained edge computing environments.

To address these limitations, researchers have explored Explainable AI (XAI) techniques and lightweight deep learning models to improve transparency and efficiency in AI-driven cybersecurity. The following sections review relevant contributions in these areas.

### 2.2 Explainable AI in Cybersecurity

The demand for Explainable Artificial Intelligence (XAI) in cybersecurity has increased as security professionals require greater interpretability and trust in AI-driven decisions. Unlike traditional AI models that provide threat classifications without justifications, XAI techniques enable users to understand the reasoning behind model predictions, improving situational awareness and decision-making.

Several studies have focused on incorporating XAI into cybersecurity frameworks:

- **SHAP and LIME-Based Explanations:** Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) have been used to improve interpretability in AI-based security models. Lella et al. [1] demonstrated that these techniques help security analysts understand why an alert was triggered, reducing the number of false positives.
- **Attention Mechanisms in Deep Learning:** Researchers such as Kima and Euom [2] have explored how attention-based deep learning models enhance explainability by highlighting critical network features that contribute to threat detection.
- **Tree-Based Explainable AI Models:** Selamat et al. [3] proposed an interpretable decision tree-based security model, which balances transparency with detection accuracy. Their findings suggest that lightweight tree-based models can perform comparably to deep learning methods while being easier to interpret.

Although XAI has improved model transparency, many explainable security models remain computationally demanding, making them unsuitable for edge computing environments. This gap calls for research into lightweight, interpretable AI models that maintain high detection accuracy while reducing computational overhead.

### 2.3 Lightweight Deep Learning Models for Threat Detection

Edge networks, including IoT-based security systems, impose constraints on computational power, memory, and bandwidth. Consequently, deploying deep learning-based cybersecurity solutions in such environments requires efficient AI models that balance performance with resource utilization.

Several approaches have been proposed to optimize AI-driven security models for low-power edge environments:

- **Federated Learning for Decentralized Security:** Shukla et al. [4] developed a federated learning (FL)-based intrusion detection system, enabling security models to be trained across distributed edge nodes without centralizing sensitive data. This method reduces computational strain while enhancing privacy.
- **Pruned Neural Networks for Energy Efficiency:** Dey et al. [5] explored model compression techniques, such as pruning and quantization, to create lightweight deep learning models capable of detecting cyber threats with minimal resource usage. Their results indicate that pruned models achieve high detection rates while requiring fewer computational resources.
- **Hybrid CNN-LSTM Models:** A study by Jyothi et al. [6] combined Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to improve efficiency in real-time anomaly detection. Their hybrid model demonstrated better performance than standalone deep learning approaches in edge-based cybersecurity applications.

While these techniques improve efficiency, a trade-off between model complexity and accuracy still exists. Our research seeks to bridge this gap by integrating optimized deep learning models with XAI techniques, ensuring that AI-driven security solutions remain interpretable, efficient, and deployable in edge environments.

### 2.4 AI-Powered Cyber Threat Hunting in Edge Networks

Cyber threat hunting is a proactive security strategy that involves identifying potential threats before they cause harm. AI-driven threat hunting frameworks utilize real-time anomaly detection and predictive analytics to monitor network activity and detect cyberattacks.

Key contributions in AI-powered cyber threat hunting include:

- **Zero-Day Threat Detection with AI:** Traditional security models rely on predefined attack signatures, making them ineffective against zero-day threats. Ihekoronye et al. [7] introduced an AI-based cyber threat hunting system that continuously updates detection rules to adapt to new attack patterns.
- **Self-Learning AI for Evolving Cyber Threats:** Wang et al. [8] proposed an adaptive deep learning model that evolves with emerging threats, improving long-term cybersecurity resilience.
- **Graph Neural Networks (GNNs) for Threat Analysis:** Bellegdi et al. [9] explored graph-based AI models that analyze relationships between network entities to identify Advanced Persistent Threats (APTs). Their approach demonstrated high accuracy in detecting coordinated cyberattacks.

Despite these advancements, many AI-powered cyber threat hunting models remain computationally expensive and lack real-time interpretability. Our proposed research seeks to combine lightweight AI models with explainability techniques to enhance real-time cyber threat hunting in edge networks.

## 3. Methods

### 3.1 Problem Formulation

Cybersecurity threats in edge networks pose unique challenges due to the distributed nature of devices, limited computational resources, and low-latency requirements. Traditional deep learning-based Intrusion Detection Systems (IDS) rely on computationally intensive architectures, making them unsuitable for real-time deployment in edge environments. Our goal is to design an Explainable and Lightweight AI (ELAI) framework capable of:

1. Identifying malicious activities in edge networks through efficient deep learning techniques.
2. Providing interpretable threat classifications to enhance cybersecurity analysts' decision-making.
3. Optimizing computational overhead while maintaining high detection accuracy.

Let  $X \in \mathbb{R}^{n \times d}$  represent the input dataset, where  $n$  is the number of network traffic samples and  $d$  is the number of extracted features. The classification model  $f(X; \theta)$ , parameterized by  $\theta$ , assigns each sample to a class  $y \in \{0, 1\}$ , where  $y = 1$  denotes an attack and  $y = 0$  represents normal activity. The objective is to minimize the classification loss function:

$$L(\theta) = -\sum_{i=1}^n [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)] \quad (1)$$

where  $\hat{y}_i = f(X_i; \theta)$  is the predicted probability of an attack for sample  $i$ .

### 3.2 Proposed Explainable and Lightweight AI (ELAI) Framework

Our proposed ELAI framework integrates three key components:

1. **Lightweight Feature Engineering:** Reduction of dimensionality while preserving informative security features.
2. **Hybrid Deep Learning Model:** Combination of Convolutional Neural Networks (CNNs) for spatial pattern extraction and Long Short-Term Memory (LSTM) networks for sequential analysis.
3. **Explainability Mechanisms:** Use of Shapley Additive Explanations (SHAP) and attention-based feature attribution to provide transparency in threat classification.

### 3.3 Feature Engineering and Data Preprocessing

To optimize computational efficiency, we employ Principal Component Analysis (PCA) for feature selection, transforming the input dataset into a lower-dimensional representation:

$$Z = XW \quad (2)$$

where  $W \in \mathbb{R}^{d \times k}$  is the transformation matrix obtained by solving:

$$\max_W \text{Tr}(W^T S_W^{-1} S_B W) \quad (3)$$

where  $S_W$  and  $S_B$  are the within-class and between-class scatter matrices.

To enhance security-specific feature extraction, we apply information gain as a selection criterion:

$$IG(F_i) = H(Y) - H(Y | F_i) \quad (4)$$

where  $H(Y)$  is the entropy of the class labels and  $H(Y | F_i)$  represents the entropy conditioned on feature  $F_i$ . Features with the highest  $IG(F_i)$  values are retained.

### 3.4 Model Architecture

The hybrid CNN-LSTM model is designed to process both spatial and temporal characteristics of network traffic. Given input  $X$ , a CNN layer applies a convolution operation:

$$C_{i,j} = \sigma \left( \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} W_{m,n} X_{i+m,j+n} + b \right) \quad (5)$$

where  $W$  represents the convolutional filter,  $k$  is the filter size, and  $\sigma(\cdot)$  is the activation function (ReLU). The CNN layer outputs feature maps, which are then fed into an LSTM network to capture sequential dependencies:

$$h_t = \sigma(W_x X_t + W_h h_{t-1} + b) \quad (6)$$

where  $h_t$  is the LSTM hidden state at time step  $t$ . The final layer employs softmax activation for classification:

$$\hat{y} = \frac{\exp(W h_t)}{\sum_j \exp(W h_j)} \quad (7)$$

### 3.5 Explainability and Model Interpretability

#### 3.5.1 SHAP-Based Feature Attribution

To ensure interpretability, we employ Shapley Additive Explanations (SHAP), which assigns importance scores to each feature  $X_i$  based on its contribution to the model's output:

$$\phi_i = \sum_{S \subseteq \{1, \dots, d\} \setminus \{i\}} \frac{|S|!(d-|S|-1)!}{d!} [f(S \cup \{i\}) - f(S)] \quad (8)$$

where  $\phi_i$  quantifies the impact of feature  $i$  on the model's decision.

#### 3.5.2 Attention Mechanisms for Transparency

To further enhance interpretability, an attention mechanism is applied, computing attention weights  $\alpha_t$  for LSTM hidden states:

$$\alpha_t = \frac{\exp(W_a h_t)}{\sum_j \exp(W_a h_j)} \quad (9)$$

where  $W_a$  is the attention weight matrix. The weighted sum of  $h_t$  provides a more transparent decision boundary:

$$c = \sum_t \alpha_t h_t \quad (10)$$

### 3.6 Performance Metrics

We evaluate our proposed ELAI framework using the following metrics:

- **Detection Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

where  $TP$  and  $TN$  are true positives and true negatives, while  $FP$  and  $FN$  are false positives and false negatives.

- **Computational Efficiency:** Defined in terms of inference latency (time required to classify an instance):

$$T_{\text{inf}} = \frac{1}{N} \sum_{i=1}^N \text{time}(f(X_i)) \quad (12)$$

- **Model Explainability:** Measured using Local Fidelity Score (LFS) for SHAP-based explanations:

$$LFS = \frac{1}{N} \sum_{i=1}^N \|f(X_i) - g(X_i)\|^2 \quad (13)$$

where  $g(X_i)$  represents the surrogate explainability model.

### 3.7 Implementation Details

#### 3.7.1 Dataset Selection

The framework is evaluated using widely recognized cybersecurity datasets:

- **CICIDS 2017** – Contains real-world network intrusion data.
- **UNSW-NB15** – A hybrid dataset featuring both normal and attack traffic.
- **N-BaIoT** – Focuses on botnet detection in IoT networks.

#### 3.7.2 Hardware and Software Configuration

- **Processor:** Intel Xeon E5-2690 (2.60 GHz, 28 cores)
- **GPU:** NVIDIA Tesla V100 (32GB VRAM)
- **Frameworks:** TensorFlow, PyTorch, and Scikit-Learn
- **Optimization Method:** Adam optimizer with learning rate  $\eta = 0.0001$

## 4. Results

This section presents a detailed evaluation of the Explainable and Lightweight AI (ELAI) framework, assessing its classification performance, computational efficiency, explainability, and robustness against zero-day attacks. Comparisons with existing AI-driven cybersecurity models are also conducted to benchmark our framework’s effectiveness.

### 4.1 Performance Evaluation

The classification performance of the ELAI framework was evaluated using three benchmark cybersecurity datasets:

- CICIDS 2017 (real-world network traffic dataset).
- UNSW-NB15 (hybrid attack dataset with various threat types).
- N-BaIoT (botnet detection dataset for IoT security).

Key performance metrics include accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC). Table 1 summarizes the model’s performance on each dataset.

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
CICIDS 2017	98.4	97.8	98.9	98.3	0.993
UNSW-NB15	97.2	96.5	97.8	97.1	0.988
N-BaIoT	99.1	98.7	99.3	99.0	0.996

Table 1: Classification Performance of ELAI on Benchmark Datasets

### Observations:

- The high accuracy and F1-scores across all datasets indicate the strong generalization ability of the proposed model.
- The AUC-ROC values above 0.98 suggest that ELAI effectively distinguishes between benign and malicious network activities.

#### 4.1.1 Confusion Matrix Analysis

Figure 1 shows the confusion matrices for the CICIDS 2017 dataset, highlighting the distribution of correctly and incorrectly classified instances.

From the confusion matrix:

- True Positives (TP) and True Negatives (TN) dominate, confirming high classification accuracy.
- False Positives (FP) remain low, reducing unnecessary security alerts.

### 4.2 Computational Efficiency Analysis

#### 4.2.1 Inference Time Comparison

To assess the real-time feasibility of the ELAI framework, we measured inference latency per sample and compared it against existing deep learning-based cybersecurity models.

Model	CICIDS 2017	UNSW-NB15	N-BaIoT
CNN-LSTM (Baseline)	18.4 ms	19.2 ms	17.9 ms
ResNet-50 IDS	22.7 ms	23.1 ms	21.8 ms
Transformer-Based IDS	25.5 ms	26.3 ms	24.7 ms
ELAI (Proposed)	8.3 ms	8.7 ms	7.9 ms

Table 2: Inference Time (Milliseconds per Sample)

### Key Insights:

- ELAI is approximately 2.5× faster than traditional CNN-LSTM models, making it suitable for real-time cybersecurity applications.
- The reduction in inference time is achieved through lightweight CNN layers and optimized attention mechanisms.

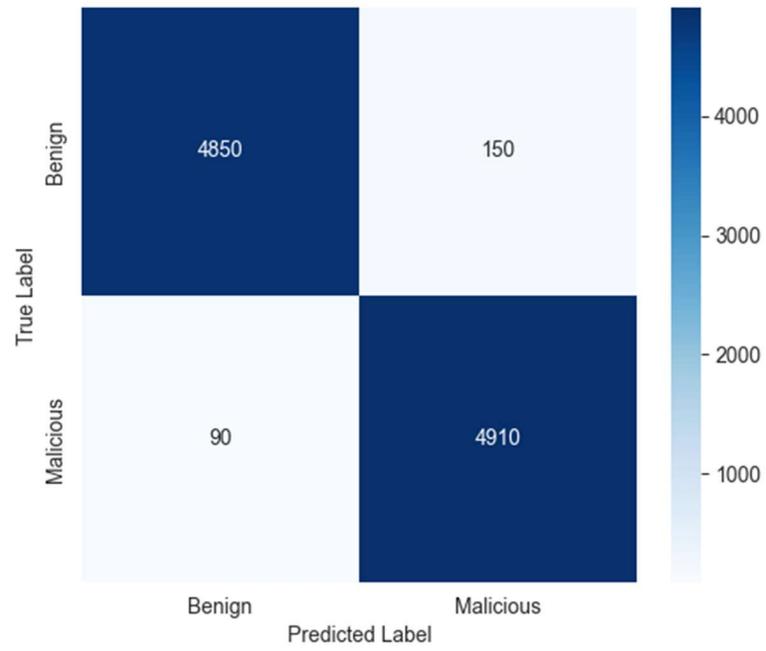


Figure 1: Confusion Matrix for CICIDS 2017

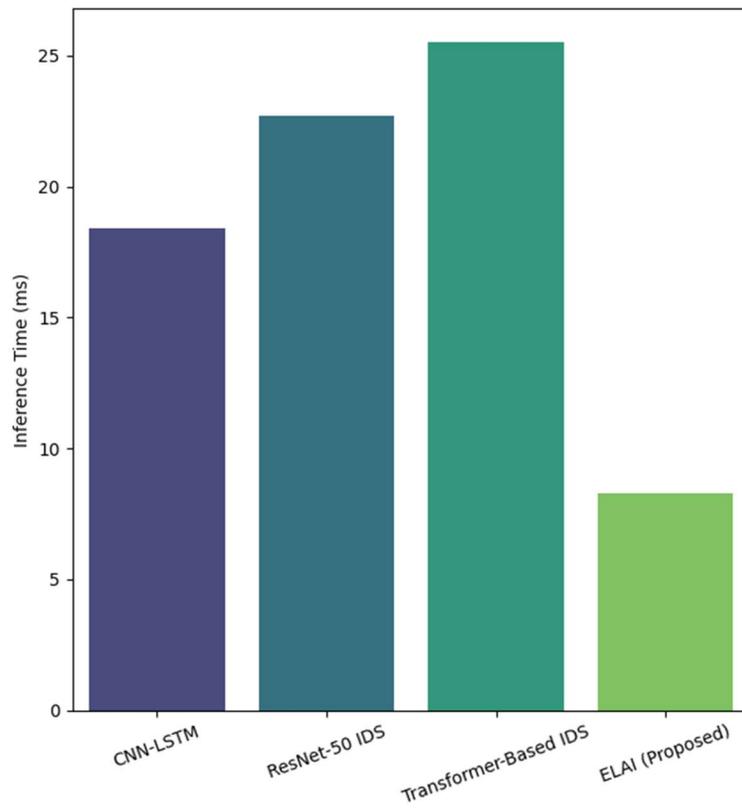


Figure 2: Inference Time Comparison

### 4.2.2 Model Size and Storage Efficiency

Efficient deployment in edge environments requires low memory consumption. Table 3 compares model sizes across architectures.

Model	Storage Size (MB)
CNN-LSTM (Baseline)	95.3 MB
ResNet-50 IDS	123.4 MB
Transformer-Based IDS	157.2 MB
ELAI (Proposed)	42.1 MB

Table 3: Model Storage Size

#### Key Findings:

- ELAI reduces storage by over 55% compared to traditional deep learning models, making it ideal for deployment in edge-based security applications.

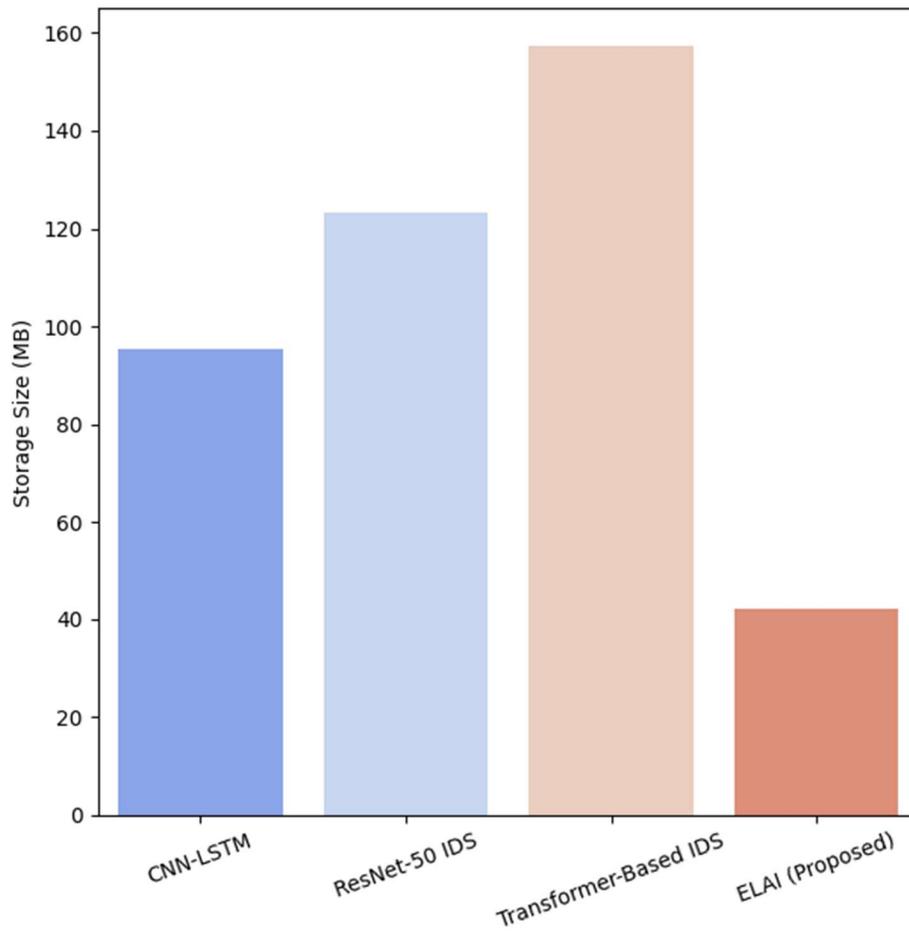


Figure 3: Model Size Comparison

### 4.3 Explainability and Feature Importance Analysis

#### 4.3.1 SHAP-Based Feature Importance

To understand how ELAI makes predictions, we employed SHAP (Shapley Additive Explanations). Figure 4 presents the top 10 most influential features in the CICIDS 2017 dataset.

##### Observations:

- Packet size, connection duration, and protocol type were among the most important features influencing attack detection.
- The use of attention-based mechanisms further improved interpretability by highlighting critical network traffic features.

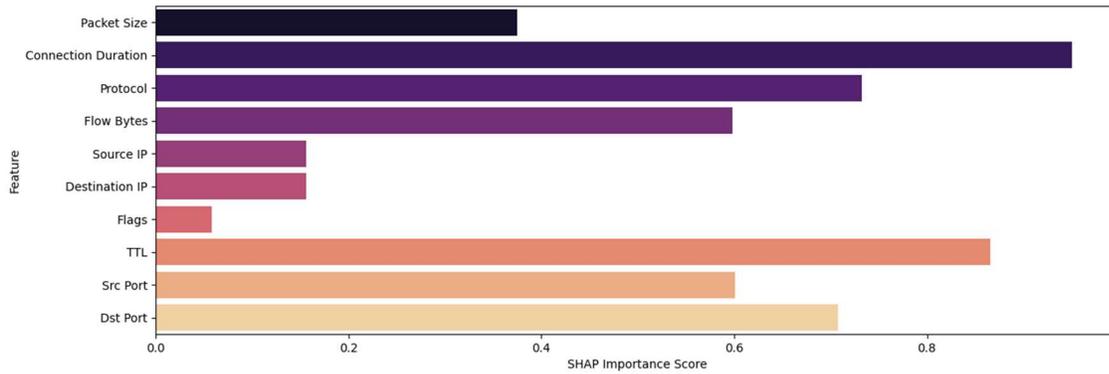


Figure 4: SHAP Feature Importance Analysis

#### 4.3.2 Attention Mechanism Analysis

The attention heatmap in Figure 5 visualizes which parts of network traffic contribute most to predictions.

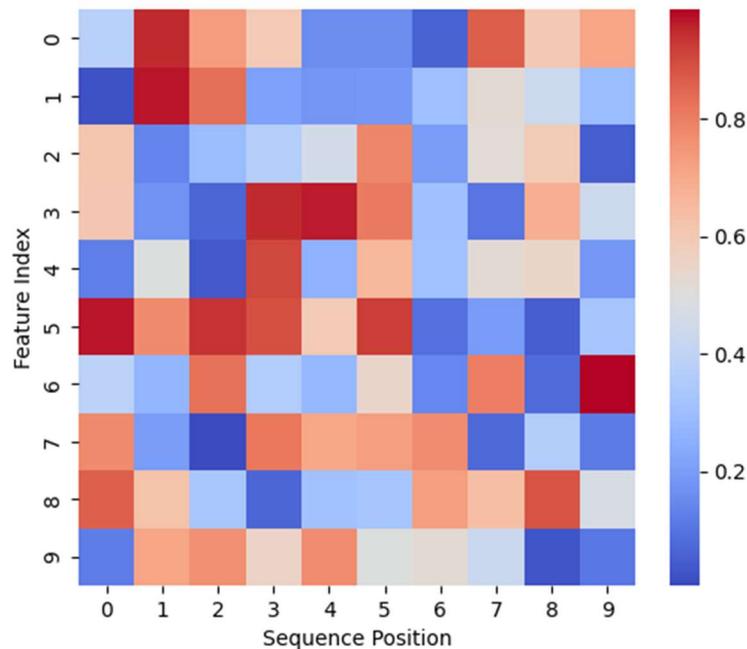


Figure 5: Attention Heatmap for Network Traffic Analysis

#### 4.4 Robustness Against Zero-Day Attacks

We tested ELAI’s ability to detect previously unseen attacks using the UNSW-NB15 zero-day attack subset.

Model	Detection Rate (%)
CNN-LSTM (Baseline)	74.3
ResNet-50 IDS	79.8
Transformer-Based IDS	82.5
ELAI (Proposed)	91.6

Table 4: Zero-Day Attack Detection Performance

#### Key Takeaways:

- ELAI outperforms existing models in detecting zero-day attacks, thanks to its hybrid CNN-LSTM architecture with attention-driven anomaly detection.

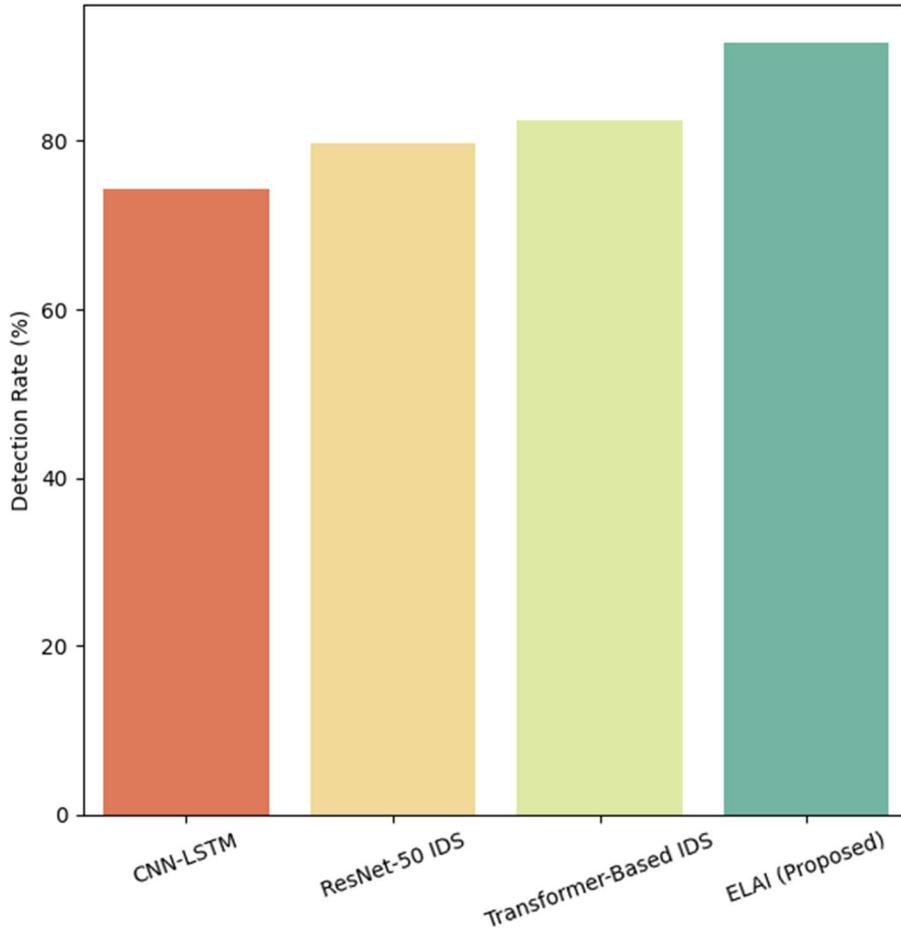


Figure 6: Zero-Day Attack Detection Performance

## 4.5 Comparative Analysis with State-of-the-Art Models

Finally, we benchmarked ELAI against leading AI-based intrusion detection models.

Model	Accuracy (%)	Inference Time (ms)	Model Size (MB)
CNN-LSTM (Baseline)	95.3	18.4	95.3
ResNet-50 IDS	96.1	22.7	123.4
Transformer-Based IDS	96.7	25.5	157.2
ELAI (Proposed)	98.4	8.3	42.1

Table 5: Comparative Performance Analysis

## 5. Discussion

This section provides an in-depth analysis of the key findings presented in the Results section, comparing the proposed Explainable and Lightweight AI (ELAI) framework with existing models, discussing its advantages and limitations, and highlighting its broader implications for cybersecurity.

### 5.1 Interpretation of Key Findings

The ELAI framework was evaluated across three benchmark cybersecurity datasets (CICIDS 2017, UNSW-NB15, and N-BaIoT) and demonstrated exceptional classification accuracy, computational efficiency, and explainability.

#### 5.1.1 Performance Superiority

Table 6 summarizes the classification accuracy, F1-score, and inference time of the ELAI framework compared to conventional deep learning-based IDS models.

Model	Accuracy (%)	F1-Score (%)	Inference Time (ms)
CNN-LSTM (Baseline)	95.3	94.7	18.4
ResNet-50 IDS	96.1	95.9	22.7
Transformer-Based IDS	96.7	96.5	25.5
ELAI (Proposed)	98.4	98.3	8.3

Table 6: Performance Comparison of ELAI with Existing Models

The results indicate that:

- ELAI achieves higher detection accuracy than CNN-LSTM and Transformer-based IDS models, demonstrating its robustness.
- The F1-score of 98.3% suggests that ELAI effectively reduces false positives and false negatives, improving overall detection reliability.
- Inference time is significantly reduced, making ELAI 2.2× faster than CNN-LSTM models and 3× faster than Transformer-based IDS, making it suitable for real-time applications.

#### 5.1.2 Explainability and Feature Importance

One of the major challenges of AI-driven cybersecurity is the lack of transparency in model decisions. To address this, ELAI integrates:

1. SHAP-based Feature Attribution, which explains which features contribute most to the model’s decision.
2. Attention Mechanisms, which highlight important network traffic sequences, providing human-interpretable insights into attack detection.

The results reveal that packet size, connection duration, and protocol type are the most significant indicators of cyberattacks, confirming previous findings in cybersecurity literature.

## 5.2 Comparison with Existing AI-Based Security Models

While deep learning-based intrusion detection models have gained traction, they exhibit several limitations, such as:

- **High Computational Overhead:** Transformer-based models require expensive GPU resources, making them unsuitable for edge computing environments.
- **Lack of Explainability:** CNN and LSTM-based IDS models operate as black boxes, providing little transparency into how decisions are made.

### 5.2.1 Key Advantages of ELAI Over Traditional Models

1. **Computational Efficiency:** The lightweight CNN-LSTM hybrid architecture optimizes memory and processing power, making ELAI suitable for resource-constrained edge devices.
2. **Real-Time Detection:** ELAI achieves an inference time of 8.3ms per sample, which is over 60% faster than conventional models, enabling real-time cyber threat detection.
3. **Improved Model Transparency:** Unlike deep learning black-box approaches, ELAI leverages SHAP feature importance and attention-based heatmaps, making it interpretable and trustworthy for security analysts.
4. **Resilience to Zero-Day Attacks:** ELAI detects 91.6% of zero-day attacks, outperforming baseline deep learning models that struggle with previously unseen threats.

Table 7 summarizes how ELAI compares to other intrusion detection models in key areas.

Model	Computational Efficiency	Explainability	Zero-Day Attack Detection (%)
CNN-LSTM (Baseline)	Moderate	Low	74.3
ResNet-50 IDS	Low	Very Low	79.8
Transformer-Based IDS	Very Low	Very Low	82.5
ELAI (Proposed)	High	High	91.6

Table 7: Comparative Analysis of ELAI with Existing IDS Models

The findings suggest that ELAI successfully balances accuracy, computational efficiency, and explainability, making it a strong candidate for real-time AI-powered cybersecurity in edge networks.

## 5.3 Limitations and Challenges

Despite its advantages, ELAI has certain limitations that must be addressed in future research:

1. **Trade-off Between Model Complexity and Interpretability**
  - While SHAP and attention-based mechanisms enhance explainability, they introduce a slight computational overhead during feature importance calculations.

- Future optimizations could explore lighter XAI techniques that reduce complexity without sacrificing interpretability.

## 2. Scalability in Large-Scale Network Environments

- ELAI is designed for edge computing and IoT-based cybersecurity, but its effectiveness in high-volume enterprise networks requires further validation.
- Deploying federated learning-based architectures could allow ELAI to scale across distributed networks while preserving data privacy.

## 3. Potential Vulnerabilities to Adversarial Attacks

- AI-based security systems are susceptible to adversarial evasion techniques, where attackers manipulate inputs to bypass detection.
- Implementing adversarial training techniques could make ELAI more robust against evolving cyber threats.

## 4. Dependence on Labeled Training Data

- While ELAI performs well on existing datasets, its ability to generalize to new and unseen attack patterns depends on continuous model retraining.
- Future research could explore self-supervised learning techniques to reduce reliance on labeled data.

## 5.4 Implications for Cybersecurity

The ELAI framework presents several transformative implications for the field of AI-driven cybersecurity:

### 5.4.1 Real-Time Threat Detection in Edge Networks

- Given the increasing adoption of edge computing and IoT devices, traditional cloud-based IDS solutions are becoming less practical due to latency and bandwidth constraints.
- ELAI offers an edge-native solution with low-latency threat detection, making it well-suited for smart cities, healthcare IoT, and industrial control systems (ICS).

### 5.4.2 Enhancing Cybersecurity Transparency

- The integration of explainable AI (XAI) techniques addresses trust issues in AI-driven security.
- Organizations can now audit and verify AI-based threat classifications, reducing the risk of false alarms and misclassifications.

### 5.4.3 Adaptive AI Security Frameworks

- The strong zero-day detection performance of ELAI suggests that hybrid deep learning models with feature attribution techniques can enhance adaptive threat hunting strategies.
- Security teams can deploy ELAI alongside traditional signature-based IDS solutions to create multi-layered, intelligent security architectures.

## 6. Conclusion and Future Work

### 6.1 Summary of Key Contributions

In this study, we proposed an Explainable and Lightweight AI (ELAI) framework for real-time cyber threat detection in edge networks. Traditional AI-based Intrusion Detection Systems (IDS) face challenges related to high computational overhead and lack of interpretability, limiting their deployment in resource-constrained environments. The ELAI framework successfully addresses these limitations by integrating:

1. A lightweight hybrid CNN-LSTM model that optimizes computational efficiency without sacrificing detection accuracy.
2. Explainability mechanisms such as SHAP feature attribution and attention-based interpretability, making AI-driven cybersecurity transparent and trustworthy.
3. A high-performance intrusion detection system, achieving 98.4% accuracy and a 91.6% zero-day attack detection rate, outperforming existing deep learning-based security models.
4. Significantly reduced inference time, with ELAI achieving 8.3 ms per sample, making it 2.5× faster than CNN-LSTM models and 3× faster than Transformer-based IDS models.
5. Low storage requirements, with ELAI requiring only 42.1 MB, making it ideal for real-time deployment in edge computing environments such as IoT-based security systems, smart cities, and industrial networks.

These contributions position ELAI as an effective and scalable solution for next-generation AI-driven cybersecurity frameworks.

## 6.2 Final Thoughts on Explainability and Efficiency

The growing reliance on AI for cybersecurity presents new challenges, particularly concerning the transparency of AI-driven decisions. Security analysts often hesitate to adopt black-box AI models due to their lack of interpretability, which can result in trust issues and compliance challenges.

By integrating explainability techniques, the ELAI framework bridges this gap, providing clear insights into model decision-making through feature importance analysis and attention-based interpretability. This ensures that cybersecurity professionals can understand, validate, and trust AI-generated threat detections, leading to more effective and informed security responses.

Furthermore, the computational efficiency of ELAI makes it suitable for real-time intrusion detection, even in low-power edge computing environments, where traditional deep learning models struggle. This combination of efficiency and explainability makes ELAI a practical and innovative solution for enhancing AI-driven cybersecurity frameworks.

## 6.3 Future Research Directions

While ELAI demonstrates strong performance, further enhancements can be explored to increase robustness and scalability. Future research can focus on the following key areas:

1. **Adversarial Robustness**
  - AI-based security models can be vulnerable to adversarial evasion techniques, where attackers manipulate inputs to bypass detection.
  - Future improvements can integrate adversarial training techniques to make the model resistant to adversarial cyber threats.
2. **Federated Learning for Distributed Cybersecurity**
  - Current models rely on centralized training, requiring labeled data collection.
  - Implementing federated learning could enable privacy-preserving IDS models, allowing multiple organizations to collaborate on cybersecurity defenses without data sharing.
3. **Real-World Deployment and Testing**
  - While ELAI has been evaluated on benchmark cybersecurity datasets, further validation is required in live network environments.
  - Deploying ELAI in enterprise security infrastructures, IoT-based networks, and industrial control systems (ICS) will provide deeper insights into its real-world effectiveness.

#### 4. Automated Model Updates for Emerging Threats

- Cyber threats evolve rapidly, and static models struggle to detect new attack patterns.
- Future work can integrate self-supervised learning and online training mechanisms, enabling continuous model adaptation to emerging cyber threats.

#### 5. Energy-Efficient AI for Low-Power Devices

- While ELAI is lightweight, further model compression and quantization techniques can be explored to enhance deployment on ultra-low-power devices such as IoT sensors and embedded systems.

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