

# LLM-Based Threat Detection and Prevention Framework for IoT Ecosystems

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**Abstract**—The increasing complexity and scale of the Internet of Things (IoT) have made security a critical concern. This paper presents a novel Large Language Model (LLM)-based framework for comprehensive threat detection and prevention in IoT environments. The system integrates lightweight LLMs fine-tuned on IoT-specific datasets (IoT-23, TON\_IoT) for real-time anomaly detection and automated, context-aware mitigation strategies optimized for resource-constrained devices. A modular Docker-based deployment enables scalable and reproducible evaluation across diverse network conditions. Experimental results in simulated IoT environments demonstrate significant improvements in detection accuracy, response latency, and resource efficiency over traditional security methods. The proposed framework highlights the potential of LLM-driven, autonomous security solutions for future IoT ecosystems.

**Index Terms**—Artificial Intelligence of Things (AIoT), Large Learning Models (LLMs), Internet of Things (IoT), Intrusion Detection, Intrusion Prevention

## I. INTRODUCTION

THE rapid growth of Internet of Things (IoT) ecosystems has introduced complex challenges in managing and optimizing system performance. IoT environments generate vast amounts of data, requiring efficient real-time processing and advanced operations such as resource allocation, predictive maintenance, and energy management. The diverse and dynamic nature of IoT devices further complicates these challenges, as devices often operate under heterogeneous conditions with varying computational and network capabilities [1]. The rapid expansion of IoT ecosystems introduces growing complexities in securing large-scale networks [2]. Traditional IoT security techniques often struggle to detect evolving and sophisticated threats. Recent advances in Large Learning Models (LLMs) have shown promise in improving security systems, offering adaptability to evolving threats, scalability across diverse IoT environments, and effectiveness in managing complex datasets. Recent studies demonstrate the growing potential of LLMs in cybersecurity applications. For example, the authors of [3] explored using domain-specific fine-tuning in LLMs for detecting zero-day vulnerabilities. Similarly, the authors of [4] proposed a hybrid approach combining LLMs with graph-based anomaly detection to secure IoT networks against emerging threats. The integration of LLMs with federated learning frameworks has also been successful in enhancing data privacy while maintaining robust security in distributed IoT

environments as shown by the work [5]. Moreover, the authors in [6] highlighted the effectiveness of context-aware LLMs in identifying complex attack patterns specific to IoT ecosystems. The work [7] underlined the importance of adaptive learning techniques for LLMs to ensure continuous improvement in threat detection and prevention. Our model presents an LLM-based security system tailored to IoT environments, focusing on a two-component approach for threat detection and prevention. The proposed system integrates the strengths of LLMs, utilizing prompt engineering, fine-tuning, and domain-specific training to identify and respond to security breaches in real-time. By leveraging IoT-specific datasets such as IoT-23 and TON\_IoT, the system continuously adapts to new threats, ensuring it remains effective in dynamic environments. This framework represents a significant step toward overcoming the limitations of traditional solutions while addressing the unique challenges of integrating advanced AI models into IoT ecosystems. The main contributions of this work are the following:

- This work presents a novel LLM-based IoT security framework capable of real-time detection of sophisticated cyber threats and automated mitigation without human intervention.
- The proposed system fine-tunes LLMs using IoT-specific datasets, such as IoT-23 and TON IoT, to significantly improve detection accuracy and maintain adaptability to evolving attack patterns.
- A scalable and reproducible deployment model is developed using Docker-based virtualization. This model enables flexible testing across various edge and cloud environments while supporting future integration with federated learning for privacy-preserving continuous improvement.

Unlike existing approaches focusing solely on detection, our framework uniquely combines lightweight LLM-based anomaly detection with real-time, rule-based prevention optimized for resource-constrained IoT environments. A modular Docker deployment for scalable and reproducible evaluation across diverse network conditions supports it. The balance of this paper is structured as follows: Section II reviews related work, highlighting existing approaches to IoT security and the application of LLMs in cybersecurity. Section III details the proposed LLM-based threat detection and prevention framework, including the system architecture, detection,

and response mechanisms. Section IV presents the evaluation results, comparing the proposed method against traditional IoT security approaches. Finally, Section V concludes the paper by summarizing the findings and outlining directions for future research.

## II. RELATED WORKS

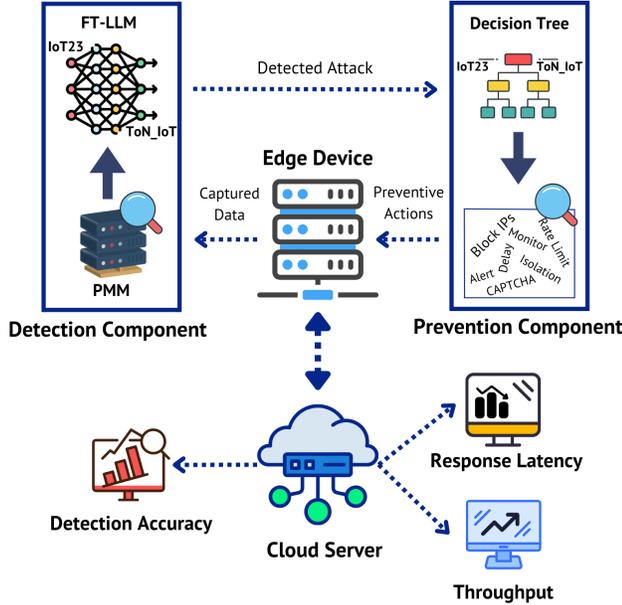


Fig. 1: Model Architecture Overview

In recent years, IoT security has been an active research area, with numerous studies exploring Machine Learning (ML) techniques for anomaly detection and intrusion prevention. Several works have demonstrated the potential of ML algorithms to identify unusual patterns in IoT network traffic and provide adequate responses to emerging threats. For instance, the work [8] presented a comprehensive study on the use of ML for anomaly detection in IoT systems, emphasizing the ability to detect unauthorized access and other security breaches accurately. The authors of [9] expanded upon this by proposing a multi-layered machine learning approach for intrusion detection that significantly outperformed traditional rule-based systems, showing superior results in identifying complex attack patterns and reducing false positives. Beyond conventional ML techniques, deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been extensively utilized for intrusion detection in IoT networks. For example, the authors of [10] proposed an autoencoder-based deep learning model that effectively identifies zero-day attacks while maintaining a low false-positive rate. Another significant work [11] integrated reinforcement learning with anomaly detection, allowing IoT security systems to adapt dynamically to new attack patterns without extensive retraining. In parallel, applying LLMs to cybersecurity has garnered increasing interest due to their ability to handle complex, unstructured data. The authors of [12] introduced an LLM-based approach to network traffic analysis,

utilizing prompt engineering to improve the model’s ability to identify malicious activities in IoT networks. Their findings suggested that LLMs could achieve results comparable to deep learning models, but with reduced computational overhead and improved resource efficiency. Another critical advancement in IoT security is the adoption of Federated Learning (FL) for distributed threat detection. Since IoT devices generate vast amounts of decentralized data, transmitting all traffic logs to a centralized server introduces privacy risks and scalability challenges. Federated learning addresses this by enabling devices to collaboratively train models without sharing raw data [13].

## III. PROPOSED FRAMEWORK

### A. Architecture Overview

As shown in Figure 1, the proposed architecture integrates an attack detection and prevention system within an edge-cloud framework to enhance IoT security. The Detection Component leverages a Fine-Tuned Large Language Model (FT-LLM) trained on IoT23 and ToN\_IoT datasets to identify cyber threats, supported by a Prompt Module Management (PMM) system. At the same time, the Prevention Component applies a Decision Tree-based System to enforce real-time countermeasures such as blocking IPs, rate limiting, monitoring, isolation, and CAPTCHA verification. An essential part of this architecture is the Cloud Server, which centralizes system operations and collects and analyzes data from connected edge devices.

1) *Detection Component:* The Detection Component uses LLMs to detect anomalies within IoT network traffic. By analyzing traffic data from IoT-specific datasets, e.g., IoT-23, TON\_IoT, the LLM identifies potential threats or security breaches based on deviations from normal network behaviour.

2) *Prevention Component:* While traditional IoT intrusion detection systems often require manual post-analysis or cloud-centered interventions, our proposed prevention system dynamically triggers context-aware countermeasures at the network edge based on live LLM detection outputs, ensuring immediate and autonomous threat response even in decentralized environments. The Prevention Component employs a decision tree model to trigger automated security actions. Upon detecting a threat, the system generates preventive measures such as isolating compromised devices, blocking malicious traffic, or alerting administrators.

Algorithm 1 mitigates Distributed Denial-of-Service (DDoS) attacks in real-time at the network edge. It processes incoming network data and classifies potential attacks using a decision tree model. Appropriate countermeasures are applied based on the attack’s intensity, source IP distribution, system load, and duration, including rate limiting, IP blocking, CAPTCHA deployment, and traffic redirection. Due to the page limitation, we focus solely on presenting the DDoS mitigation algorithm.

3) *Cloud Component:* One of the main parts of this component is performance monitoring, which tracks key metrics such as detection accuracy, response latency, and system throughput. The cloud infrastructure processes and visualizes this data

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**Algorithm 1** DDoS Prevention at the Edge

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1: Input:  $D = \{d_1, d_2, \dots, d_n\}$ , where  $d_i$  is captured network data
   at time  $i$ .
2: Output: Prevention actions  $A$  applied to the network.
3: for each  $d_i \in D$  do
4:    $attack\_type_i \leftarrow LLM(d_i)$ 
5:   if  $attack\_type_i = \text{DDoS}$  then
6:      $I_i \leftarrow intensity(d_i)$ 
7:      $S_i \leftarrow source\_IPs(d_i)$ 
8:      $L_i \leftarrow system\_load(d_i)$ 
9:      $T_i \leftarrow attack\_duration(d_i)$ 
10:     $A_i \leftarrow \emptyset$ 
11:    if  $I_i = \text{moderate}$  then
12:       $A_i \leftarrow A_i \cup \{\text{rate\_limiting}\}$ 
13:    else if  $I_i = \text{extreme}$  then
14:       $A_i \leftarrow A_i \cup \{\text{block\_IPs, redirect\_traffic}\}$ 
15:    end if
16:    if  $|S_i|$  is small then
17:       $A_i \leftarrow A_i \cup \{\text{IP\_filtering}\}$ 
18:    else if  $|S_i|$  is large then
19:       $A_i \leftarrow A_i \cup \{\text{CAPTCHA\_deployment}\}$ 
20:    end if
21:    if  $L_i$  exceeds threshold  $L_{max}$  then
22:       $A_i \leftarrow A_i \cup \{\text{aggressive\_blocking}\}$ 
23:    end if
24:    if  $T_i$  exceeds duration threshold  $T_{max}$  then
25:       $A_i \leftarrow A_i \cup \{\text{honeypot\_redirection}\}$ 
26:    end if
27:    Apply  $A_i$ 
28:  end if
29: end for
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through a performance monitoring dashboard, providing insights into the effectiveness of the security mechanisms and facilitating timely adjustments. Furthermore, a communication module facilitates data flow across the system, ensuring seamless interaction between edge devices and cloud-based components.

### B. Implementation Details

The LLM is fine-tuned using IoT-specific datasets to optimize its detection and response capabilities.

1) *Datasets:* To ensure robust performance and adaptability of the detection and prevention components, the system leverages comprehensive, IoT-specific datasets for fine-tuning. Two key datasets employed in this architecture are IoT-23 and TON\_IoT, which provide diverse and real-world data to optimize detection accuracy and support dynamic threat response capabilities. The IoT-23 dataset [14] is a benchmark dataset designed specifically for network-based intrusion detection in IoT environments. It contains extensive packet capture (PCAP) files representing normal and malicious IoT network traffic. IoT-23 captures various attacks, such as Distributed Denial of Service (DDoS) and port scanning. These scenarios make the dataset highly relevant for detecting anomalies and threat patterns within IoT networks. The IoT-23 dataset, available on Hugging Face, is a structured version of the original dataset. It contains around 6 million rows of data, each representing network flows or connection records with detailed features,

such as IP addresses, ports, protocols, and labelled activity types, including both normal and malicious behaviours. This structured format ensures efficient processing and seamless integration into machine learning pipelines for anomaly detection and threat analysis. The dataset's diversity in traffic sources ensures that the detection component of the system is adaptable to multiple device types. Its inclusion in the fine-tuning process allows the Detection Component to effectively recognize subtle deviations in network behaviour, improving its ability to identify and isolate compromised devices early. Moreover, IoT-23's coverage of botnet and DDoS attack variants enhances the architecture's ability to respond rapidly to evolving, large-scale threats. The table provides an overview of the labels, descriptions, and proportions of traffic types and cyberattack categories in the Ton\_IoT dataset. The dataset includes Normal traffic and various attack types, with network scanning (31.963%) and DDoS attacks (27.597%) being the most prevalent threats. Other notable attack types include Denial-of-Service (DoS) attacks, Cross-Site Scripting (XSS) attacks, and password-based attack attempts. Less frequent but significant threats include backdoor-based malicious activity, code injection, and ransomware attacks. The rarest category in the dataset is Man-in-the-Middle (MITM) attacks, highlighting their relatively low occurrence compared to other cyber threats. Each attack type is assigned a numerical label used in classification. Table II presents the labels, descriptions, and proportions of different network traffic types in the IoT-23 dataset, which is used for intrusion detection in IoT environments. The dataset includes both Normal traffic and various attack types. The most prevalent malicious activity is horizontal port scanning, followed by Okiru botnet activity and DDoS attacks, indicating that these attack types dominate IoT security threats. The dataset also contains various command and control (C&C) activities, such as C&C communication, heartbeat signals, and file downloads from C&C servers, which are essential for detecting botnet activities. Other rare but notable attack types include Torii botnet communication, Mirai botnet C&C communication, and Okiru botnet attacks. The other dataset used includes the TON\_IoT dataset [15] with around 22.3 million rows of data, which comprises a collection of heterogeneous data sources designed to evaluate the performance of cybersecurity applications, particularly those leveraging AI and ML techniques. Developed by the University of New South Wales (UNSW) Canberra Cyber at the Australian Defence Force Academy (ADFA), these datasets simulate realistic and large-scale IoT and Industrial IoT (IIoT) environments. The TON\_IoT dataset expands the scope of security monitoring by incorporating telemetry data from various IoT devices, industrial sensors, and operating system logs. It is specifically curated for research on cyberattacks in IoT and Industrial IoT (IIoT) systems. Unlike IoT-23, which focuses primarily on network activity, TON\_IoT includes multi-source data from operating systems, network telemetry, and physical devices, providing a holistic view of potential anomalies.

TABLE I: Labels, Descriptions, and Proportions in the Ton\_IoT Dataset

Type	Description	Proportion (%)	Label
Scanning	Network scanning activity.	31.963	20
DDoS	Distributed Denial-of-Service attack.	27.597	10
DoS	Denial-of-Service attack.	15.110	11
XSS	Cross-site scripting attack.	9.441	21
Password	Password-based attack attempts.	7.692	18
Normal	Normal traffic.	3.565	3
Backdoor	Backdoor-based malicious activity.	2.275	2
Injection	Code injection attack.	2.026	13
Ransomware	Ransomware attack.	0.326	19
MITM	Man-in-the-middle attack.	0.005	14

TABLE II: Labels, Descriptions, and Proportions in the IoT-23 Dataset

Type	Description	Proportion (%)	Label
PartOfAHorizontalPortScan	Horizontal port scanning activity.	56.048	17
Okiru	Okiru botnet activity.	21.715	15
Benign	Normal traffic.	11.392	3
DDoS	Distributed Denial-of-Service attack.	10.560	10
C&C	Command and control communication.	0.253	4
C&C-HeartBeat	Periodic heartbeat signal to C&C.	0.022	5
Attack	General attack activity.	0.009	1
C&C-FileDownload	File download from C&C server.	0.001	5
C&C-Torii	Torii botnet C&C communication.	0.0005	9
FileDownload	File download activity.	0.0002	12
C&C-HeartBeat-FileDownload	Combination of heartbeat and file download.	0.0001	7
Okiru-Attack	Okiru botnet attack.	0.00005	16
C&C-Mirai	Mirai botnet C&C communication.	0.00002	8

2) *Experimental Setup*: To evaluate the effectiveness of the proposed IoT Threat Detection and Prevention system, we designed a comprehensive experimental framework leveraging Docker containers, which provide lightweight, isolated environments for running applications. Docker enables the simulation of scalable and realistic deployments of IoT edge and cloud devices by packaging applications with their dependencies, ensuring consistency, portability, and resource efficiency across different computing environments. The framework integrates detection and prevention components in real-time environments, providing the model’s adaptability and robustness across diverse IoT networks. The experimental setup was designed to replicate real-world IoT ecosystems with various device-specific configurations and workloads. Docker was chosen for its lightweight, flexible containerization capabilities, enabling efficient simulation of both edge and cloud layers: **Edge Layer**: Docker containers were deployed on local machines to simulate IoT devices, such as smart cameras, industrial sensors, and smart meters, each configured to generate network traffic logs. Local LLMs were embedded in edge containers, performing real-time anomaly detection and triggering preventive actions autonomously. **Cloud layer**: A separate set of Docker containers was dedicated to cloud servers. The cloud environment also included the Performance Monitoring Dashboard for tracking key performance metrics such as detection accuracy, response latency, and system throughput. **Prompt**: The effectiveness of the proposed Detection Component relies on carefully designed

prompts that provide comprehensive contextual information about network traffic and device behaviour. The prompt structure is tailored to help the Local LLM effectively detect anomalies and potential threats within the IoT ecosystem. Below, we detail the prompt’s construction and role in identifying abnormal behaviours. The prompt provides a descriptive, structured summary of each network connection, embedding key traffic and session details critical for detecting anomalies. The structure of the prompt is as follows:

```
Traffic from Port 49864 to Port 80 over TCP Protocol.
Duration: 0.049751s, Service: http, Bytes Sent: 243, Bytes
Received: 3440, Missed Bytes: 0, Total IP Bytes Sent: 511,
Total IP Bytes Received: 3760, Packets Sent: 5, Packets
Received: 6, Connection State: SF
```

#### IV. RESULTS AND EVALUATION

Figure 2 presents training and validation loss curves for different LLMs over four epochs. The models include TinyBERT, BERT-Small, and BERT-Mini, with their respective training losses represented by solid lines and validation losses by dashed lines. The loss decreases progressively across epochs, demonstrating convergence, with BERT-Small (red line) exhibiting the lowest loss, followed by TinyBERT (blue line) and BERT-Mini (green line). As shown in Table III, all three BERT-based variants exhibit strong performance across accuracy metrics,

TABLE III: Performance Metrics and Resource Usage for the LLMs

Model	Train Loss	Validation Loss	Test Accuracy	Test F1-Score	Test Precision	Test Recall	Energy Consumption (J/Req)	Inference (Req/Sec)
BERT Small	0.0089	0.0086	99.75%	99.75%	99.75%	99.75%	0.1434	287.82
BERT Mini	0.0104	0.0097	99.72%	99.72%	99.72%	99.72%	0.1175	293.56
TinyBERT [16]	0.0098	0.0096	99.73%	99.73%	99.73%	99.73%	0.1522	232.35

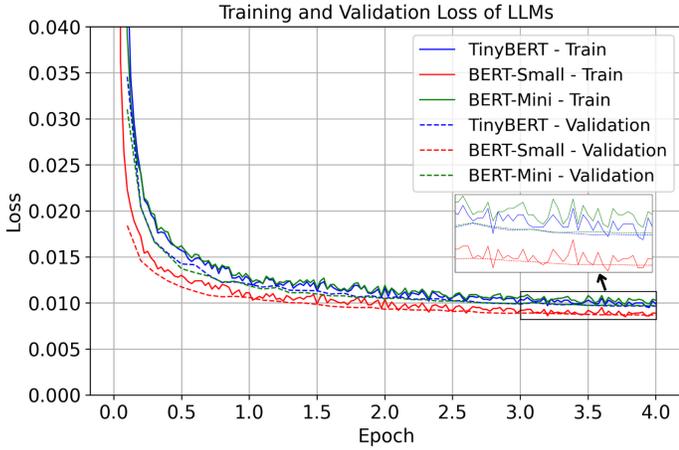


Fig. 2: Training and Validation Loss of LLMs

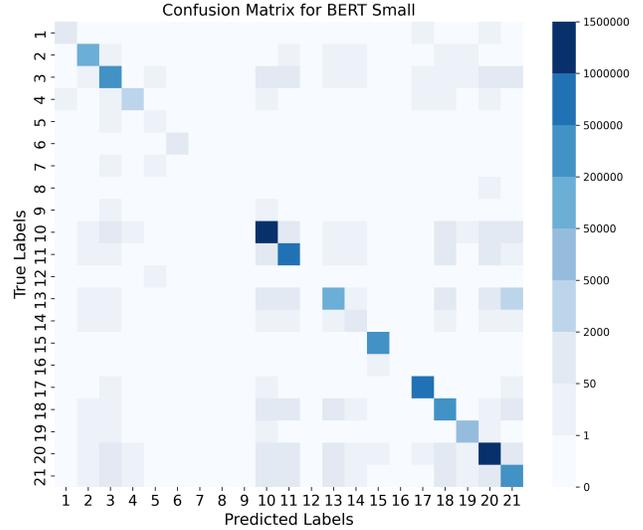


Fig. 4: Confusion Matrix of BERT Small

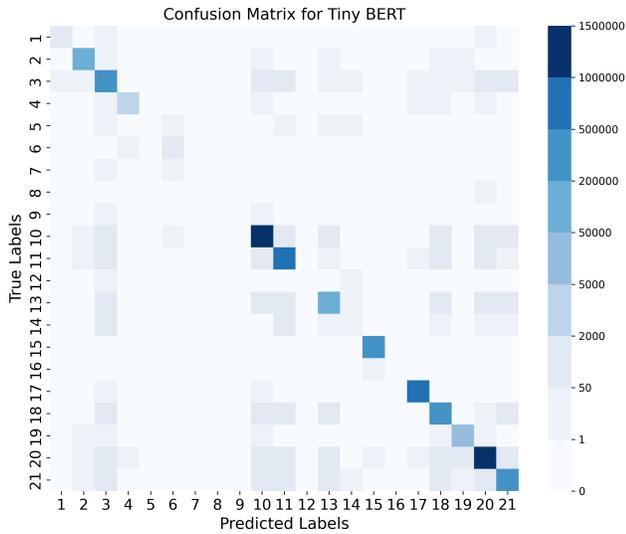


Fig. 3: Confusion Matrix of Tiny BERT

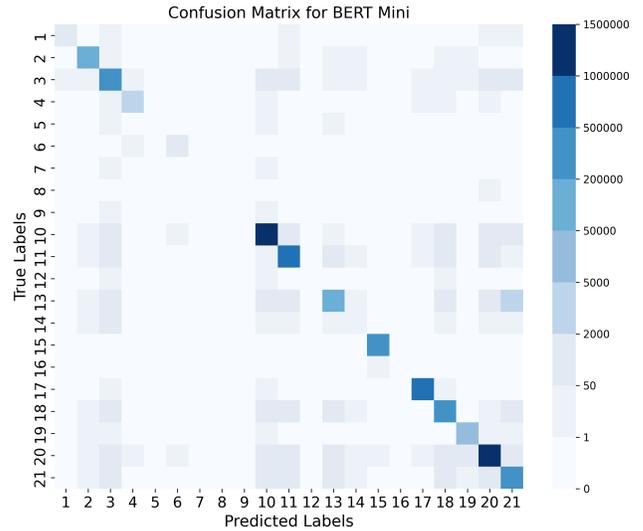


Fig. 5: Confusion Matrix of BERT Mini

with BERT Small slightly edging out the others at 99.75% for test accuracy, F1-score, precision, and recall. Notably, BERT Small also shows the lowest training and validation losses (0.0089 and 0.0086, respectively), suggesting more effective optimization. Although BERT Mini achieves a marginally faster inference rate (293.56 req/sec vs. 287.82 req/sec for BERT Small), its slightly higher losses (0.0104 train, 0.0097 validation) and marginally lower accuracy metrics (99.72%) make BERT Small the most balanced choice in terms of both learning efficiency and predictive performance. Meanwhile, TinyBERT demonstrates near-equivalent accuracy (99.73%) but has a lower inference rate of 232.35 req/sec, reinforcing BERT Small’s overall advantage. The proposed system’s performance

was evaluated in a simulated IoT network environment built using Docker, utilizing a combination of the IoT23 and To\_IoT datasets. The dataset was split into 60% training, 20% validation, and 20% testing to ensure a balanced evaluation of the model’s generalization capabilities. The experiments were conducted using an L4 GPU with 24GB of memory, ensuring efficient execution of the LLM. The BERT Small language model was employed for the detection phase, benefiting from its lightweight architecture, which is well-suited for resource-constrained IoT environments. For the prevention phase, a Decision Tree-based approach was used to mitigate detected

threats, providing a computationally efficient and interpretable method for real-time response. For a model outputting logits  $z_1, z_2, \dots, z_{21}$  for 21 classes, the softmax function converts these logits into probabilities as follows:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{21} e^{z_j}}, \quad \text{for } i = 1, 2, \dots, 21.$$

Here,  $\hat{y}_i$  represents the predicted probability for class  $i$ . The cross-entropy loss is defined as:

$$\mathcal{L}(y, \hat{y}) = - \sum_{c=1}^{21} y_c \log(\hat{y}_c)$$

where  $y_c$  is the true label indicator (1 if the class is the correct class, 0 otherwise).

Micro F1 score aggregates the contributions of all classes by summing up the individual true positives, false positives, and false negatives:

$$\text{Micro-F1} = \frac{2 \cdot \sum_{i=1}^{21} \text{TP}_i}{2 \cdot \sum_{i=1}^{21} \text{TP}_i + \sum_{i=1}^{21} \text{FP}_i + \sum_{i=1}^{21} \text{FN}_i}.$$

Where  $\text{TP}_i$  (true positives) are the correctly predicted instances of class  $i$ ,  $\text{FP}_i$  (false positives) are the instances incorrectly predicted as class  $i$ , and  $\text{FN}_i$  (false negatives) are the instances of class  $i$  that were not correctly predicted. Figures 3, 4, and 5 present the confusion matrix for the evaluation of our LLMs on the test set, providing a detailed visualization of classification performance across 21 distinct classes. BERT Small generally achieves the strongest performance, evidenced by its consistently darker diagonal and fewer off-diagonal confusions across most labels, compared to BERT Mini and Tiny BERT. BERT Mini delivers moderate accuracy, with a slightly lighter diagonal and some notable misclassifications for particular classes. Despite differences in accuracy, all three models show greater success on high-frequency classes (reflected by darker blocks along the diagonal) and struggle more with less frequent classes, suggesting that both model size and label frequency influence classification outcomes.

## V. CONCLUSION

This paper presents an innovative LLM-based framework for IoT threat detection and prevention, addressing the increasing security challenges in interconnected IoT environments. The proposed system leverages the adaptability and contextual understanding of LLMs to enhance anomaly detection and automated response mechanisms. Through fine-tuning IoT-specific datasets, including IoT-23 and TON\_IoT, the system achieves superior detection accuracy and robustness against evolving cyber threats. The experimental evaluation, conducted within a Docker-based simulation environment, demonstrates the system's effectiveness in detecting sophisticated attacks while maintaining computational efficiency. The results highlight the advantages of LLM-driven security solutions over traditional machine learning and rule-based intrusion detection systems, particularly in their ability to generalize across diverse IoT

scenarios. Despite the promising outcomes, challenges remain in optimizing model deployment for real-time applications, ensuring computational efficiency on resource-constrained IoT devices, and improving adversarial robustness. The modular and lightweight nature of the proposed framework positions it for practical deployment in real-world IoT infrastructures, where resource constraints and rapid threat adaptation are critical. This work lays a foundation for scalable and autonomous IoT security solutions powered by advanced AI models. Future work will focus on expanding the framework to support real-time federated learning for decentralized IoT security, enhancing interpretability through XAI techniques, and integrating the system into operational IoT environments for large-scale validation.

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