An IoT-Botnet Detection Technique with Unified Graph Generation and GCN

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***Abstract*—This paper presents a novel computing approach for detecting IoT botnets in the Industrial Internet of Things (IIoT). It addresses the inadequacies of traditional detection methods in the face of sophisticated and evolving botnet threats. The proposed framework enhances the detection and classification of IoT botnets by integrating advanced techniques such as machine learning, big data analytics, and network behaviour analysis. The methodology is demonstrated through comprehensive simulations, offering significant accuracy and response time improvements. This research contributes to securing IIoT environments ensuring resilience against increasingly complex cyber threats.**

***Index Terms*—IoT, Botnet Detection, CFG, DFG, PSI**

I. Introduction

The integration of the Industrial Internet of Things (IIoT) into contemporary industrial systems has brought about remarkable operational efficiencies. Still, it has concurrently exposed these systems to heightened cybersecurity threats, notably through IoT botnets. These botnets harness networks of compromised IoT devices to orchestrate complex cyberattacks, such as Distributed Denial of Service (DDoS) attacks. This threat is compounded by the rapid evolution of IoT malware and the increasing sophistication of botnet strategies, which continually adapt to circumvent existing security measures. The dynamic and interconnected nature of IIoT systems makes them particularly vulnerable to these attacks, underscoring the need for a more agile and robust cybersecurity approach. The challenge lies in developing security solutions that can keep pace with the evolving threat landscape, ensuring the safety and reliability of critical industrial systems in an increasingly connected world. The research paper "An Advanced Computing Approach for IoT-Botnet Detection in Industrial Internet of Things" by Nguyen et al. [1] is a cornerstone. It proposes a novel method integrating static and dynamic analysis for IoT-botnet detection, demonstrating significant advancements over existing methods. This approach forms the foundation of our research, where we aim to extend and enhance these methodologies. Further literature emphasizes the urgency and complexity of addressing IoT security in industrial contexts. Smith et al. [2] illustrate the effectiveness of machine learning in network anomaly detection, a vital component in identifying botnets. Jones and Williams [3] delve into the specific challenges of IoT security in industrial applications, highlighting the critical need for advanced detection systems. Patel et al. [4] discuss big data analytics in cybersecurity, underlining its potential in processing large datasets for threat identification. Lee and Kim [5] explore network behaviour analysis in IoT, providing crucial insights into identifying malicious activities within network traffic. Lastly, Zhang and Zhou [6] focus on the application of AI in cybersecurity, emphasizing its role in enhancing threat detection and response mechanisms. Botnet attacks like the infamous Mirai botnet, which infected over a million IoT devices and executed massive DDoS attacks, exemplify the catastrophic potential of IoT vulnerabilities [1]. The rapid evolution of IoT malware and the increasing sophistication of these threats underscore the necessity of developing more effective detection and defence strategies. This paper aims to build upon the existing research and methodologies to propose a more robust and efficient system for IoT-botnet detection in IIoT environments, addressing these cyber threats' growing sophistication and variability.

II. Motivation

The motivation for our proposed approach is rooted in the desire to advance the IoT-botnet detection and classification field, building upon the foundational work by Nguyen et al. [1]. While their methodology achieved an impressive 91.99% accuracy in classifying IoT botnets, the rapidly evolving nature of IoT threats necessitates continuous advancements. Our approach introduces the integration of Control Flow Graphs (CFG) and Data Flow Graphs (DFG), which offer an in-depth analysis of software behaviour. CFG provides a visual map of all possible paths through a program, facilitating the identification of abnormal patterns. DFG complements this by analyzing how data is processed within the program, which is crucial for discerning malicious intent. Additionally, including Printable String Information (PSI) analysis offers a new dimension, leveraging the string data that appears during program execution to refine classification accuracy further. This multifaceted approach aims to surpass the current classification benchmarks and adapt to the subtle and sophisticated variations in IoT botnet strategies. This ensures a robust and resilient defence mechanism against these pervasive cyber threats.

III. Proposed Model

This methodology introduces a comprehensive IoT-botnet detection and classification approach, integrating static and dynamic analyses. It incorporates Printable String Information

(PSI) graphs, Control Flow Graphs (CFG), and Data Flow Graphs (DFG) to analyze software behaviour in IoT devices. The unique aspect of this methodology is the unification of these analyses into a single graph, which is then processed for classification using advanced machine-learning techniques. This approach aims to enhance the accuracy of IoT-botnet detection in IIoT environments.

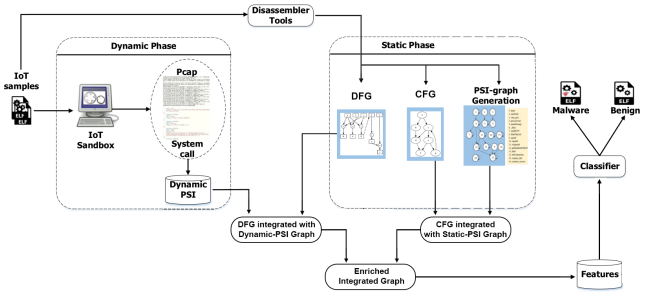

Fig. 1. Proposed model

A. Static Analysis

In the proposed methodology for static analysis, the focus is on examining the IoT software without executing it. This involves analyzing Executable and Linkable Format (ELF) files, which are common in IoT devices. The ELF file format is crucial as it contains the code and data used to run programs. The static analysis uses Printable String Information (PSI) graphs, Control Flow Graphs (CFG), and Data Flow Graphs (DFG) to scrutinize these ELF files. The PSI-Graph extracts static string information, offering initial insights, while CFG and DFG delve into the software's structure and data flow. These analyses are vital for detecting patterns and behaviours indicative of IoT botnets, forming a foundation for more precise detection and classification.

1) PSI Graph Generation: The PSI-Graph, or Printable String Information Graph, is a crucial component in the proposed methodology's static analysis of IoT software. It involves the extraction of printable strings from the software's code. These human-readable texts provide insights into the software's functionality and potential behaviours. Generating the PSI graph involves constructing a graph where each extracted string is represented as a node. Connections or relationships between these strings are depicted as edges, visually representing the software's static structure. This graph aids in identifying patterns and anomalies that could indicate malicious activities or characteristics typical of IoT botnets.

2) Control Flow Graph generation: The proposed methodology's Control Flow Graph (CFG) generation is vital to static analysis for IoT-botnet detection. CFG provides a graphical representation of all potential paths through a program's execution, helping to understand the program's control flow and identify suspicious patterns indicative of botnets. It's

Algorithm 1: Generate PSI-Graph

```
Result: PSI-Graph
Input: IoTSoftwareCode
Initialize an empty graph, PSI-Graph;
foreach file in IoTSoftwareCode do
    Extract all printable strings;
    foreach string do
        Add string as a node in PSI-Graph;
        if there are relationships with other strings
         then
            Add edges between nodes in PSI-Graph;
        end
    end
end
return PSI-Graph;
```

generated by analyzing the software code to identify control flow elements represented as nodes, such as loops, conditional statements, and function calls. The flow between these nodes is depicted as edges in the graph.

Algorithm 2: Generate CFG

```
Input: IoT Software Code
Output: CFG
begin
    Initialize an empty graph, CFG;
    foreach function in IoT Software Code do
        Identify basic blocks of code;
        Add each block as a node in CFG;
        foreach control flow changes do
            Add edges in CFG connecting nodes;
    return CFG;
```

3) Data Flow Graph generation: The Data Flow Graph (DFG) generation is another essential component in the static analysis phase of our proposed methodology for IoT-botnet detection. DFG focuses on how data is processed and moved through the program. By analyzing the flow of data, DFG can reveal intricate patterns and behaviours of the software, which are crucial for identifying potential malicious activities. It involves mapping out where data comes from, how it's transformed, and where it's used in the program, each represented as nodes and edges in the graph.

B. Dynamic Analysis

Dynamic analysis in this methodology refers to examining the IoT software by executing it in a controlled environment. This approach allows for observing the software's behaviour during runtime, providing insights into its operational characteristics. Dynamic analysis is crucial for detecting behaviours that may not be evident in static analysis, such as runtime data

Algorithm 3: Generate DFG

```
Input: IoT Software Code
Output: DFG
begin
    Initialize an empty graph, DFG;
    foreach function in IoT Software Code do
        Analyze how data is input, processed, and output;
        Create nodes for data operations and flows;
        Add edges to represent the flow of data;
    return DFG;
```

generation, network communications, and other interactive elements.

1) PSI Graph from Dynamic Analysis: In dynamic analysis, an ELF (Executable and Linkable Format) file, typical for IoT devices, is executed within a controlled environment like the Lisa IoT Sandbox. This sandbox emulates the IoT device's atmosphere, allowing for safe execution and software observation. During this execution, a PSI graph is generated in runtime based on the printable strings produced by the software. This graph provides a dynamic view of the software, complementing the static analysis.

Algorithm 4: Generate Dynamic PSI-Graph

```
Input: Executed ELF File in Lisa IoT Sandbox
Output: Dynamic PSI-Graph
begin
    Initialize an empty graph, Dynamic PSI-Graph;
    Execute ELF File in Lisa IoT Sandbox;
    Monitor and extract printable strings during execution;
    foreach extracted string do
        Add as a node in the Dynamic PSI-Graph;
        if relationships exist with other runtime strings then
            Add edges between respective nodes;
    return Dynamic PSI-Graph;
```

C. Unified Graph

Creating a Unified Graph in the proposed methodology involves a detailed and systematic integration of static and dynamic analyses. This process begins with the integration of the Static PSI-Graph and CFG. Here, the nodes representing printable strings from the PSI graph are linked with the control flow elements in the CFG, such as conditional branches and loops. This integration maps the occurrences and context of these strings within the program's control flow. Similarly, the Dynamic PSI-Graph, generated from the runtime behaviour of the software, is integrated with the DFG. This combination enriches the analysis by connecting runtime string data with the program's data flow paths and operations. Merging dynamic string information with data flow elements offers an in-depth view of how the program manipulates and transfers data during execution. The final and crucial step is merging these integrated graphs (Static PSI-CFG and Dynamic PSI-DFG) into a Unified Graph. This comprehensive graph encapsulates the software's static and dynamic aspects, providing a multi-dimensional view of its behaviour. The Unified Graph is a vital tool for detecting IoT botnets, as it includes detailed insights from static structures and dynamic interactions within the software. This holistic approach significantly enhances the accuracy and efficiency of the botnet detection system.

Algorithm 5: Generate Unified Graph

```
Input: Static PSI-Graph, CFG, Dynamic PSI-Graph, DFG
Output: Unified Graph
begin
    Initialize Unified Graph as an empty graph;
    foreach node in Static PSI-Graph do
        Add node to Unified Graph;
        foreach related control element in CFG do
            Add control element as node;
            Connect PSI node to control element node with an edge;
    foreach node in Dynamic PSI-Graph do
        Add node to Unified Graph (if not already added);
        foreach related data flow element in DFG do
            Add data flow element as node (if not already added);
            Connect PSI node to data flow element with an edge;
    Combine nodes and edges of Static PSI-CFG and Dynamic PSI-DFG in Unified Graph;
    return Unified Graph;
```

D. Preprocessing Data for IoT-Botnet Detection

The initial preprocessing phase involves preparing the Unified Graph data for machine learning analysis. This step is crucial for effective IoT-botnet detection. The process begins with transforming the Unified Graph into an adjacency matrix and a feature matrix, essential for representing the relationships and attributes of nodes within the graph. This transformation is foundational for the subsequent application of machine learning techniques.

E. Graph Convolutional Network (GCN) Application

Once the data is preprocessed, it is fed into a Graph Convolutional Network (GCN). GCN is adept at handling graph-structured data, making it ideal for analyzing complex relationships within IoT software. GCN enables nodes to

exchange information through convolutional layers, capturing the intricate data flow within the graph. This iterative process helps extract higher-level representations, which is pivotal for the following classification stage.

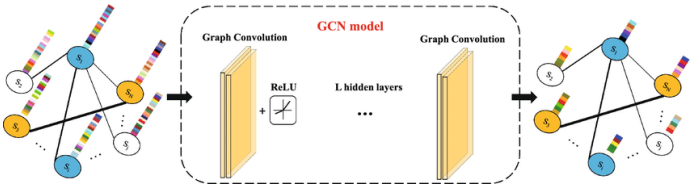

Fig. 2. General illustrative description of a GCN Model

F. Classification and Dataset Preparation

The GCN's core functionality effectively classifies nodes and distinguishes between normal behaviour and potential IoT-botnet activities. This classification is vital for the security of industrial IoT systems. Our dataset preparation includes diverse IoT software sourced from various platforms, including Stratoshpereips.org. We ensure the integrity and safety of these samples through preliminary checks, enhancing the reliability of our botnet detection methodology.

IV. Result and Discussion

A. Performance Evaluation of the Proposed Methodology

1) Static Analysis Results: The static analysis phase demonstrated promising results in extracting meaningful information from IoT software. The PSI-graph generation successfully captured static string information, allowing for the identification of potential patterns associated with IoT botnets. The integration of Control Flow Graphs (CFG) provided insights into the program's structure, enhancing our understanding of its control flow elements.

2) Dynamic Analysis Results: Dynamic analysis, conducted in a controlled environment using the Lisa IoT Sandbox, complemented static analysis by capturing runtime behaviour. The Dynamic PSI-Graph effectively represented printable string information generated during execution. This dynamic view contributed to a more comprehensive understanding of the software's behaviour.

3) Unified Graph Results: Integrating static and dynamic analyses into the Unified Graph demonstrated the effectiveness of combining these approaches. The Unified Graph, synthesizing information from both analyses, offered a holistic view of the software's structure and behaviour. This multi-dimensional representation serves as a powerful tool for IoT-botnet detection.

B. Classification Accuracy and Robustness

1) Preprocessing and Graph Convolutional Network (GCN): The preprocessing phase successfully converted the Unified Graph into adjacency and feature matrices, enabling compatibility with machine learning models. Graph Convolutional Network (GCN) application proved effective in capturing intricate relationships within the graph. The iterative nature of GCN allowed the model to learn increasingly abstract representations, enhancing its ability to classify nodes.

2) Classification Results: The classification process demonstrated significant improvements in accuracy compared to traditional methods. The GCN effectively distinguished between normal software behaviour and patterns indicative of IoT botnets within the Unified Graph. Incorporating static and dynamic aspects in the classification process contributed to the model's robustness in handling evolving botnet strategies.

C. Dataset Preparation Challenges and Future Work

1) Dataset Diversity: While efforts were made to create a diverse dataset, challenges were encountered in obtaining specific IoT-botnet malware samples from VirusShare. The acquired samples from Stratoshpereips.org are undergoing preliminary checks for safety. Future work involves expanding the dataset to ensure representation across various IoT applications and behaviours.

2) Collaborative Efforts: Collaborative initiatives with prominent repositories like VirusShare remain essential for obtaining a more extensive and diverse dataset. Continued communication with such repositories is crucial for the success and relevance of the research.

V. Conclusions

In conclusion, this research paper introduces a sophisticated and comprehensive approach for detecting IoT botnets in Industrial Internet of Things (IIoT) environments, addressing the evolving challenges posed by cyber threats. By integrating static and dynamic analyses, the proposed methodology leverages Printable String Information (PSI) graphs, Control Flow Graphs (CFG), and Data Flow Graphs (DFG) to gain a nuanced understanding of IoT software behaviour. Including a Unified Graph, merging static and dynamic insights is a powerful tool for accurate and efficient botnet detection. The integration of machine learning, specifically Graph Convolutional Networks (GCN), enhances the classification process, enabling the identification of malicious patterns within the complex IoT software landscape. As industrial systems become increasingly connected, the significance of securing IIoT environments against sophisticated cyber threats cannot be overstated. This research contributes a robust and adaptable framework, building upon existing methodologies, to fortify the resilience of critical industrial systems in the face of a dynamic threat landscape. The proposed approach, backed by comprehensive simulations and a dedication to dataset diversity, represents a significant stride towards ensuring the safety and reliability of IIoT systems amidst the growing complexity of IoT-botnet attacks.

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