



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

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ABSTRACT

This paper addresses the critical issue of safeguarding Internet of Things (IoT) devices from two significant threats: Botnet attacks and Distributed Denial of Service (DDoS) attacks. These malicious activities can disrupt the functionality of our devices and compromise their security. Our innovative solution employs advanced monitoring techniques to constantly observe network behaviour. By learning from normal patterns, it swiftly identifies anomalies indicative of Botnet or DDoS attacks, enabling prompt intervention. Moreover, our system continuously adapts and evolves to counter emerging threats effectively. Through rigorous testing across various environments, we have demonstrated the robustness and reliability of our approach. Ultimately, this project contributes to enhancing the security posture of IoT ecosystems, ensuring a safer digital environment for all users.

Keywords: Internet of Things (IoT), Cybersecurity, Botnet Attacks, Distributed Denial of Service (DDoS) attacks, Machine Learning, Anomaly Detection, Threat Intelligence, Real-Time Detection.

1 Introduction

The rapid proliferation of IoT networks and applications has brought about both significant advancements and numerous challenges. Among these challenges is the detection of behavioural anomalies indicative of attacks on IoT networks. The resilience of IoT networks depends on the evaluation of both Internet and Intranet systems, leading to operations across private and public networks. The success of IoT and the Internet stems from their openness to new applications, which, while facilitating access to various services, also introduces sensitive discriminatory consequences.

Reports from the Computer Emergency Response Team (CERT) highlight that many IoT attacks exploit vulnerabilities, necessitating robust security mechanisms to address current demands. Researchers have contributed to enhancing security standards through encryption, authentication schemes, firewall implementations, and antivirus solutions. Firewalls, for



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

instance, enforce predefined rules to monitor and control the flow of packets within networks, allowing or denying access based on these rules.

Intrusion Detection Systems (IDS) play a crucial role in monitoring network traffic for suspicious activity, particularly concerning botnet-related threats. Botnets, utilized extensively by cybercriminals, pose a diverse and evolving threat, complicating efforts to combat cybercrime. Various attacks, such as Distributed Denial of Service (DDoS), leverage vulnerabilities in IoT devices, causing disruptions and financial losses for organizations. Addressing these challenges requires innovative approaches, particularly in the realm of botnet detection and defense mechanisms.

Traditional security measures, including firewalls and IDS, face limitations in detecting and mitigating sophisticated attacks, such as request floods. Deep packet inspection strategies used in IDS may struggle to distinguish between normal and malicious traffic, underscoring the need for more effective solutions. Proposed mechanisms, such as the Botnet Attack Detection and Defense (BADD) system, leverage supervised learning algorithms to analyze traffic flow features and predict botnet attacks in real-time.

Botnet attacks orchestrated through coordinated efforts pose significant challenges due to their decentralized nature, making attribution difficult. Preventive measures against botnets have been studied extensively, with researchers exploring countermeasures against different botnet topologies, including Internet Relay Chat (IRC)-based and Peer-to-Peer (P2P) botnets. However, existing approaches often focus on damage control rather than fundamental problem-solving, highlighting the ongoing need for innovative solutions to mitigate the botnet threat effectively. By examining botnet features and existing research, this paper aims to address open issues in botnet detection and prevention, ultimately enhancing the security of IoT networks and mitigating the broader threat landscape posed by coordinated cyberattack.

2 Literature Survey

1. X. Wang, Y. Liu, Machine Learning-Based Intrusion Detection Systems for IoT: A Comparative Analysis. This paper compares various machine learning-based intrusion detection systems applied to IoT environments. It evaluates the performance of algorithms such as decision trees, support vector machines, and neural networks in detecting malicious activities. The study emphasizes the need for adaptive models that can evolve with changing attack patterns.
2. Smith, B. Johnson, A Survey of Botnet Detection Techniques in IoT Networks: This paper provides an extensive survey of various techniques employed for detecting Botnet activities in IoT networks. It explores the use of machine learning, signature-based methods, and anomaly detection, offering insights into their effectiveness in identifying and mitigating Botnet threats. The study evaluates the advantages and challenges associated with each technique and highlights the importance of a



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

comprehensive approach to address the dynamic nature of Botnet attacks in IoT environments.

3. Z. Chen, H. Wang, Challenges and Opportunities in IoT Security: This review paper provides a holistic overview of security challenges in IoT, including a section on potential threats like Botnets and DDoS attacks. It discusses the importance of securing communication channels, device authentication, and the integration of anomaly detection techniques. The study explores both technical and non-technical aspects of IoT security.
4. M. Patel, S. Gupta, Enhancing IoT Security through Collaborative Threat Intelligence Sharing: This paper focuses on the importance of collaborative threat intelligence sharing in bolstering IoT security. It discusses the role of information sharing platforms, standards, and protocols in creating a collective defense against cyber threats. The study highlights the benefits of a collaborative approach in detecting and responding to emerging threats in real-time.

3 Existing System

In the existing project Deep learning systems can be effective at detecting intrusions, but they can also be less accurate than traditional methods. Deep learning models are trained on large amounts of data, and if the training data does not include a wide variety of attacks, the system may be less effective at detecting new or unknown attacks. Deep learning systems can also generate a high number of false positives, which means that the system may identify normal traffic as malicious. Because deep learning models are complex, it can be difficult to understand how they arrive at their decisions. This can make it difficult to debug the system or to explain why it has made a particular classification. They can be difficult to interpret. This can make it difficult to understand why a particular intrusion is detected and how to improve the accuracy of the system. They can be vulnerable to adversarial attacks. These are attacks that are designed to fool the system into making a wrong decision. Despite these disadvantages, deep learning intrusion detection systems are a promising new approach to network security. As deep learning models continue to develop, they are likely to become more accurate and efficient.



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

3.1 Existing System Block Diagram:

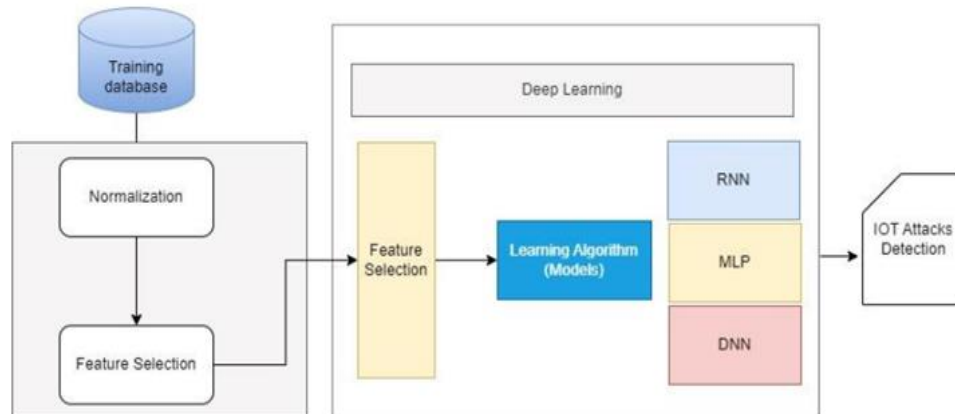


Figure 1: Block diagram of Malicious Intrusion detection of deep learning model.

3.2 Drawbacks

- Real-Time Detection Deficiency
- Limited Integration of Threat Intelligence
- Neglect of IoT-Specific Challenges
- Inadequate Adaptability to Dynamic Threats
- Scalability Concerns in Large-Scale IoT Environments
- Lack of Specificity in Machine Learning Approaches
- Overarching Security Challenges vs. Specific Threats

4 Proposed System

To address the identified challenges in real-time detection of malicious intrusions and attacks, specifically focusing on Botnet and DDoS threats in IoT-enabled cybersecurity infrastructures, a comprehensive solution is proposed. The multifaceted approach integrates advanced technologies, collaborative frameworks, and adaptive methodologies to enhance the resilience of IoT ecosystems. The training corpus of IoT network transactions contains a set of records such that each record represents a user session. The attributes represent these records may vary from one corpus to others, but each record represents a user session. The proposed model is a machine learning technique that performs simple binary classification through supervised learning. The method performs in two phases, and they are the learning phase and classification phase.



Article Title: **Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure**

4.1 Proposed System

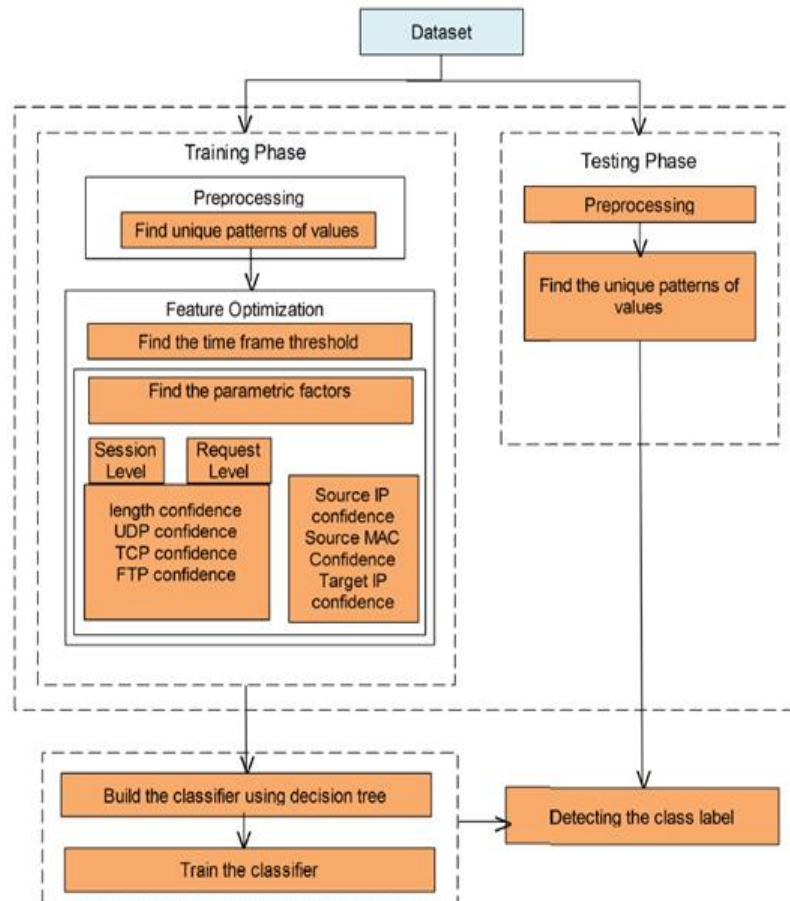


Figure 2: Block diagram of Botnet & DDoS Detection System.

The learning phase performs on the given corpus of labeled records. proposing a set of parametric features, which are derived from the network transactions of the fixed time frames. Hence, the proposal initially prepares the training corpus from the given labeled records.

- The dataset
- Discovering Time Frame Threshold
- The Parametric Factor
- Training Data preparation

4.2 Implementation

- Botnet attacks Detection and Defense

The learning phase of the proposal that builds a simple binary classifier using the values of the optimal parametric features.

1) Training Phase (build the classifier)



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

- 2) Defining Hierarchy of the features by Information Gain
- 3) Assessing the Class Label (Detection Phase)
 - Performance Analysis

The proposed BADD method is compared with the other contemporary methods called N-BaIoT BIFAD and MEC-shield in terms of mode significance and scalability. Here, this is attained by cross-validation factors like TNR, TPR, PPV, NPV, FPR, FNR, Accuracy, misclassification rate.

4.3 System Requirements

A. Anaconda



Figure 3: *Anaconda Software .*

Anaconda version 3.6.8 is a milestone release, boasting improved compatibility across operating systems for seamless installation. This update enhances essential libraries like NumPy, pandas, and scikit-learn, optimizing performance and introducing new features. The package management system, powered by Conda, streamlines dependency management and workflow. Security measures are bolstered to safeguard data and projects against vulnerabilities. Overall, Anaconda strengthens its standing as a premier data science platform, offering robust tools and a user-friendly interface for professionals.

B. Spyder IDE



Figure 4: *Spyder Integrated Development Environment.*



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

Spider IDE is tailored for Python and data science, featuring a user-friendly interface and rich features for efficient coding and analysis. Its customizable workspace boosts productivity, while bundled tools support data exploration and visualization. Integration with key libraries like NumPy and pandas streamlines development, and its built-in IPython console facilitates interactive prototyping. Spider supports robust debugging with step-by-step execution and variable inspection. It also seamlessly integrates with Jupyter Notebooks, enhancing collaboration and reproducibility. Overall, Spider IDE is a versatile environment, ideal for both beginners and experienced data professionals.

C. Jupyter Notebook



Figure 5: *Jupyter Notebook*

Jupyter Notebook is a web-based platform for creating interactive documents combining live code, text, and visualizations. Primarily used with Python, it supports multiple languages and integrates with libraries like NumPy and pandas. Its cell-based interface promotes dynamic, iterative analysis, enhancing collaboration and reproducibility. Users can execute code individually or collectively for interactive data exploration. The platform's interactive plotting and widget capabilities allow for dynamic visualizations and custom user interfaces. Supporting LaTeX and HTML, it enables rich, expressive documents with math and multimedia. Overall, Jupyter Notebook revolutionizes how professionals interact with code and data.

D. Anaconda Prompt

Anaconda Prompt is a command-line interface in Anaconda, streamlining Python package and environment management. Integrated with Conda, it simplifies package installation and version control, ensuring consistency across projects. Users can create isolated environments for multiple projects, maintaining integrity and facilitating collaboration. With compatibility across Windows and Unix systems, it offers a consistent user experience. It supports command-line utilities like Git and pip, enabling tasks such as version control and package installation.



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

Additionally, it allows scripting and automation for custom workflows and increased productivity. Overall, Anaconda Prompt is an essential, powerful tool for Python and data science tasks.

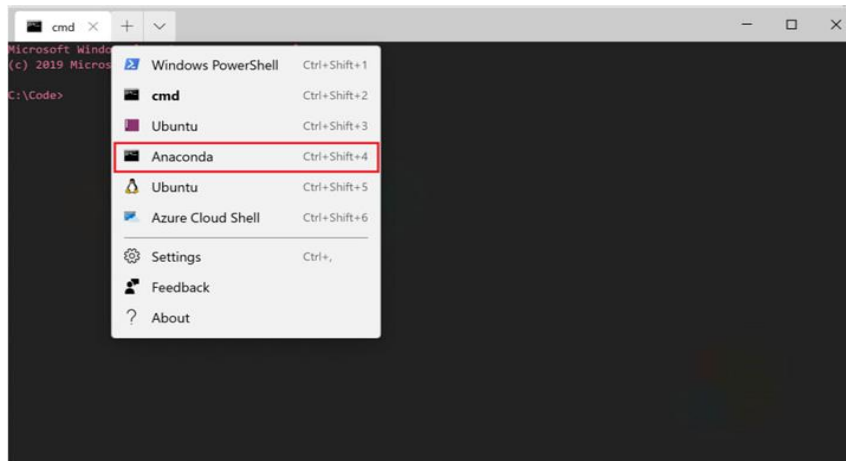


Figure 6: Anaconda prompt.

5 Result and Discussion

5.1 Execution

```

Anaconda Prompt - python 1
(base) C:\Users\vadde>cd Downloads
(base) C:\Users\vadde\Downloads>cd "CODE IOT Attack"
The system cannot find the path specified.
(base) C:\Users\vadde\Downloads>cd "CODE IOT-Attack"
(base) C:\Users\vadde\Downloads\CODE IOT-Attack>dir
Volume in drive C is OS
Volume Serial Number is 3A77-0824

Directory of C:\Users\vadde\Downloads\CODE IOT-Attack

30-03-2024 07:04 <DIR> .
28-03-2024 05:36 <DIR> ..
13-03-2024 09:53 <DIR> ..ipynb_checkpoints
13-03-2024 08:48 <DIR> 9,248 BADD_Train.py
13-03-2024 08:48 8,476 Botnet_Attack.py
21-04-2020 08:07 17,988 correlation.xlsx
13-03-2024 09:53 <DIR> Data
21-04-2020 08:07 26,766 factor-analysis.xlsx
13-03-2024 08:42 <DIR> Plots
21-04-2020 08:07 12,929,449 test_data.csv
21-04-2020 08:07 245,822 test_target.csv
13-03-2024 08:09 17,971 train.py
21-04-2020 08:07 13,498,347 train_data.csv
21-04-2020 08:07 245,999 train_target.csv
13-03-2024 09:02 92,281,952 UNSW_2018_IoT_Botnet_Final_10_best_Testing.csv
13-03-2024 09:02 369,183,929 UNSW_2018_IoT_Botnet_Final_10_best_Training.csv
11 File(s) 489,282,839 bytes
5 Dir(s) 216,163,858,880 bytes free

(base) C:\Users\vadde\Downloads\CODE IOT-Attack>python BADD_Train.py
Importing libraries
2024-04-01 07:28:12.4085366: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to flo
ating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
2024-04-01 07:28:14.858422: I tensorflow/core/util/port.cc:113] oneDNN custom operations are on. You may see slightly different numerical results due to flo
ating-point round-off errors from different computation orders. To turn them off, set the environment variable 'TF_ENABLE_ONEDNN_OPTS=0'.
Reporting and Preprocessing of data
train_data shape: (82331, 41)

```

Figure 7: The Execution of the System in the Anaconda prompt.

- First search for Anaconda prompt in searchbar
- Then click the Anaconda prompt and the run the program
- Change the path directory using command cd to downloads
- Again change path directory to the CODE IOT ATTACK folder
- Then run the python program as command PYTHON BADD_Train.py



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

```

test_target: 0.9999... (11/17)...
Defining our experiment workflow
Determine the best number of epochs by running the model with 100 epochs and seeing where it starts to overfit
2024-04-01 07:20:27.838593: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instructions in pe
formance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
Iteration 1
2573/2573 ----- 6s 2ms/step - accuracy: 0.7079 - loss: 0.7773
2537/2537 - 4s - 1ms/step - accuracy: 0.6708 - loss: 0.4549
Iteration 2
2573/2573 ----- 5s 2ms/step - accuracy: 0.8252 - loss: 0.5987
2537/2537 - 3s - 1ms/step - accuracy: 0.8018 - loss: 0.4662
Iteration 3
2573/2573 ----- 5s 2ms/step - accuracy: 0.8334 - loss: 0.4696
2537/2537 - 3s - 1ms/step - accuracy: 0.8701 - loss: 0.5839
Iteration 4
2573/2573 ----- 4s 1ms/step - accuracy: 0.8418 - loss: 0.4587
2537/2537 - 3s - 1ms/step - accuracy: 0.8762 - loss: 0.5133
Iteration 5
2573/2573 ----- 4s 1ms/step - accuracy: 0.8464 - loss: 0.4338
2537/2537 - 4s - 2ms/step - accuracy: 0.8797 - loss: 0.5399
Iteration 6
2573/2573 ----- 4s 1ms/step - accuracy: 0.8462 - loss: 0.4249
2537/2537 - 3s - 1ms/step - accuracy: 0.8793 - loss: 0.5302
Iteration 7
2573/2573 ----- 3s 1ms/step - accuracy: 0.8486 - loss: 0.4244
2537/2537 - 3s - 1ms/step - accuracy: 0.8888 - loss: 0.5188
Iteration 8
2573/2573 ----- 3s 1ms/step - accuracy: 0.8486 - loss: 0.4132
2537/2537 - 3s - 1ms/step - accuracy: 0.8884 - loss: 0.5397
Iteration 9
2573/2573 ----- 3s 1ms/step - accuracy: 0.8519 - loss: 0.4066
2537/2537 - 3s - 1ms/step - accuracy: 0.8734 - loss: 0.6490
Iteration 10
2573/2573 ----- 4s 2ms/step - accuracy: 0.8528 - loss: 0.4066
2537/2537 - 3s - 1ms/step - accuracy: 0.8748 - loss: 0.5951
Iteration 11
2573/2573 ----- 3s 1ms/step - accuracy: 0.8557 - loss: 0.3946
2537/2537 - 3s - 1ms/step - accuracy: 0.8789 - loss: 0.6624
Iteration 12
2573/2573 ----- 3s 1ms/step - accuracy: 0.8522 - loss: 0.3959
    
```

Figure 8: Model 1 running.

```

Model 2
Adam optimizer and Gaussian noise layer
Iteration 1
2573/2573 ----- 2s 620ms/step - accuracy: 0.7421 - loss: 0.7738
2537/2537 - 1s - 530ms/step - accuracy: 0.8543 - loss: 0.5385
Iteration 2
2573/2573 ----- 2s 610ms/step - accuracy: 0.8227 - loss: 0.5324
2537/2537 - 1s - 585ms/step - accuracy: 0.8643 - loss: 0.4983
Iteration 3
2573/2573 ----- 2s 610ms/step - accuracy: 0.8337 - loss: 0.4689
2537/2537 - 1s - 511ms/step - accuracy: 0.8738 - loss: 0.4939
Iteration 4
2573/2573 ----- 2s 610ms/step - accuracy: 0.8415 - loss: 0.4448
2537/2537 - 1s - 517ms/step - accuracy: 0.8669 - loss: 0.5306
Iteration 5
2573/2573 ----- 2s 610ms/step - accuracy: 0.8439 - loss: 0.4368
2537/2537 - 1s - 505ms/step - accuracy: 0.8712 - loss: 0.5472
Iteration 6
2573/2573 ----- 2s 620ms/step - accuracy: 0.8451 - loss: 0.4233
2537/2537 - 1s - 505ms/step - accuracy: 0.8584 - loss: 0.5996
Iteration 7
2573/2573 ----- 2s 620ms/step - accuracy: 0.8438 - loss: 0.4279
2537/2537 - 1s - 505ms/step - accuracy: 0.8705 - loss: 0.5686
Iteration 8
2573/2573 ----- 2s 630ms/step - accuracy: 0.8512 - loss: 0.4891
2537/2537 - 1s - 585ms/step - accuracy: 0.8633 - loss: 0.6781
Iteration 9
2573/2573 ----- 2s 630ms/step - accuracy: 0.8513 - loss: 0.4874
2537/2537 - 1s - 585ms/step - accuracy: 0.8758 - loss: 0.6368
Iteration 10
2573/2573 ----- 2s 630ms/step - accuracy: 0.8525 - loss: 0.4827
2537/2537 - 1s - 511ms/step - accuracy: 0.8588 - loss: 0.7183
Iteration 11
2573/2573 ----- 2s 610ms/step - accuracy: 0.8535 - loss: 0.4813
2537/2537 - 1s - 505ms/step - accuracy: 0.8584 - loss: 0.6359
Iteration 12
2573/2573 ----- 2s 620ms/step - accuracy: 0.8513 - loss: 0.3989
2537/2537 - 1s - 511ms/step - accuracy: 0.8445 - loss: 0.7025
Iteration 13
88/2573 ----- 1s 710ms/step - accuracy: 0.8538 - loss: 0.4829
    
```

Figure 9: Model 2 running.



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

```

Aravind@pragati: python 8 x +
2537/2537 - 1s - 511us/step - accuracy: 0.8527 - loss: 0.6447
2537/2537 - 1s - 561us/step
Model 3 using Dense layer with relu activation function
Iteration 1
2573/2573 - 3s - 681us/step - accuracy: 0.7388 - loss: 0.7828
2537/2537 - 1s - 536us/step - accuracy: 0.8671 - loss: 0.5975
Iteration 2
2573/2573 - 2s - 681us/step - accuracy: 0.8271 - loss: 0.5639
2537/2537 - 1s - 499us/step - accuracy: 0.8864 - loss: 0.5334
Iteration 3
2573/2573 - 2s - 681us/step - accuracy: 0.8368 - loss: 0.4656
2537/2537 - 1s - 585us/step - accuracy: 0.8843 - loss: 0.4586
Iteration 4
2573/2573 - 2s - 687us/step - accuracy: 0.8394 - loss: 0.4469
2537/2537 - 1s - 585us/step - accuracy: 0.8769 - loss: 0.5378
Iteration 5
2573/2573 - 2s - 687us/step - accuracy: 0.8444 - loss: 0.4348
2537/2537 - 1s - 511us/step - accuracy: 0.8712 - loss: 0.5354
Iteration 6
2573/2573 - 2s - 688us/step - accuracy: 0.8488 - loss: 0.4175
2537/2537 - 1s - 585us/step - accuracy: 0.8679 - loss: 0.5728
Iteration 7
2573/2573 - 2s - 585us/step - accuracy: 0.8583 - loss: 0.4154
2537/2537 - 1s - 565us/step - accuracy: 0.8635 - loss: 0.3778
Iteration 8
2573/2573 - 2s - 681us/step - accuracy: 0.8516 - loss: 0.4847
2537/2537 - 1s - 585us/step - accuracy: 0.8588 - loss: 0.6295
Iteration 9
2573/2573 - 2s - 687us/step - accuracy: 0.8518 - loss: 0.4821
2537/2537 - 1s - 585us/step - accuracy: 0.8528 - loss: 0.6688
Iteration 10
2573/2573 - 2s - 687us/step - accuracy: 0.8561 - loss: 0.3948
2537/2537 - 1s - 585us/step - accuracy: 0.8614 - loss: 0.6579
Iteration 11
2573/2573 - 2s - 681us/step - accuracy: 0.8524 - loss: 0.3964
2537/2537 - 1s - 585us/step - accuracy: 0.8572 - loss: 0.7194
Iteration 12
2573/2573 - 2s - 681us/step - accuracy: 0.8568 - loss: 0.3893
2537/2537 - 1s - 565us/step - accuracy: 0.8491 - loss: 0.7396
Iteration 13
2573/2573 - 2s - 687us/step - accuracy: 0.8565 - loss: 0.3871
    
```

Figure 10: Model 3 running.

```

Aravind@pragati: python 8 x +
2573/2573 - 2s - 614us/step - accuracy: 0.8503 - loss: 0.3951
2537/2537 - 1s - 511us/step - accuracy: 0.8573 - loss: 0.6715
2537/2537 - 1s - 567us/step
Model 4 using Gaussian noise layer with Dense Layer with relu activation function
Iteration 1
2573/2573 - 3s - 658us/step - accuracy: 0.7381 - loss: 0.7972
2537/2537 - 1s - 567us/step - accuracy: 0.8512 - loss: 0.5636
Iteration 2
2573/2573 - 2s - 690us/step - accuracy: 0.8278 - loss: 0.5839
2537/2537 - 1s - 585us/step - accuracy: 0.8588 - loss: 0.5884
Iteration 3
2573/2573 - 2s - 644us/step - accuracy: 0.8136 - loss: 0.4894
2537/2537 - 1s - 511us/step - accuracy: 0.8655 - loss: 0.5170
Iteration 4
2573/2573 - 2s - 638us/step - accuracy: 0.8416 - loss: 0.4864
2537/2537 - 1s - 499us/step - accuracy: 0.8679 - loss: 0.5242
Iteration 5
2573/2573 - 2s - 644us/step - accuracy: 0.8435 - loss: 0.4318
2537/2537 - 1s - 585us/step - accuracy: 0.8695 - loss: 0.5545
Iteration 6
2573/2573 - 2s - 644us/step - accuracy: 0.8454 - loss: 0.4254
2537/2537 - 1s - 585us/step - accuracy: 0.8681 - loss: 0.6112
Iteration 7
2573/2573 - 2s - 658us/step - accuracy: 0.8458 - loss: 0.4246
2537/2537 - 1s - 585us/step - accuracy: 0.8588 - loss: 0.6332
Iteration 8
2573/2573 - 2s - 644us/step - accuracy: 0.8478 - loss: 0.4185
2537/2537 - 1s - 585us/step - accuracy: 0.8535 - loss: 0.6956
Iteration 9
2573/2573 - 2s - 658us/step - accuracy: 0.8514 - loss: 0.4848
2537/2537 - 1s - 499us/step - accuracy: 0.8484 - loss: 0.7686
Iteration 10
2573/2573 - 2s - 658us/step - accuracy: 0.8523 - loss: 0.4886
2537/2537 - 1s - 499us/step - accuracy: 0.8376 - loss: 0.8168
Iteration 11
2573/2573 - 2s - 658us/step - accuracy: 0.8524 - loss: 0.3948
2537/2537 - 1s - 585us/step - accuracy: 0.8488 - loss: 0.7211
Iteration 12
2573/2573 - 2s - 658us/step - accuracy: 0.8543 - loss: 0.3876
2537/2537 - 1s - 523us/step - accuracy: 0.8488 - loss: 0.7798
Iteration 13
    
```

Figure 11: Model 4 running



Article Title: **Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure**

5.3 Results

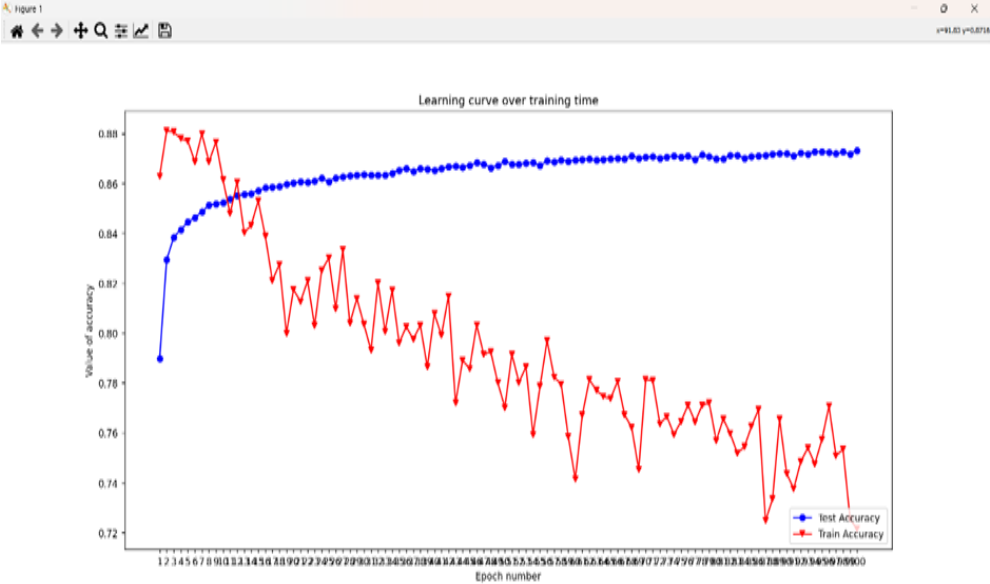


Figure 12: Graph of Training phase and Testing phase.

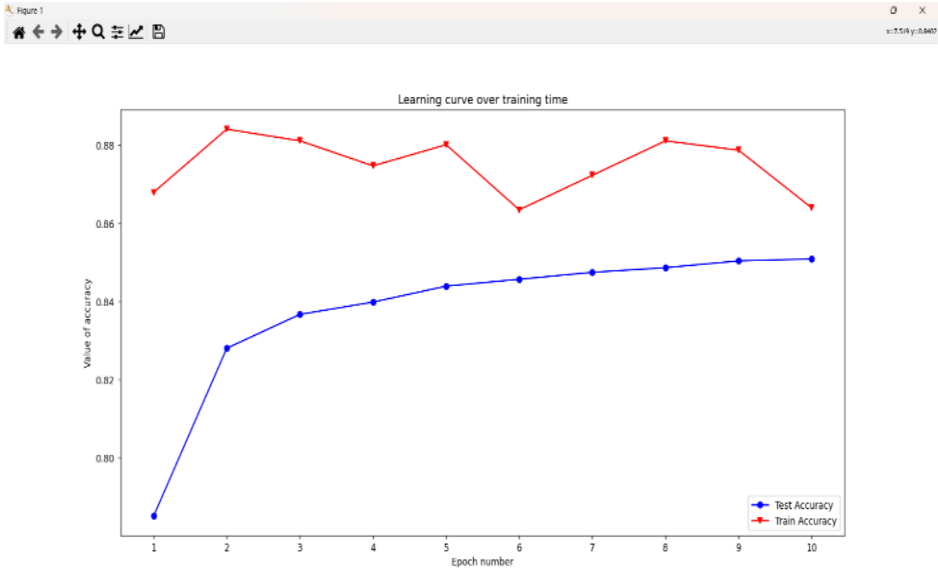


Figure 13: Graph of Training phase and Testing phase.



Article Title: **Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure**

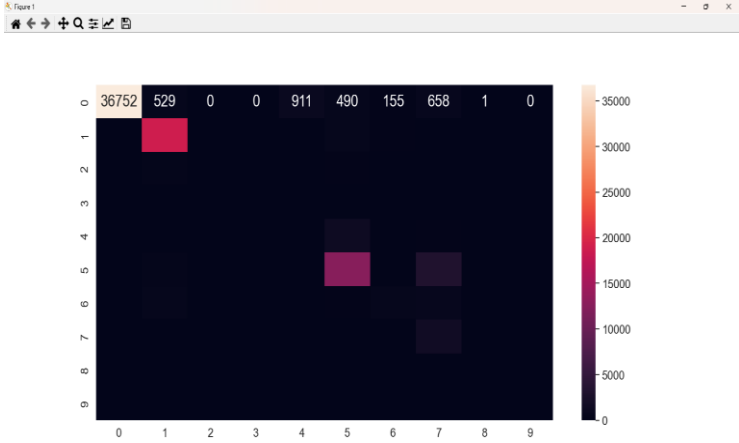


Figure 14: Confusion matrix.

```

(base) C:\Users\vadde\Downloads\CODE IOT-Attack>python Botnet_Attack.py
C:\Users\vadde\Downloads\CODE IOT-Attack\Botnet_Attack.py:65: FutureWarning: pandas.value_counts is deprecated and will be removed in a future version. Use
pd.Series(obj).value_counts() instead.
  count_class = pd.value_counts(data['Class'], sort=True).sort_index()
Class
0      62130
1      766186
Name: count, dtype: int64
-----
766186
[0 1 2 3 4]
[816315 488544 365994 322351 165697]
37813
37293
C:\Users\vadde\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with
  feature names
  warnings.warn(
Accuracy Score : 0.9999731853162792
1.0
0.9999643317769549
0.9999731853162792
*****
+Classification Report:
  precision    recall  f1-score   support

   0       1.00     1.00     1.00    18660
   1       1.00     1.00     1.00    18633

 accuracy          1.00     37293
 macro avg          1.00     37293
weighted avg          1.00     37293

[1.0, 1.0, 1.0]
[1.0, 1.0, 1.0]
plotMets: [[1.0, 1.0, 1.0], [1.0, 1.0, 1.0]]
support: [18660, 18633]
Traceback (most recent call last):
  File "C:\Users\vadde\Downloads\CODE IOT-Attack\Botnet_Attack.py", line 247, in <module>

```

Figure 15: Final result which shows Overall accuracy of the system, Test and Train Accuracy

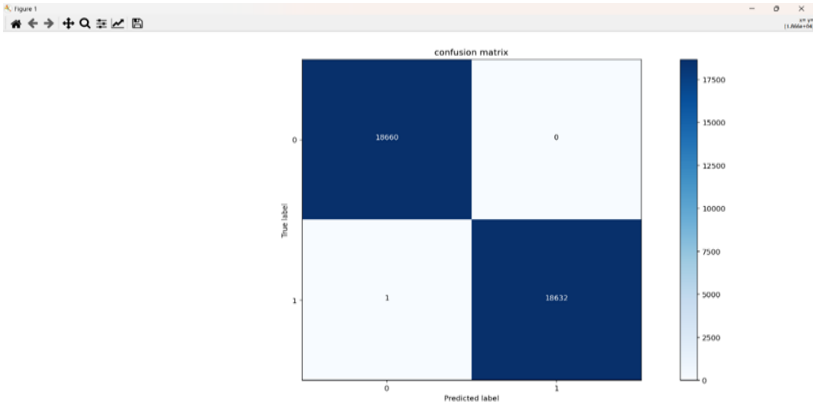


Figure 16: Confusion matrix



Article Title: Detection of Real-Time Malicious Intrusions and Attacks in IoT Empowered Cybersecurity Infrastructure

6 Conclusion

The manuscript introduces a novel detection and defense method specifically designed to counter botnet attacks targeting IoT devices. Unlike many current approaches that focus on user sessions as inputs to mitigate network transaction floods caused by bots, this method takes a different approach. It likely leverages advanced algorithms and machine learning techniques to analyze network traffic patterns and device behaviour, enabling it to identify and block malicious botnet activity more effectively. This innovative approach could offer enhanced protection for IoT ecosystems, safeguarding them from the increasing threat of botnet attacks.

Future Scope

The method uses predictive analysis to forecast botnet attack scope and impact. It analyzes transactions within a fixed time frame to spot patterns hinting at botnet activity. This proactive approach enables early threat detection and mitigation. Organizations can then strengthen defenses and safeguard IoT infrastructures effectively. This predictive feature distinguishes the method, providing a holistic defense strategy for IoT environments.

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