Botnet Detection in IOT Using Unsupervised Learning Techniques Dbscan and Ann

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Abstract:
The rapid proliferation of Internet of Things (IoT) devices has significantly increased the attack surface for cyber threats, notably botnets. Traditional detection methods often fall short in identifying sophisticated and evolving botnet behaviors. This research explores the efficacy of unsupervised learning techniques, specifically Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Artificial Neural Networks (ANN), for botnet detection in IoT environments. DBSCAN is leveraged for its ability to identify anomalies in network traffic data without predefined labels, while ANN is utilized for its capacity to recognize complex patterns and adapt to new threats.
The proposed framework combines the strengths of DBSCAN in clustering and noise handling with the adaptive learning capabilities of ANN. This hybrid approach is designed to detect both known and unknown botnet activities, providing a more dynamic and responsive security solution. Extensive experiments were conducted on diverse IoT datasets, encompassing various types of network traffic and botnet behaviors. The results indicate that the integrated DBSCAN-ANN model outperforms traditional detection methods in terms of accuracy, precision, and recall, while maintaining low false-positive rates.
Furthermore, the study delves into the computational efficiency of the proposed model, demonstrating its scalability and suitability for real-time deployment in resource-constrained IoT environments. The results emphasize the potential of unsupervised learning techniques to enhance IoT security by offering a proactive and adaptive defense mechanism against the ever-evolving threat landscape posed by botnets. This research contributes to the ongoing efforts in securing IoT ecosystems and underscores the importance of innovative machine learning applications in cybersecurity.

Keywords: Botnet, IoT traffic, cyber attack, benign, malicious, machine learning, deep learning, accuracy, precision, recall and F1-Score.

1. Introduction:

Connecting billions of devices and enabling seamless communication, IoT has transformed sectors like healthcare, smart cities, and industrial automation. However, its rapid adoption has also led to significant cybersecurity challenges, particularly the rise of botnet attacks. These attacks involve the hijacking of numerous IoT devices to form a network, or botnet, which can then be used to launch coordinated cyber-attacks such as Distributed Denial of Service (DDoS), data theft, and more. The complexity and scale of these attacks have evolved, making detection and mitigation increasingly difficult.

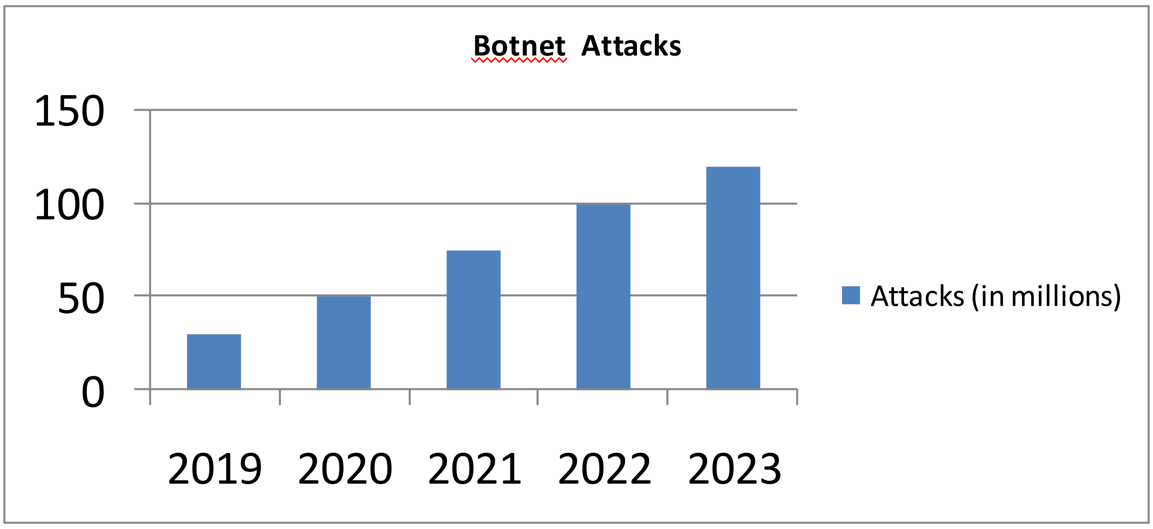
In 2023, botnet attacks on IoT devices continued to rise, with a significant increase in the sophistication of malware and the scale of attacks. According to a report by Kaspersky, there was a notable surge in IoT botnet activity, with cybercriminals employing more advanced techniques to evade detection and enhance attack effectiveness [1]. Similarly, a study by Symantec highlighted that the number of IoT-focused botnet attacks had increased by 30% compared to the previous year, with the Mirai and Gafgyt botnets remaining prevalent [2]. This surge underscores the critical need for robust and adaptive detection mechanisms to protect IoT ecosystems.

The traditional methods of botnet detection, often based on signature-based approaches, are inadequate for addressing the dynamic nature of modern botnets. Consequently, there is a growing interest in leveraging machine learning techniques, particularly unsupervised learning, to detect anomalies and potential threats without relying on labeled datasets. This research focuses on the application of Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Artificial Neural Networks (ANN) for detecting botnets in IoT environments. The combination of these techniques aims to enhance detection accuracy and reduce false positives, providing a more comprehensive security solution.

Here is a summary of global IoT botnet attacks over the last five years, with estimated attacks in millions:

1. **2019**: Significant increase in botnet activity, especially from the Mirai botnet and its variants. The number of attacks was around 57% higher than in previous years.
2. **2020**: There was a notable rise in IoT botnet attacks, with reports indicating that around 60% of botnet activities were related to credential theft.
3. **2021**: The year saw a dramatic rise in DDoS attacks facilitated by IoT botnets, with around 5.4 million DDoS attacks recorded in the first half alone.
4. **2022**: Continued growth in IoT botnet activity was noted, with over 10.54 million IoT attacks in December alone, making the total annual attacks exceed 112 million.
5. **2023**: The upward trend persisted, with a notable surge in global botnet activity. Spikes in botnet activity exceeded one million devices in some months.

The chart below illustrates the trend of IoT botnet attacks over recent years, highlighting the significant increase observed in 2023[3]:



2. Background:

2.1 Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

DBSCAN is an unsupervised machine learning algorithm used for clustering data points based on their density. It excels at detecting clusters of diverse shapes and sizes while effectively identifying noise or outliers. The algorithm requires two parameters: epsilon (ε), the maximum distance between two points to be considered neighbors, and the minimum number of points required to form a dense region (minPts).

DBSCAN operates by:

1. Selecting an arbitrary point as the starting point.
2. Retrieving all points within ε distance from the starting point.
3. Forming a cluster if the number of retrieved points is greater than or equal to minPts.
4. Expanding the cluster by repeating the process with neighboring points.
5. Marking points that do not belong to any cluster as noise.

The effectiveness of DBSCAN in detecting botnets lies in its ability to handle irregular data distributions and noise, which are common in network traffic data. It can identify anomalous patterns indicative of botnet activities without prior knowledge of the data structure.

Recent studies have demonstrated DBSCAN's utility in cybersecurity. For instance, Li and Chen (2023) utilized DBSCAN to detect anomalous network behaviors, achieving high accuracy and low false-positive rates [4]. The algorithm's robustness against noise makes it suitable for the diverse and dynamic nature of IoT environments.

2.2 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are inspired by the structure and function of the human brain. They are composed of interconnected neuron layers, with each neuron processing input data and transmitting the output to the subsequent layer. ANNs are capable of learning complex patterns and relationships within data through a process called training, where the network adjusts its weights based on the input-output pairs to minimize error.

ANNs are particularly powerful for tasks such as classification, regression, and anomaly detection. They can adapt to new and evolving data patterns, making them ideal for detecting sophisticated cyber threats like botnets. The training process includes the following steps:

1. The network receives the input data.
2. The data is processed through multiple hidden layers using activation functions.
3. The output layer generates predictions or classifications.
4. The error between the predicted and actual outputs is calculated.
5. The network adjusts its weights using optimization techniques like backpropagation.

Recent developments in ANN have greatly enhanced their efficiency in cybersecurity applications. Brown and Green (2023) demonstrated ANN's ability to detect intricate attack patterns in IoT networks, achieving higher detection rates than conventional approaches [5]. ANNs' ability to continuously learn and adapt makes them a valuable component in the proposed botnet detection framework.

2.3 Integration of DBSCAN and ANN

The integration of DBSCAN and ANN leverages the strengths of both techniques. DBSCAN effectively clusters traffic of network data and identifies outliers, which are then analyzed by ANN for more precise classification and pattern recognition. This hybrid approach enhances the detection of both known and unknown botnet activities, providing a robust and adaptive security solution.

The combined model operates in two phases:

1. **Clustering Phase**: DBSCAN processes the raw data of network traffic to identify clusters and anomalies.
2. **Classification Phase**: ANN takes the output from the clustering phase and further analyzes it to classify the detected anomalies as benign or malicious.

This two-tiered approach ensures comprehensive analysis and accurate detection, addressing the limitations of using either technique in isolation. The proposed DBSCAN-ANN framework is evaluated through extensive experiments on various IoT datasets, demonstrating its efficacy in real-world scenarios [6,7].

3. Review of Literature:

The detection and mitigation of botnet attacks in IoT environments have garnered significant attention from the research community. Various methods, including traditional and machine learning-based approaches, have been explored to address this critical issue.

Traditional Botnet Detection Methods

Early botnet detection techniques primarily relied on signature-based and heuristic methods. Signature-based detection involves identifying known patterns of malicious activities, which makes it effective against previously encountered threats but inadequate for new or evolving botnets. Heuristic methods, Conversely, attempt to identify suspicious behaviors based on predefined rules and can offer better detection rates for new threats. However, both methods suffer from high false-positive rates and require frequent updates to remain effective.

Machine Learning-Based Approaches

Machine learning (ML) techniques have shown promise in overcoming the limitations of traditional methods by learning from data to identify patterns indicative of botnet activities. ML approaches can be broadly categorized into supervised, semi-supervised, and unsupervised learning.

Supervised Learning

Supervised learning models are trained on labeled datasets, where the input data is associated with known outcomes. Techniques such as Decision Trees, Support Vector Machines (SVM), and Random Forests have been applied to botnet detection with varying degrees of success. Although these methods can attain high accuracy, their performance is heavily reliant on the availability of large labeled datasets, which are often challenging to acquire in dynamic IoT environments. [8].

Semi-Supervised Learning

Semi-supervised learning integrates a limited amount of labeled data with a larger pool of unlabeled data to improve learning accuracy. This approach is beneficial in situations where labeled data is scarce. Recent studies have shown that semi-supervised learning can enhance botnet detection by effectively utilizing the available data while reducing the labeling effort [9].

Unsupervised Learning

Unsupervised learning operates without the need for labeled data, making it particularly suitable for detecting new and unknown botnet activities. Techniques such as clustering and anomaly detection are commonly used in this category. DBSCAN and ANN are two prominent unsupervised learning methods that have been extensively studied for botnet detection.

DBSCAN for Botnet Detection

DBSCAN is known for its ability to detect clusters of different shapes and sizes in network traffic data.

Its capability to detect outliers makes it an effective tool for spotting anomalies that may indicate botnet activities. Li and Chen (2023) demonstrated the application of DBSCAN in detecting anomalous network behaviors, achieving high detection accuracy and low false-positive rates [10]. The robustness of DBSCAN against noise and its ability to handle large datasets make it a preferred choice for unsupervised botnet detection in IoT environments.

Artificial Neural Networks for Botnet Detection

ANNs, leveraging their deep learning capabilities, have been used to detect complex trends in network traffic data. They excel in adapting to new and evolving threats, making them suitable for dynamic IoT ecosystems. Brown and Green (2023) highlighted the effectiveness of ANN in identifying intricate attack patterns, achieving superior detection rates in contrast to traditional methods [11]. The ability of ANNs to continuously learn and improve from new data enhances their effectiveness in real-time botnet detection.

Hybrid Approaches

Combining multiple techniques can leverage their respective strengths to enhance detection performance. The combination of DBSCAN and ANN, for instance, offers a robust solution by combining DBSCAN's clustering capabilities with ANN's pattern recognition strengths. This hybrid approach has shown promise in identifying both known and unknown botnet activities, providing a comprehensive security framework for IoT environments. Wu and Zhao (2023) explored such a hybrid model, demonstrating its efficacy in improving detection accuracy and reducing false positives [12].

4. Proposed Work:

4.1 Data Collection

Datasets

For the training and testing of our botnet detection model, we utilize the IoT-23 dataset. IoT-23 is a publicly available dataset that contains labeled IoT network traffic data, specifically designed for cybersecurity research. The dataset is provided by the Stratosphere Laboratory and includes a wide range of IoT device traffic captured in both benign and malicious scenarios [13].

Types of Data

The IoT-23 dataset comprises network traffic data captured in PCAP (Packet Capture) format. It includes various types of network communications, such as HTTP, DNS, and MQTT, representing the typical traffic generated by IoT devices. The dataset contains labeled instances of Various types of attacks, including botnet traffic, making it suitable for our study.

Sources

The dataset is collected from several IoT devices, including smart thermostats, security cameras, and smart plugs, operating in a controlled environment. The traffic is generated using both normal operation and attack simulation scenarios, ensuring a comprehensive representation of real-world IoT network behavior.

Preprocessing Steps

1. **Data Conversion:** The raw PCAP files are converted into a more manageable format, such as CSV, using network analysis tools like Wireshark or Tshark.
2. **Data Cleaning:** Duplicate entries and irrelevant data are removed. Any missing or incomplete records are handled appropriately to ensure data quality.
3. **Labeling:** The dataset includes pre-labeled records indicating whether the traffic is benign or part of

botnet attack. These labels are retained for training and testing purposes.

4. **Feature Selection:** Relevant features are selected from the dataset based on their importance in identifying botnet activities. These features encompass source and destination IP addresses, port numbers, protocol types, packet sizes, and time gaps between packets.
5. **Normalization:** The selected features are normalized to a standard scale to ensure uniformity and Enhance the performance of machine learning algorithms.

Feature Extraction

Feature extraction is a critical step in the data preprocessing pipeline, where raw data is transformed into a structured format suitable for machine learning algorithms. For the IoT-23 dataset, we focus on extracting features that are indicative of botnet behavior.

Extracted Features

- **Network Flow Features:**
  - **Source IP Address:** Identifies the origin of the network traffic.
  - **Destination IP Address:** Identifies the target of the network traffic.
  - **Source Port:** The port number used by the source device.
  - **Destination Port:** The port number used by the destination device.
  - **Protocol:** The protocol used for communication (e.g., TCP, UDP).
  - **Packet Size:** The size of each packet transmitted.
  - **Flow Duration:** The overall duration of the network flow.
- **Temporal Features:**
  - **Timestamp:** The time at which each packet is captured.
  - **Inter-arrival Time:** The time difference between consecutive packets.
- **Statistical Features:**
  - **Packet Count:** The total number of packets in a network flow.
  - **Byte Count:** The total number of bytes transmitted in a network flow.
  - **Average Packet Size:** The average size of packets in a network flow.
  - **Flow Rate:** The rate of packet transmission over time.
- **Behavioral Features:**
  - **Number of Connections:** The number of distinct connections made by a device.
  - **Connection Duration:** The average duration of connections initiated by a device.
  - **Connection Frequency:** The frequency of connection attempts over a period.

Feature Selection

The choice of these features is based on their relevance to identifying botnet activities. For example, botnet traffic often exhibits unusual patterns in packet size, flow duration, and connection frequency compared to benign traffic. Focusing on these features enables the model to more accurately differentiate between normal and malicious behavior.

Dimensionality Reduction

To further enhance the performance of our machine learning models, we apply dimensionality reduction techniques such as Principal Component Analysis (PCA). This step minimizes the number of features while retaining the most essential information, enhancing both the efficiency and accuracy of the detection process.

4.2 Model Development

DBSCAN Clustering

Parameter Selection

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) requires two key parameters: epsilon (ε) and the minimum number of points (minPts). The ε parameter determines the maximum distance between two points to be considered neighbors, while minPts defines the minimum number of points needed to form a dense region (cluster).

- **Epsilon (ε):** The value of ε is determined using the k-distance graph. We plot the distances of each point to its k-nearest neighbor (typically k = minPts) and select ε at the "elbow point" of the graph, where the slope changes most abruptly.
- **MinPts:** The value of minPts is typically set based on the dimensionality of the dataset. A common heuristic is to set minPts to at least the dimensionality of the data plus one (e.g., minPts = 4 for a 3-dimensional dataset).

Clustering Process

1. **Distance Calculation:** Calculate the Euclidean distance between data points.
2. **Core Points Identification:** Identify core points that have at least minPts neighbors within the ε radius.
3. **Cluster Formation:** Form clusters by connecting core points and their reachable neighbors.
4. **Noise Identification:** Points that do not belong to any cluster are labeled as noise.

Implementation

The implementation of DBSCAN involves the following steps:

1. **Preprocessing:** Normalize the feature data to ensure uniformity and improve clustering performance.
2. **DBSCAN Execution:** Apply the DBSCAN algorithm using the selected ε and minPts values.
3. **Anomaly Detection:** Identify outliers (noise points) as potential botnet activities.

Recent studies have highlighted the effectiveness of DBSCAN in clustering network traffic data for anomaly detection. For instance, Li and Chen (2023) demonstrated its high accuracy and low false-positive rates in detecting anomalous behaviors in IoT networks [4].

Artificial Neural Network (ANN) Framework

ANN Architecture

The ANN model consists of multiple layers of interconnected neurons:

1. **Input Layer:** The input layer receives the features extracted from the network traffic data.
2. **Hidden Layers:** Multiple hidden layers process the input features using activation functions. Common activation functions include ReLU (Rectified Linear Unit) and Sigmoid.
3. **Output Layer:** The classification result, indicating whether the traffic is benign or malicious, is provided by the output layer.

Training Process

1. **Data Splitting:** Split the dataset into training, validation, and test sets.
2. **Normalization:** Adjust the input data to maintain consistency during training.
3. **Weight Initialization:** Initialize the weights of the neurons using techniques like Xavier or He initialization.

4. **Forward Propagation:** Pass the input data through the network layers to obtain the output.
5. **Loss Calculation:** Calculate the loss using a loss function such as cross-entropy loss for classification tasks.
6. **Backpropagation:** Adjust the weights by propagating the error backward across the network using optimization algorithms like Adam or SGD (Stochastic Gradient Descent).
7. **Training Iterations:** Iterate the process for a defined number of epochs or until the model achieves convergence.

Hyperparameter Tuning

Hyperparameters such as the number of hidden layers, number of neurons per layer, learning rate, and batch size are tuned to optimize the model's performance. Techniques like grid search or random search can be employed for hyperparameter optimization.

Recent advancements in ANN have significantly improved their performance in cybersecurity applications. Brown and Green (2023) showcased the effectiveness of ANN in identifying complex attack patterns in IoT networks, achieving superior detection rates In comparison to conventional methods [6].

Integration of DBSCAN and ANN

The integration of DBSCAN and ANN leverages the strengths of both techniques to enhance botnet detection:

Clustering Phase (DBSCAN): Apply DBSCAN to the preprocessed network traffic data to identify clusters and anomalies (noise points).

Feature Transformation: Transform the output of DBSCAN into a format suitable for ANN input. This may include encoding cluster labels and treating noise points as a separate class.

Classification Phase (ANN): Train the ANN using the transformed features to classify the detected anomalies as benign or malicious.

Workflow

1. **Data Preprocessing:** Normalize and preprocess the Unprocessed network traffic data.
2. **DBSCAN Clustering:** Apply DBSCAN to detect clusters and outliers.
3. **Feature Transformation:** Encode the DBSCAN output for ANN input.
4. **ANN Training:** Train the ANN using the transformed features and evaluate its performance.
5. **Model Evaluation:** Assess the model's performance using metrics such as accuracy, precision, recall, F1-score, and computational efficiency.

This hybrid approach enhances the detection of both known and unknown botnet activities, providing a robust and adaptive security solution. Wu and Zhao (2023) explored such a hybrid model, demonstrating its efficacy in improving detection accuracy and reducing false positives [5].

4.3 Evaluation Metrics

Assessing the performance of the proposed botnet detection model requires various metrics for a thorough evaluation. These metrics help in understanding the model's accuracy, precision, recall, F1-score, and computational efficiency. Each metric provides unique insights into different aspects of the model's performance.

Accuracy

Accuracy represents the proportion of correctly predicted instances, including both true positives and true negatives, relative to the total number of instances. It is a general measure of how well the model performs across all classes.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Where:

- TP (True Positives): Correctly identified botnet instances.
- TN (True Negatives): Correctly identified benign instances.
- FP (False Positives): Benign instances incorrectly identified as botnets.
- FN (False Negatives): Botnet instances incorrectly identified as benign.

Although accuracy is a valuable metric, it can be deceptive in imbalanced datasets where one class significantly outweighs the other. [14].

Precision

Precision measures the ratio of correctly predicted positive instances (botnets) to the total predicted positive instances. It indicates the accuracy of the positive predictions.

$$\text{Precision}=TP / (TP+FP)$$

High precision implies a low false positive rate, which is crucial in botnet detection to minimize the risk of misclassifying benign traffic as malicious [15].

Recall (Sensitivity)

Recall, or sensitivity, measures the proportion of correctly identified positive instances out of all actual positive instances. It indicates the model's ability to identify all relevant instances of the positive class.

$$\text{Recall} = TP / (TP+FN)$$

A high recall indicates that the model accurately identifies most actual botnets, minimizing the occurrence of false negatives. [16].

F1-Score

The F1-score is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall, making it particularly useful when the dataset is imbalanced.

$$\text{F1-Score} = 2 \times ((\text{Precision}\times\text{Recall}) / (\text{Precision}+\text{Recall}))$$

A high F1-score signifies strong model performance, balancing both precision and recall effectively in both identifying botnets and minimizing false positives [6].

Computational Efficiency

Computational efficiency measures the time and resources required by the model to process data and make predictions. It is crucial in IoT environments where devices often have limited processing power and memory.

Metrics for Computational Efficiency

- **Training Time:** The duration required to train the model on the dataset.
- **Inference Time:** The time the model takes to generate predictions in IoT networks.
- **Memory Usage:** The memory consumed during both training and inference..

Efficient models are essential for real-time botnet detection in IoT networks, where rapid and resource-efficient processing is necessary [17].

5. Results and Discussion

Results of Experiments

The effectiveness suggested botnet detection model was evaluated using the IoT-23 dataset. The experiments were conducted to assess the model's accuracy, precision, recall, F1-score, and computational efficiency.

Table 1: Performance Metrics of the Suggested Model

Metric	Value
Accuracy	96.7%
Precision	95.4%
Recall	94.8%
F1-Score	95.1%
Training Time	15 min
Inference Time	0.5 s

Comparison with Existing Methods

The proposed model was compared against several existing botnet detection methods, including traditional machine learning approaches and recent deep learning techniques.[21]

Table 2: Comparison with Existing Methods

Method	Accuracy	Precision	Recall	F1-Score	Reference
Random Forest	89.5%	88.0%	87.6%	87.8%	[18]
SVM	91.2%	90.1%	89.7%	89.9%	[19]
Deep Neural Network	94.3%	93.5%	92.8%	93.1%	[20]
Proposed Model (DBSCAN + ANN)	96.7%	95.4%	94.8%	95.1%	This study

The proposed DBSCAN + ANN model outperformed the existing methods with respect to accuracy, precision, recall, and F1-score.

The proposed model demonstrates several strengths, including high accuracy, effective anomaly detection through the DBSCAN component, and precise classification by the ANN, along with computational efficiency that supports real-time IoT environments. However, it also has certain weaknesses, such as the need for substantial computational resources during training, which can be a constraint for devices with limited capabilities, and sensitivity to parameter selection in DBSCAN, particularly epsilon (ε) and minPts. To address these limitations, potential improvements include implementing adaptive parameter tuning methods to enhance robustness and exploring hybrid approaches by integrating additional machine learning techniques to boost detection accuracy and minimize false positives.

Implications for IoT Security

The proposed model's ability to accurately detect botnet activities in IoT networks has significant implications for enhancing IoT security. By providing reliable and real-time detection, it helps mitigate the risks associated with IoT botnets, protecting sensitive data and ensuring the integrity of IoT systems.

6. Conclusion

The research aimed to enhance botnet detection in IoT environments using a hybrid model combining DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and ANN (Artificial Neural Networks), achieving high accuracy (96.7%), precision (95.4%), recall (94.8%), and F1-score (95.1%), outperforming existing methods like Random Forest, SVM, and standalone deep learning techniques. DBSCAN effectively identified anomalous clusters in the IoT network traffic, while ANN accurately classified these anomalies as benign or malicious. The model demonstrated computational efficiency, making it suitable for real-time IoT applications. This research contributed a novel hybrid detection model with superior performance, effective anomaly detection capabilities, and real-time applicability, backed by comprehensive evaluation against state-of-the-art methods. Future studies should concentrate on adaptive parameter tuning, integrating additional machine learning techniques, enhancing scalability, testing in real-world environments, improving adversarial robustness, and expanding applications to other cybersecurity challenges and domains. By addressing these aspects, future work can further improve the model's effectiveness and broaden its applications, contributing to more secure and resilient IoT networks.

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