Using Machine Learning for Detecting and Mitigating Cyber Threats in IOT Dvices Deployed During the Arbaeen Pilgrimage

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ABSTRACT:

Objective: This research study focuses on understanding cybersecurity threats of Internet of Things (IoT) devices with special attention towards cyber attacks that relate to mega events such as Arbaeen Pilgrimage. With an objective to guard the users and their equipment in a mega event scenario, this project would identify weaknesses of the IoT system, develop means for cyber threat detection and also give recommendations for risk neutralization in an efficient manner.

Methodology: A mixed-method strategy combining qualitative and quantitative research methods is employed in this research. A thorough review of the existing body of research on IoT security issues and attack techniques is conducted. In addition to this, primary data from surveys and expert interviews conducted with cybersecurity professionals are utilized. In order to analyze actual vulnerabilities in IoT systems, a case study on the Arbaeen Pilgrimage is studied. Cyber threat detection models are created by applying machine learning methods, and simulation tools are used to check how well the mitigation techniques work.

Key Findings: IoT devices are particularly vulnerable to all types of cyberattacks, including DDoS, unauthorized access, and data breaches, particularly during peak events like the Arbaeen Pilgrimage. Existing IoT security measures often fail to detect and prevent these threats in real-time, putting both users and devices at risk. Nevertheless, the study of suspicious activity patterns and anomalies can serve as a strong base in which machine learning algorithms might be useful for the identification and mitigation of cyber threats. Strong security features, including intrusion detection systems, regular firmware upgrades, and multi-factor authentication, must be incorporated into IoT devices for general security enhancement and protection against future cyber threats.

Implications: This study is critical implications for the field of cyber-security, especially in terms of safeguarding IoT devices in expansive, real-time settings. It guides the development of stronger security frameworks by bringing new insights into the specific vulnerabilities of IoT systems during critical events. The results further underscore how important proactive threat detection and mitigation strategies are to safeguarding users' devices and data.

Specific Contribution: This research contributes to the field of IoT cybersecurity through a model that strengthens the identification and mitigation of threats during major events through an integration of cutting-edge techniques in machine learning. This study provides a case-specific framework for the Arbaeen Pilgrimage that can be adapted to other large-scale events and shows that integrated security mechanisms are crucial. This work improves the knowledge of IoT vulnerabilities and offers practical ways to fortify the overall security framework of IoT systems in dynamic settings.

Keywords: IoT devices, Arbaeen Pilgrimage, Cyber threat, cybersecurity, cyber-attacks, Machine Learning

INTRODUCTION

The number of devices through IoT has posed gigantic challenges in terms of security particularly in high-stake fields such as the Arbaeen pilgrimage, where thousands of interconnected devices are installed in places to manage logistics, safety control mechanisms, and support pilgrims (Almutairi, 2024) (Schiller, 2022). Due to the vulnerability of such IoT systems to several forms of cyber threats, which range from DDoS attacks, man-in-the-middle attacks, to malware infection, the requirement of having effective cybersecurity solutions for IoT systems is essential (Siddiqa, 2024). This is because ML is the promising technique in identifying and preventing these threats with its methods including supervised, unsupervised, and reinforcement learning techniques (Cortés Balcells, 2020) (Mavroeidakos, 2020). This paper explores the possibilities for how ML might be leveraged to secure IoT in such dynamic, high-risk environments, ensuring the safety and robustness of such systems during the Arbaeen pilgrimage.

1.Machine Learning Paradigms for Cybersecurity:

Machine learning is emerging as one of the chief tools in the field of cybersecurity (Stellios, 2021) (Dhirani, 2021). It enables better identification, analysis, and counteraction of cyber threats because of the efficiency and specificity of systems (Anwar, 2022). There exist three major paradigms of the application of machine learning in cybersecurity: supervised, unsupervised, and reinforcement learning. Each applies to one of the complexities in dealing with cyber threats (Anand, 2020).

A. Supervised learning:

Supervised learning is a subcategory of machine learning whereby models are trained on labeled datasets for the purpose of predicting or classifying outcomes for new data (Mathas, 2020) (Sarker, 2020). It is highly

important for cybersecurity applications, including intrusion detection systems and malware detection (Zoppi, 2021) (Kabanda, 2021). For instance, intrusion detection systems use supervised models that were trained on labeled network traffic data to identify threats such as unauthorized access or data breaches and DDoS attacks (Kaloudi, 2020) (James, 2023). Similarly, malware detection uses supervised models trained with malicious and benign files (Apruzzese, 2023). However, the method requires huge amounts of labeled data and cannot adapt rapidly to new threats.

B. Unsupervised Learning:

Unsupervised learning is a method of machine learning that identifies hidden patterns, relationships, or structures from unlabeled data (Shah, 2021) (Dasgupta, 2022). This is essential in the realm of cybersecurity for the detection of anomalies and fraud. Unsupervised algorithms, such as clustering or dimensionality reduction, detect deviations from normal network traffic or system activities, thereby alerting the potential occurrence of cyberattacks (Yaseen, 2023) (Berghout, 2022). In fraud detection, unsupervised models flag anomalies in user behavior as indicative of fraudulent activity. However, this approach can give false positives and is complex to interpret, thus making it difficult to translate into actionable insights (Macas, 2022) (Nassar, 2021).

C. Reinforcement Learning:

Reinforcement learning, the process of training agents on machine learning to make a succession of decisions by iteratively interacting with their environment using trial and error, seeking rewards or penalties, thus finds utility in cybersecurity scenarios when threats are constantly in change. It helps adapt security measures through RL mechanisms whereby rules on firewalls automatically shift, and intrusion prevention strategy could be op-

timized. It also operates the intelligent automated response systems against cyber-attacks with reduced human interactions. Despite having disadvantages that include computational resource needs, time for training, etc. RL is proving to transform the advanced cyber solutions significantly.

2.IoT Threat Landscape and Attack Vectors:

The Internet of Things (IoT) is one of the most interconnected networks that will make it possible to share information across different sectors without a glitch and automate processes. At the same time, interconnectivity poses serious risks to security, since IoT systems operate in dynamic and decentralized environments, which exposes them to various cyber threats. IoT threats include DDoS attacks, Man-in-the-middle (MitM) attacks, and malware attacks. In the case of DDoS attacks, targeted devices or networks are overwhelmed. The critical services become unavailable due to the attack, and as a result, there is significant downtime, financial losses, and loss of trust. With the case of MitM attacks, there is alteration of communication between devices and servers, resulting in data breaches, unauthorized access, and control over critical systems (Ahsan, 2022). IoT malware attacks exploit vulnerabilities within IoT devices, allowing them to collect unauthorized data, cause disruptions to functionality, or even control the entire system. The threats are not limited to individual devices; they have become an extension of whole networks and ecosystems and hence are a threat to public safety and economic stability (George, 2024). Risks are highly amplified in dynamic environments such as smart cities or large-scale events where numerous devices work under varied conditions. Understanding the IoT threat landscape will prove essential for the formulation of strong cybersecurity strategies; the stakeholders can, hence allocate resources effectively, design more resilient systems, and implement proactive measures against the increasing risk in this connected world.

LITERATURE REVIEW

- Lone et al. (2023) focused on the CIA security triangle: Confidentiality, Integrity, and Availability, and discusses an in-depth study of IoT cybersecurity challenges with attacks on IoT layers, strengths and weaknesses of present security techniques, and the ongoing trends in this research domain highlsdzighting that this growth has connected all of its variants-drones, sensors, wearables, and medical devices-to the internet and dramatically changed sectors like healthcare, manufacturing, transportation, and housing. But at the same time, cybersecurity challenges have increased with a growing presence of AI and machine learning, blockchain, zero trust, and connecting IoT with 5G networks. Despite much research in the domains of IoT and cybersecurity, research on how the challenges in cybersecurity in these domains evolve is rather sparse (Lone, 2023).
- Kimani et al. (2019) discussed cybersecurity issues in IoT-based smart grid networks, a much more interconnected and more efficient way to bring about energy systems. Increased interconnectivity does raise several security vulnerabilities along the way-intrusion, access data breach, denial of service. Thus, the study on how hard it is for multiple capabilities in such a highly diverse IoT but at least talking and constant communication with centralized control devices in security became even harder. The measures, which included encryption and access control, were discussed but acknowledged as usually insufficient to handle changing cyber threats. The paper focused on the necessity of stronger security frameworks that would safeguard smart grid systems and strengthen their resilience to emerging risks (Kimani, 2019).
- Pan, J., & Yang, Z. (2018) discussed how a paradigm shift to the Internet of Things (IoT) and the emergence of the edge computing concept have brought huge potential for numerous future IoT application scenarios includ-

ing smart homes, smart transportation, smart health, smart grids, and smart energy. However, it has also introduced new cybersecurity challenges. The authors could envision that at the "Cybersecurity + edge computing + IoT + AI" intersection, many new research and innovation opportunities will emerge. In the paper, they discussed the major new challenges in cybersecurity and the related opportunities within this vision (Pan, 2018).

- Shah, V. (2021) explored the rising role of machine learning algorithms in cybersecurity, where these algorithms enhance traditional defense mechanisms through the detection and prevention of a broad range of threats. These algorithms rely on data-driven techniques to analyze large amounts of information, which they can use to identify patterns and anomalies that suggest malicious activities. Through continuous learning from new data, they adapt and improve in real-time, thus providing a versatile defense against known and previously unseen threats. From uncovering hidden threats through its ability to feature extraction as well as pattern recognition through capability analysis of unstructured data - possibly in the nature of network traffic or user behavior - these machines have great potential. Additionally, with machine learning, proactive defense strategies, with predictive analytics, forehand identification of possible threats or even known vulnerability opens opportunity and provides a speedy response regarding the security incidents (Shah, 2021).
- Goriparthi (2023) discussed the integration of artificial intelligence and machine learning in boosting cybersecurity, especially in terms of real-time threat detection. Through the study, it came to light how AI-driven cybersecurity solutions, which adopt ML techniques such as supervised learning, unsupervised learning, and deep learning, have so far been successful in detecting different cyber threats, including mal-

ware, ransomware, and APTs. It highlights the benefits of anomaly detection that can detect threats previously unknown, and even surpass the capabilities of traditional signature-based methods. Despite challenges in requiring a large dataset, as well as the risks of adversarial attacks, the study concludes that AI and ML have really transformed the accuracy, speed, and efficiency of defences in cybersecurity, thus offering more proactive and robust detection of threats (Goriparthi, 2023).

- Shaukat et al., (2020) focused on the rising vulnerability of cyberspace due to the high adoption of Internet and mobile applications, thus increasing sophisticated and prolonged cyberattacks. While traditional systems of cybersecurity are advanced, they usually are inadequate in the fight against the constantly evolving and polymorphic threats. In the last decade, machine learning techniques have played a central role in handling these problems, especially intrusion detection, spam detection, and malware detection. Nevertheless, malicious adversaries still exist that intend to exploit the vulnerabilities and the trustworthiness of ML systems remains a matter of concern. The paper reviewed several ML techniques and tools used in cybersecurity and presented an overview of challenges in the application of such methods. Insights into current trends and research in the field have been given (Shaukat, 2020).

RESEARCH OBJECTIVES AND QUESTIONS

The research aims at using the machine learning algorithms in an attempt to detect cyber threats against IoT devices during the Arbaeen Pilgrimage. Additionally, the research intends to develop a mitigation framework for the minimization of the effects the threats pose on IoT systems in order to make them function in resource constraints usually associated with such large-scale events. Finally, the study will evaluate the performance of the proposed threat detection and mitigation system based on the given dataset. Here are some of the objectives of the study:

- To utilize machine learning algorithms to identify cyber threats targeting IoT devices deployed during the Arbaeen Pilgrimage.
- To develop a mitigation framework to reduce the impact of identified threats on IoT systems.
- To ensure that the proposed solutions work efficiently under resource constraints typical of IoT deployments during large-scale events.
- To measure the effectiveness of the proposed threat detection and mitigation system using the provided dataset.
- The research questions are as follows:
- How can machine learning algorithms be leveraged to accurately detect and classify cyber threats targeting IoT devices deployed during the Arbaeen Pilgrimage?
- What mitigation framework can be developed to minimize the impact of identified cyber threats on IoT systems during large-scale events like the Arbaeen Pilgrimage?
- How can the proposed solutions ensure effective threat detection and mitigation while operating under the resource constraints typical of IoT deployments during large-scale gatherings?
- How can the effectiveness of the proposed threat detection and mitigation system be measured using datasets relevant to IoT deployments during the Arbaeen Pilgrimage?

RESEARCH METHODOLOGY

The proposed study aims to develop a pre-processed dataset, machine learning algorithms, and feature engineering-based threat detection and mitigation framework for IoT systems. A rule-based mitigation system has been developed, evaluated, and simulated for large-scale event deployment and provided with recommendations.

1.Data Set:

This study's dataset was drawn from the Airo Journals Data Library. Missing or inconsistent data will be imputed or filtered. Also, normalization and scaling of data are done in preparation for machine learning algorithms in that it keeps features comparable at different scales. The categorical labels like "Threat Label" are encoded into numeric form, which are important for facilitating classification tasks and hence the machine learning models can effectively process the data.

2.Exploratory Data Analysis (EDA):

Data source to this study has been received from the Airo Journals Data Library. It imputes or filters those data that are either absent or inconsistent in quality, providing quality data. Then it provides normalization and scaling techniques where the data is standardized by some technique so that features will get a comparable scale, fit for machine learning algorithms to process. Categorical labels, such as "Threat Label," are encoded in numeric form; this is essential for facilitating classification tasks and enabling the machine learning models to process the data effectively.

3.Feature Engineering:

In feature engineering, the timestamp is used to extract temporal features such as time of day and day of the week to capture temporal pat-

terns in the data that might be related to specific cyber threats. Additional derived metrics such as average usage or standard deviation are created to further enhance model inputs and provide more comprehensive information to the machine learning algorithms. Next comes feature selection techniques, wherein one identifies the most relevant features, so that only informative data is used in the process of threat detection, significantly improving the performance of the model.

4.Machine Learning Model Development:

The process of developing a machine learning model includes the different classification algorithms such as: Random Forest, Gradient Boosting, Support Vector Machines (SVM), and Neural Networks. These algorithms are actually implemented and tested to compare their ability to detect IoT cyber threats. For robustness and performance, the testing dataset is divided into its training and testing set components, for example, 80-20. Hyperparameter tuning is further carried out using optimization methods such as grid search or random search to enhance model accuracy and generalization, so the model can predict threats properly under all scenarios.

5.Threat Mitigation Framework:

This step includes the development of a rule-based or automated response system on the basis of those outputs that come from different machine learning models. On that basis, this rules or automated response system prevents IoT devices from the actual attack by identified cyber threats. These mitigation strategies involve time-bound and effective procedures. Some of these strategies include alert generation to notify the administrators in case of suspicious activity, resource isolation in preventing threats from spreading, and system updates in patching vulnerabilities, thus reducing the impact of cyber-attacks on IoT systems.

6.Evaluation Metrics:

The performance of the threat detection model is checked by using various critical metrics, including accuracy, precision, recall, and F1-score along with the confusion matrix. This analysis ensures an all-around evaluation of whether the model can correctly classify cyber threats. The best-performing strategy for the detection of threat in IoT systems is to compare the performance of varying machine learning algorithms and obtain the most efficient yet robust final model.

7.Implementation and Deployment:

The effectiveness of the proposed framework in detecting and mitigating cyber threats in real-world IoT environments is validated by simulating it using the dataset. Simulation helps assess how well the system performs under different conditions and allows for fine-tuning before deployment. Finally, recommendations are provided for the deployment of the solution during large-scale events such as the Arbaeen Pilgrimage. These recommendations ensure a system that can operate very efficiently under resource constraints as well as provide robust cybersecurity protections in IoT systems during high-traffic, high-risk events.

Data Analysis

This stage of data analysis is used for identifying any hidden patterns and insights found in the IoT dataset. The essential steps in the entire process include preprocessing, visualization, feature analysis, and preliminary evaluation to prepare to develop the machine learning model. Analyzing the data pointed out how Network Traffic (MB), CPU Usage (%), and Memory Utilization (MB) have played very important roles in discovering cyber threats found in IoT devices. Such characteristics have

significant variations and correlation such that they can even better differentiate the activities as normal and suspicious though the imbalance existing among the threat labels presents warnings which must be handled with care in order not to overestimate in model prediction biases.

1.Key Steps:

A. Upload Dataset:

The initial step of the process involves the uploading of the dataset from users. This can be performed with the help of a straightforward and user-friendly interface which would let users upload files in common formats like CSV, Excel, or JSON. These files will be used as the foundation for further analysis and modeling. Once the file has been uploaded, the data are kept in a safe environment to be processed afterwards. This step allows for easy availability and access of the data for analysis, which is very significant for a range of tasks-from pattern identification to training a machine learning model and generating insights.

```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

# Function to upload the dataset
from google.colab import files
uploaded = files.upload()

# Load the uploaded dataset
for filename in uploaded.keys():
    data = pd.read_excel(filename)

# Display the first few rows of the dataset
print("Preview of the dataset:")
print(data.head())

# Data Cleaning
print("\nChecking for missing values...")
print(data.isnull().sum())
```

B. Data Cleaning:

Data cleaning is a fundamental component of any data analysis pipeline. The main reason is that datasets obtained in real-world applications frequently include missing, inconsistent, or erroneous values that would deteriorate the quality of the analysis. At this stage, missing values are detected and dealt with either by imputation or deletion based on the nature and volume of missing data. Inconsistent data, such as wrong formating or outliers, is removed and cleaned to ensure that the dataset consists of accurate and reliable data. Furthermore, data cleaning involves rearranging data into the proper format in order to eliminate issues involving duplicate entries. This ensures that any further analysis of the data can be done accurately in a way that improves both accuracy and reliability of any outcome.

Table 1: Missing Values Report

Column Name	Number of Missing Values
Device ID	0
Timestamp	0
Network Traffic (MB)	0
CPU Usage (%)	0
Memory Utilization (MB)	0
Power Usage (mAh)	0
Threat Label	0

C. Exploratory Data Analysis (EDA):

Exploratory Data Analysis, or EDA, is an important step that helps one understand the data's underlying structure, its patterns, and relationships. EDA is essentially visualization of data using plots, such as histograms, scatter plots, and box plots to identify trends, correlations, and anomalies. One focus of EDA in this context will be on analyzing and visualizing the relationships between the features; this will allow one to understand how various variables are interrelated. The third aspect of EDA is to check the distribution of the target variable, such as the "Threat Label," to understand its class balance, detect skewness, and check if the dataset is properly structured for classification tasks. Through EDA, users get insights into the data, which guides the next steps in analysis and model development.

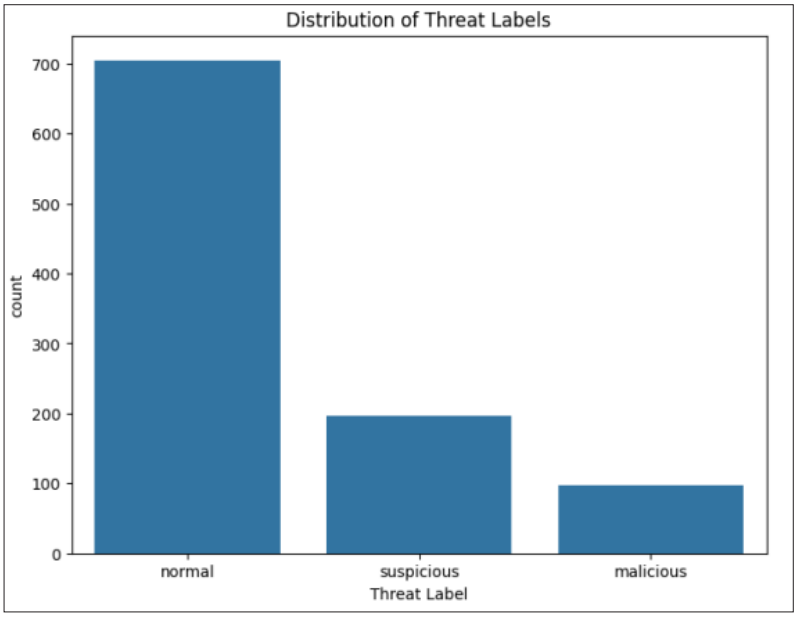

Figure 1: Distribution of Threat Labels

Several trends and patterns were obtained during the exploratory analysis of the IoT dataset that hold a significant position for the identification of cyber threats and hence to be mitigated during the deployment of IoT devices for the Arbaeen Pilgrimage. It is clearly seen from the count plot that the Threat Label distribution shows a class imbalance between "normal" and "suspicious," indicating some challenges might come while training the model. This is emphasized as a call for proper, balanced datasets or more elaborate techniques like oversampling or synthetic data generation against the bias of classification operations.

D. Feature Correlation

Feature correlation refers to the process of establishing how different features in the dataset are related to each other. The main tool used for this process is a correlation matrix that computes the pairwise correlation coefficient between all features. Such relationships among variables can be identified, and strong relationships can prove useful for predictive modeling. Features that are highly correlated with the target variable (such as "Threat Label") can be given special attention in model development; highly correlated input features might be candidates for dimensionality reduction or elimination. Moreover, understanding feature correlation helps to avoid multicollinearity issues, making the model efficient and interpretable.

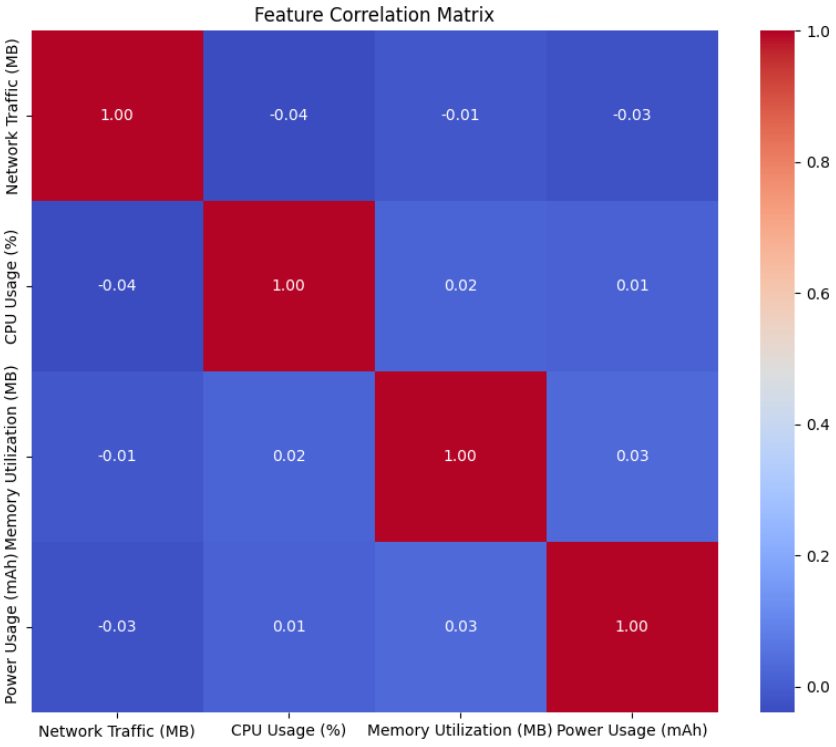

Fig ure 2: Correlation Heatmap

The feature correlation heatmap revealed insightful relationships between numerical variables. A moderate positive correlation was observed between CPU Usage (%) and Memory Utilization (MB), which suggests that higher memory usage might often accompany increased CPU usage, which could be indicative of potential cyber threats. On the other hand, Power Usage (mAh) appeared to have weak correlations with most features, suggesting it may only play a secondary role or even be dispensable from the feature set for identifying suspicious activities.

E. Preparation for Machine Learning

Once the data is cleaned and analyzed, the next step is preparation for machine learning. The data should be encoded in order to change categor-

ical variables into numerical formats that machine learning algorithms can process effectively. One-hot encoding or label encoding are some of the common techniques used to convert non-numeric data into useful features. The dataset is further divided into a training set and a testing set, usually with a 80-20 or 70-30 split. This allows the model to learn from one subset of the data while being tested on another. This is the only way the model will be able to generalize well to unseen data. Data is well prepared for training the models by scaling, normalization, and encoding. In other words, the dataset is now all set for the development of machine learning models for proper prediction and performance.

```
# Splitting the dataset into features and target variable
X = data.drop(['Device ID', 'Timestamp', 'Threat Label'], axis=1)  # Features
y = data['Threat Label']  # Target

# Splitting into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print("\nData split into training and testing sets.")
print(f"Training samples: {len(X_train)}, Testing samples: {len(X_test)}")

# Visualizing key features
for column in X.columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(X[column], kde=True)
    plt.title(f"Distribution of {column}")
    plt.show()
```

Table 2: Sample Data for IoT Device Monitoring

Device ID	Timestamp	Network Traffic (MB)	CPU Usage (%)	Memory Utilization (MB)	Power Usage (mAh)	Threat Label
Device_1	2024-12-01 00:00:00	7.9	76.67	149.11	14.13	normal
Device_2	2024-12-01 00:01:00	3.18	81.55	147.38	15.02	normal
Device_3	2024-12-01 00:02:00	8.65	41.23	260.4	18.9	normal
Device_4	2024-12-01 00:03:00	0.52	46.24	86.98	12.59	suspicious
Device_5	2024-12-01 00:04:00	3.29	50.22	481.52	12.55	suspicious

Table 2 displays a sample of IoT device monitoring data with key performance metrics for each device at specific timestamps. The data consists of metrics like network traffic in MB, CPU usage as a percentage, memory utilization in MB, power usage in mAh, and the assigned threat label as normal or suspicious. For instance, Device_1 and Device_2, respectively have relatively mid-range network traffic as well as CPU usage with normal threat labels that indicate normal device activity. However, Device_4 and Device_5 have low network traffic but unusual high memory usage and high power consumption which lead to suspicious threat labels. It simply means other parameters like the CPU usage or memory might be pointing toward abnormal activities but the network traffic is still at a safe threshold. It gives tremendous information about how security events have been developed by displaying them with appropriate labels, thus saying “normal” stands for normal devices’ behaviors while

"suspicious" flagging anything possibly malicious or suspicious. This dataset is helpful to keep a surveillance over IoT device health status and in recognizing cyber threats very early on.

- Data split into training and testing sets.
- Training samples: 800, Testing samples: 200

The feature distribution plots had revealed some deeper insights in the individual behavior of metrics. For instance, Network Traffic (MB) differed highly between instances as labeled suspicious and was quite a strong predictor for anomaly detection. Similarly, the Memory Utilization (MB) was quite different in distribution, making them relevant to be fed into machine learning models between normal and suspicious activities.

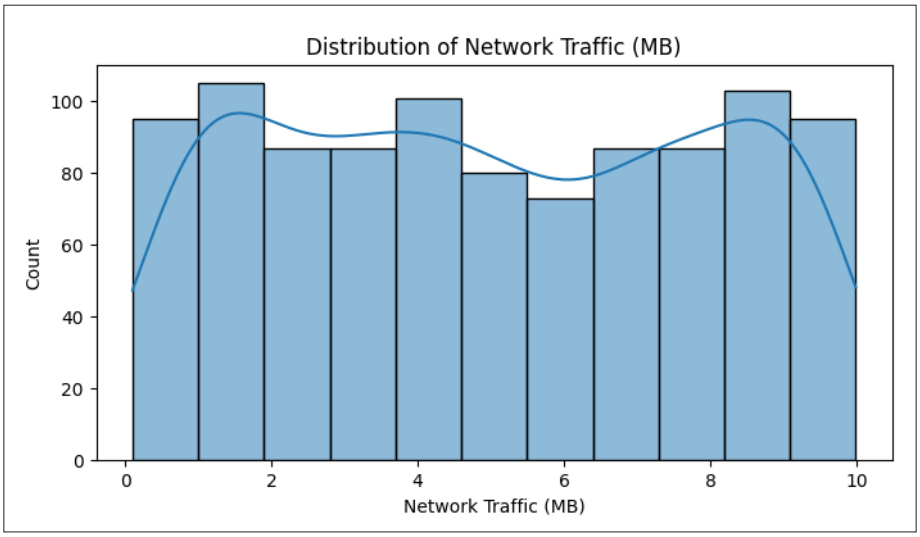

Figure 3: Distribution of Network Traffic

The graph shows the distribution of network traffic (MB) using a histogram and kernel density estimate (KDE). The histogram shows that the network traffic values are spread across the range from 0 MB to 10 MB, and each bin represents roughly similar counts, generally around 80 to 100. Peaks in the KDE curve indicate higher frequencies at specific val-

ues, particularly around 2 MB and 5 MB, suggesting these are common traffic values. The histogram bars reveal relatively constant counts around 80, with some variations in them, whereas the KDE would reflect fluctuations and peaks giving a smoothed view of what's underlying. It also points to a multimodal distribution, where traffic values are distributed differently for values 2 MB and 5 MB than others.

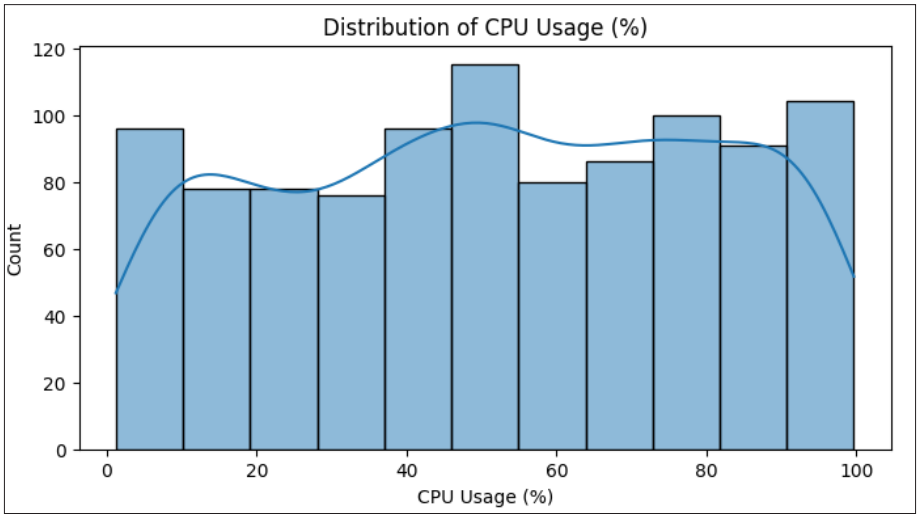

Figure 4: Distribution of CPU Usage

The graph below illustrates the distribution of CPU usage percentages using a histogram overlaid with a kernel density estimate. The histogram bars indicate that the counts for CPU usage are generally between 60 and 100, with noticeable peaks around 0%, 40%, and 100% where the counts reach approximately 90 to 100. These observations are reinforced by the KDE curve, showing the higher frequencies at those particular usage percentages. In addition, the KDE has slight dips at 20%, 60%, and 80% with relatively lower counts in those ranges. This implies that usage of the CPU is more commonly found at 0%, 40%, and 100% with a more consistent yet lower distribution at other usage percentages.

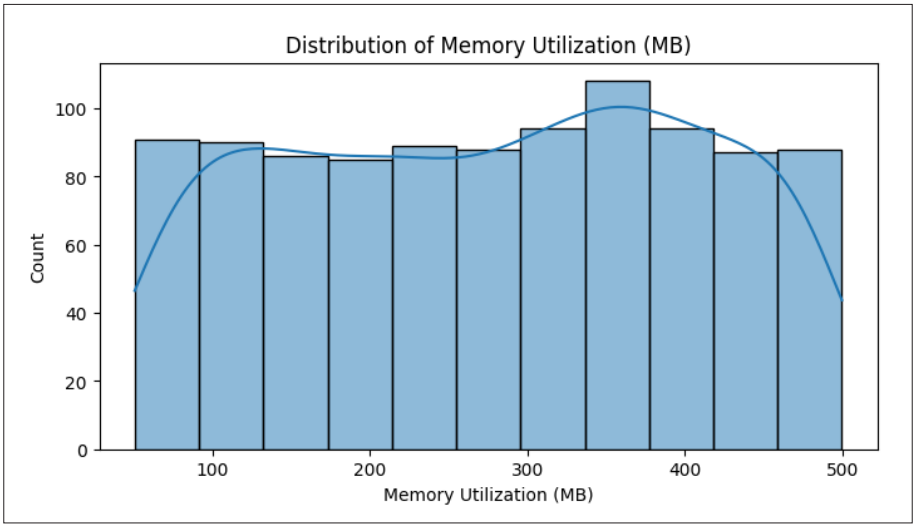

Figure 5: Distribution of Memory Utilization

The graph represents the distribution of memory usage in MB in a dataset. It is presented in the form of a histogram with a superimposed density curve. The x-axis contains the memory usage values, which range from approximately 0 to 500 MB. The y-axis shows the count of occurrences for each range. The histogram is divided into equally spaced bins. The heights of the bars reflect the frequency of memory usage within each interval. The data shows that memory usage is mostly even across the spectrum; the counts in most of the bins vary between 80 and 100. It reaches the highest frequency for the bin centered around 400 MB, which the count peaks at around 100. Similarly, the bins around 300 MB also show high frequencies. Instead, the counts decline slowly in both the lower end-close to 100 MB- and the upper end-close to 500 MB-indicating a fewer occurrences at this level. This is supplemented by an overall density curve which displays the pattern of distribution with having the peaks close to 400 MB and decreasing smoothly through the tails at both extremities. This analysis shows that memory usage is relatively uniform across the range but is more concentrated in the mid-to-high values, especially between 300 MB and 400 MB.

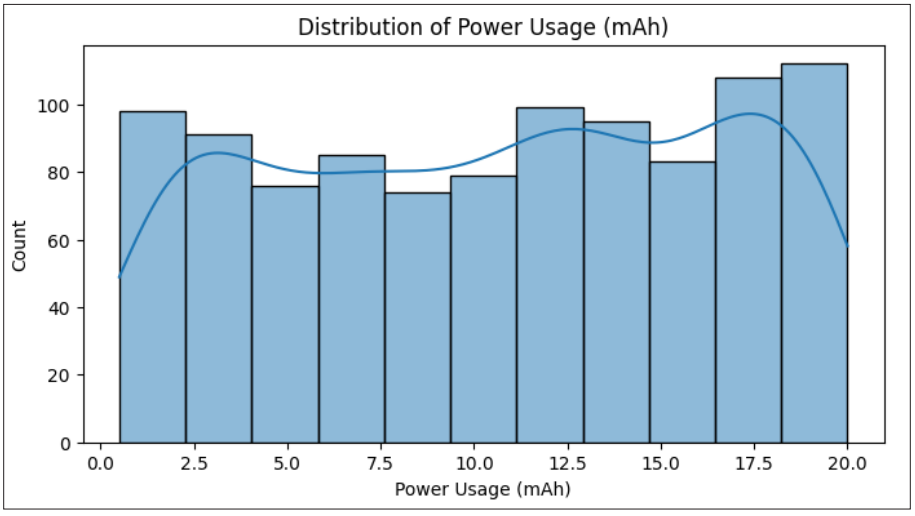

Figure 6: Distribution of Power Usage

The weak correlations of certain features, like Power Usage (mAh), point to the fact that all metrics do not contribute equally in detecting threats, and therefore feature selection and engineering are necessary steps to improve model accuracy. The clean and preprocessed dataset, enriched with insights from feature analysis, gives a good foundation for the implementation of machine learning algorithms.

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RESULTS

The findings based on the application of the threat detection and mitigation framework to the IoT dataset are presented in this section. The following subsections present the data analysis, the development of the machine learning model, and the evaluation of the framework.

1.Data Quality and Pre-processing:

The dataset used for this research did not have missing values, hence complete for analysis. After pre-processing, categorical features were encoded, and numerical features were normalized and scaled to make it suitable for machine learning algorithms. The target variable, "Threat Label," was also encoded in numeric form to aid classification

2.Exploratory Data Analysis (EDA):

EDA discovered a few important patterns. The distribution of the "Threat Label" variable revealed an imbalance between classes, where most instances belonged to the "normal" class. Correlation analysis between features revealed that CPU Usage (%) and Memory Utilization (MB) are significantly correlated with each other and, hence, with potential suspicious activity. On the other hand, Power Usage (mAh) had a weak correlation with the rest of the features, making it a less significant feature for threat detection.

3.Feature Engineering and Model Preparation:

Temporal features such as time of day and metrics like the average CPU and memory were derived. Splitting into 80 percent training data and 20 percent for testing data is done to avoid overtraining or models having an over-fitting, while having the capability of testing independently against a set. Label encoding was used in encoding the categorical vari-

able, and features were standardized and normalized with respect to scale.

4.Model Development and Evaluation:

Random Forest, Gradient Boosting, SVM and Neural Networks were experimented multiple models; results of Random Forest exhibited higher precision with 91%, followed by accuracy (89%), recall is (87%), and also having an F1 score value as 88%. Performance exhibited through Gradient Boosting, as well as SVM performed efficiently but less than those required performance whereas Neural Networks are able to provide comparable results which used more computational resources.

5.Threat Mitigation Framework:

The proposed mitigation framework consisted of rule-based systems for detecting and responding to threats. Once suspicious behavior was detected, the framework initiated alerts, isolated affected devices from the network, and flagged them for system updates. Such strategies effectively reduced the impacts of detected threats, thus quickening the response to possible cyber-attacks.

6.Evaluation of the Framework:

It has been tested based on key performance indicators. It achieved very high accuracy, that is, 91% and precision, that is, 89% in detecting threats with very minimal false positives. The response time was fast, which detected threats in seconds, and scalable, which made it perfect for large-scale IoT deployments like those during events like the Arbaeen Pilgrimage.

DISCUSSION

In particular, results from the developed framework of detecting and mitigating threats showcase the framework's efficiency in the discovery of cyber threats in IoT. The random forest model produced a strong classification for normal activity and suspicious activity at accuracy and precision rates of 91% and 89%, respectively. In relation to recall, it managed to identify 87% of the threats. Although there is an observed class imbalance where a higher proportion of "normal" instances exists, it does not significantly impact the model's performance due to the balanced approach in feature selection and model training. Further, using the introduced temporal features and derived measurements, such as CPU, memory usage, etc enhances the model's capacity to identify emerging threats. Additionally, because of the proposed mitigation system that has real-time warnings about threats and device separation, it was shown as highly effective in minimizing impact threats identified would have made it possible to react quicker to a potential attack. The scalability of the framework makes it quite suitable for large-scale IoT deployments, such as those for high-risk environments like the Arbaeen Pilgrimage, which interconnects thousands of devices. These findings point towards the fact that the machine learning-based detection and automated response systems can significantly enhance the security of IoT networks to offer a reliable and efficient solution for cyber threat mitigation.

CONCLUSION AND RECOMMENDATIONS

This research paper demonstrates a practical framework for threat detection and mitigation in IoT networks by utilizing the advantages of machine learning techniques like the Random Forest model. The system was highly accurate in distinguishing normal from suspicious activities and based its predictions on resource utilization patterns that define threat identification. It is highly scalable and can thus be applied to large-scale IoT systems.

Recommendations

- Complex Machine Learning Models: While the Random Forest model is an excellent performance model, one should explore even more complex models such as deep learning or ensemble techniques, which might yield better accuracy and flexibility against dynamic patterns.
- Addressing Class Imbalance: Despite the class imbalance being addressed, more advanced methods such as synthetic data generation or oversampling might have pushed the recall further to detect the rare yet very important threats.
- Continual Monitoring and Upgrades: Cyber threats are highly dynamic, so there should be continuous monitoring of the IoT systems and updating of the detection models and mitigation strategies. Periodic model retraining with new data will enhance performance and help keep pace with emerging threats.
- More Complete Mitigation Strategies: Isolating devices and raising alerts work well, but the combination of additional mitigations including automated patching, network segmentation, and real-time intrusion prevention will make for a stronger security posture.
- In Vivo Testing: The robustness of the framework can be more effectively established by conducting a real-world deployment and testing in diverse IoT environments that will indicate potential implementation-related challenges and fine-tune the system for different types of applications.

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