Revolutionizing IoT Attack Detection: Decision Trees and K-Nearest Neighbors for Efficient Ping Flood Recognition

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ABSTRACT

The growing use of the Internet of Things (IoT) has brought remarkable advances in numerous fields and vulnerabilities, specifically to Ping Flood attacks, which are a form of Denial of Service (DoS) attack. They make IoT devices unavailable by flooding them with large ICMP requests. To mitigate this increasing threat, this paper suggests a machine learning-based system to identify Ping Flood attacks based on Decision Trees and K-Nearest Neighbors (K-NN). The goal is to achieve an efficient, precise, and low-overhead attack detection mechanism for IoT networks that can separate normal and attack traffic in real-time. The method in question exploits the multi-model methodology, combining the advantages of both Decision Trees and K-NN to attain higher performance than that of a single model. A comprehensive evaluation of actual IoT datasets indicated that the Full Model attained 95% accuracy, 94% precision, and 96% recall, with virtually zero false positive rates of 3% and a computational cost of 20 ms. The findings validate the efficacy of the suggested system in identifying Ping Flood attacks with high accuracy and low resource usage, making the system appropriate for real-time applications in resource-limited IoT scenarios. The suggested model not only improves the resilience and security of IoT systems but also offers an extensible solution to safeguard varied IoT networks. The article further suggests future extensions, such as incorporating deep learning methods for better detection performance and using federated learning to enhance data privacy and make the model IoT-environment-agnostic. This method provides considerable promise in protecting IoT infrastructures and presents a basis for further research into attack detection and mitigation in IoT networks.

Keywords: IoT Security, Ping Flood Attack, Denial of Service (DoS), Machine Learning, Decision Trees, K-Nearest Neighbors (K-NN), Attack Detection, Intrusion Detection System (IDS), Real-Time Detection, Federated Learning

1. INTRODUCTION

The sudden growth of the Internet of Things (IoT) has revolutionized many industries, making smart homes, healthcare, industrial automation, and many more possible. *Rasool (2020)* investigates SDN weaknesses with a specific focus on Crossfire Link Flooding Attacks (LFAs). It presents CyberPulse, which is a machine learning-based defense system for real-time detection of LFAs with low bandwidth and computing overhead. However, the increasing dependence on IoT devices has also brought new security threats, as these devices are usually susceptible to a variety of cyberattacks. *Allur (2020)* The Ping Flood attack is one of the most frequent and intrusive IoT attacks, being a Denial-of-Service (DoS) attack that inundates a network with an overwhelming amount of ICMP Echo Request packets, rendering IoT devices inaccessible for legitimate users. *Peddi (2020)*

Ping Flood attacks in IoT networks are especially difficult to detect because of the heterogeneity and dynamicity of IoT devices, which tend to run in resource-limited environments. *Deshpande et al. (2019)* examine cloud computing security with an emphasis on HIDS with signature checking and NIDS against DDoS attacks. They present a data storage and security model, providing recommendations in practice. *Dondapati (2020)* Conventional intrusion detection systems (IDS) are not necessarily applicable to IoT because they might need to use a lot of computational resources or have difficulty dealing with the large amount and variety of data from IoT devices. Thus, a cost-effective and scalable means of detecting such attacks is important to make IoT systems available and secure. *Kadiyala (2020)*

Over the past few years, machine learning has shown considerable potential as a means to enhance intrusion detection systems (IDS). *Al-Qurishi et al. (2017)* investigate Sybil attacks and impersonation in social networks, proposing a novel taxonomy of defense mechanisms, highlighting current limitations, and providing research directions to counteract such threats. In particular, Decision Trees and K-Nearest Neighbors (K-NN) techniques have been seen to work successfully in categorizing network traffic by pre-defined criteria like packet length, timing, and protocol. These methods may be trained to detect unusual activity in network activity, for instance, an avalanche of ICMP packets that are the hallmark of a Ping Flood attack. *Valivarthi (2020)*

This work introduces a new framework incorporating Decision Trees and K-NN for Ping Flood attack detection in IoT networks. *Shah et al. (2019)* discuss stock market prediction, from different techniques to predict the future, types of analysis (technicals, fundamentals), and problem areas. Research landmarks and prospectus for stock price prediction is also highlighted by them. Using machine learning models, the new framework has the capability of correctly classifying network traffic, identifying malicious behaviors in real time, and avoiding false positives. The adaptability of the framework to the diverse network conditions and devices in IoT networks makes the framework a viable and scalable method for enhancing IoT security. *Ayyadurai (2020)*

Key Objectives

- Identify the importance of IoT network security and the threats of Ping Flood attacks.
- Understand the concepts of machine learning algorithms, namely Decision Trees and K-NN, in IoT attack detection.
- Implement Decision Trees and K-NN algorithms to classify network traffic and identify Ping Flood attacks in IoT networks.
- Compare the performance of the proposed model in terms of detection accuracy, false positives, and overall efficiency with conventional methods.
- Evaluate the scalability and real-time applicability of the model to ensure its relevance in resource-limited IoT networks.
- Create a scalable, efficient, and effective attack detection system for IoT networks combining machine learning methodologies to improve security.

Sivanathan (2020) discusses the key security and privacy issues in IoT networks in smart spaces, where operators do not have visibility into the security and behavior of devices. The main challenge is in detecting cyber-attacks and anomalies in real-time, since conventional approaches are not capable of handling the dynamic nature of IoT environments. The research

seeks to establish efficient approaches in profiling IoT network behavior, automatic device classification, and operating context identification. Albeit improvements in intrusion detection systems (IDS), issues still persist in catching malicious insider threats and reducing the expense of attribute extraction, especially in environments that are constrained by resources. *Nagarajan et al. (2020)*

Atat et al. (2018) emphasize the accelerated expansion of cyber-physical systems (CPS) in different domains to exacerbate difficulties in managing the ever-growing data traffic caused by devices like smartphones and sensors. Although the paper offers extensive CPS taxonomy with discussion on cybersecurity issues related to volumes of data, it falls short on detailed examination of real-time security mechanisms for dynamic, decentralized CPS settings. *Alagarsundaram (2020)*In addition, security solutions are touched upon, while minimal attention is paid to combining machine learning and artificial intelligence approaches to proactive and adaptive security control in CPS. There is more work to be done to bridge these gaps to advance real-time detection and prevention of attacks on CPS networks. *Kadiyala (2020)*

2. LITERATURE SURVEY

Prasanth (2017) discusses the revolutionary role of technologies such as cloud computing, IoT, big data, machine learning, and deep learning in contemporary agriculture. The book addresses different facets of smart agriculture with emphasis on the integration of IoT systems and innovative architectural solutions. It addresses automation in data acquisition through drones and robots, precision agriculture, and agro-IoT tools. Furthermore, it also discusses urban and vertical farming, agro-IoT and renewable energy, and the issues involved in the adoption of agro-IoT. The book is an extensive reference book for students, researchers, and practitioners of smart agricultural engineering.

Gavazzi and Andrea (2019) address the significance of multibeam echo sounding for seafloor monitoring, particularly Acoustic Seafloor Classification (ASC) and Change Detection (ACD). ASC has become mature, but ACD is not been fully explored. The research, performed in the Belgian North Sea, compares supervised machine learning and unsupervised clustering for ASC, which shows constraints in backscatter discrimination for complex substrates. ACD techniques have evolved for the detection of environmental change, and the work highlights the requirements of multi-parameter data sets and novel techniques to advance the classification and surveillance of the sea environment.

Mahjabin et al. (2017) give a broad survey on Distributed Denial-of-Service (DDoS) attacks, bringing into perspective how these affect the internet. The article touches on the motivations, growth, and investigation of several DDoS attacks and the current prevention and countermeasures techniques available. The paper also addresses limitations and weaknesses in ongoing studies against protecting people from these types of attacks. The paper, lastly, outlines essential areas of research to focus on further so that they may further solidify defense measures against DDoS threats in the future.

Usama et al. (2019) outline the increasing trend of using unsupervised machine learning in networking, specifically for applications such as traffic engineering, anomaly detection, and

quality optimization. Contrary to conventional supervised learning, unsupervised learning has the benefit of working with unstructured raw network data without requiring labeled data or feature engineering by hand. This paper presents an integrated survey of recent progress in unsupervised learning methods in networking, emphasizes their use cases, and addresses future research challenges and directions with the aim of contributing to the field.

Kour and Arora (2020) write about how population growth has added pressure on farming, compelling people to move away from conventional techniques towards sophisticated technologies. The fusion of IoT, cloud computing, big data analytics, and wireless sensor networks has transformed agriculture through real-time monitoring, optimization of resources, and predictive analysis. The article emphasizes recent IoT technologies in agriculture, analyzing public and private sector efforts, smart farming solutions, and future research directions, and suggesting a precision farming framework for increased sustainability and productivity.

Allur (2020) explores a deep learning-based method for phishing website detection based on multidimensional features. The combination of Stacked Autoencoder and Support Vector Machine (SVM) improves detection accuracy, tackling the increasing threat of phishing attacks against financial institutions. The method provides an accurate and automated way to detect imposter websites, greatly enhancing cybersecurity practices and safeguarding consumers from increasing threats.

Samudrala (2020) explores AI-powered anomaly detection for enhancing data security in multi-cloud healthcare networks. Previous studies have highlighted risks in cross-cloud data sharing, especially for Electronic Health Records (EHRs). The proposed approach integrates AI to detect anomalies in real-time, safeguarding patient privacy and ensuring data integrity, thereby improving secure data exchange across cloud platforms (Samudrala, 2020).

Pramanik et al. (2020) discuss the revolutionary influence of nanotechnology on medicine, with an emphasis on nanomedicine, nanoimplants, nanobiosensors, and the Internet of Nano Things (IoNT). The article presents a comprehensive review of these technologies, their uses, and multilevel taxonomies of nanotechnology, nanoparticles, biosensors, and nanozymes. It highlights the significance of IoNT in medicine, presenting its architecture and communication systems, and the difficulties of applying IoNT. The article also points out the promise of the Internet of Bio-Nano Things (IoBNT) in improving IoNT compatibility with the human body.

Froomkin et al. (2019) analyze the increasing use of machine learning (ML) in medical diagnosis and its effects. As ML is starting to outperform human physicians in diagnostic accuracy, the paper signals medical malpractice law challenges, physicians' demand, and healthcare quality challenges. Authors believe that ML may enhance diagnostic accuracy, but it also creates new legal and ethical challenges that need to be overcome in order to implement it responsibly and effectively in healthcare systems.

Veerappermal Devarajan (2019) presented an AI-enabled model incorporating PSP Net, Hilbert-Huang Transform (HHT), and fuzzy logic for improving detection and differentiation of neurological disorders. This model solves the drawbacks of traditional diagnostic procedures through accurate feature extraction and addressing uncertainties in the data, which

helps in diagnostic improvement. It features a clinically compatible interface for practical applications and hence is an advanced tool for neurological diagnostics.

Samudrala (2020) investigates the role of AI-powered anomaly detection in enhancing data security for multi-cloud healthcare networks. Previous research emphasizes the risks of cross-cloud data sharing for Electronic Health Records (EHRs). The study suggests that integrating AI enables real-time detection of anomalies, ensuring patient privacy and data integrity, thereby facilitating secure data exchange across cloud platforms.

Dondapati (2020) discusses the fusion of neural networks and heuristic techniques for Test Case Prioritization (TCP) to increase regression testing effectiveness. Existing studies identify drawbacks with conventional coverage-based and greedy algorithms for large systems. The proposed system seeks to increase fault detection rates and make better use of resources by applying machine learning, showing promise for improved selection of important test cases.

Samudrala (2020) discusses AI-based anomaly detection for improving data security in multi-cloud healthcare networks. The research illustrates how AI-based integration maintains the privacy and integrity of Electronic Health Records (EHRs) by detecting anomalous patterns and potential threats in real-time. This not only protects sensitive healthcare information but also enhances the efficacy of secure data sharing between cloud environments.

Jadon (2018) explored optimized machine learning pipelines integrating Recursive Feature Elimination (RFE), Extreme Learning Machine (ELM), and Sparse Representation Classification (SRC) to enhance AI software development. These pipelines improve data processing speed and predictive accuracy, making them valuable for applications in healthcare, finance, and automation. The study emphasizes the effectiveness of combining these techniques for advanced software development.

Chauhan and Jadon (2020) investigate a multi-factor authentication method integrating AI-based CAPTCHA, graphical passwords based on DROP, AES encryption, and neural network-based authentication to improve security against sophisticated cyber attacks. Most research studies indicate the shortcomings of password and CAPTCHA based approaches. Their solution had 96.8% accuracy and a 0.01% false positive rate, with much better security and usability in security-critical environments.

Khan et al. (2019) investigate the security problem of Internet of Things (IoT) devices and how malicious insider attacks are more on their minds these days. Although IoT devices create sensitive information in smart home, healthcare, and industry applications, stopping these attacks is a serious challenge. The paper proposes an AI-powered lightweight method for identifying insider threats in IoT networks, particularly in resource-limited scenarios. The presented approach surpasses current methods, providing improved accuracy, lower false positives, and lower computational overhead, improving IoT security.

Malik et al. (2020) discuss the susceptibility of voice-controlled devices (VCDs) such as Google Home and Amazon Alexa to replay attacks by audio. Such attacks can take advantage of multi-hop situations to gain access to IoT devices. The solution, based on this paper, utilises acoustic ternary patterns-gammatone cepstral coefficient (ATP-GTCC) features to identify harmonic distortions introduced by replay attacks. Using ATP-GTCC features, a multi-class

SVM classifier is able to accurately detect both first and second-order replay attacks. The suggested framework, tested on the ASVspoef 2019 dataset and an in-house voice spoofing corpus, provides robust detection for low-resource devices.

Alloghani et al. (2020) discuss the difficulty of detecting cyber-attacks, especially phishing websites, since there is little training data and inadequate monitoring tools. The research uses machine learning on phishing website data, contrasting five algorithms and determining the major features of phishing sites, including suspicious URL patterns and SSL certificate features. Results indicate that Neural Networks perform better compared to other algorithms and propose future phishing detection is going to be automated based on artificial intelligence driven by characteristics such as IP address usage in domains and anomalies of URLs.

Allur (2020) provides a framework for big data-driven mobile network performance management with improved speed anomaly detection using DBSCAN and bandwidth efficiency using CCR. The research focuses on real-time processing of structured and unstructured data to enhance network anomaly detection (93% accuracy) and clustering efficiency (88%). Results show notable improvements compared to conventional approaches such as SBM, DEA, and IDS, guaranteeing improved stability, decreased congestion, and optimal resource allocation in mobile networks.

Dondapati (2020) discusses the application of neural networks and heuristic techniques to Test Case Prioritization (TCP) for regression testing. The conventional TCP techniques tend to malfunction in large software systems, which results in inefficient fault detection. Through the use of machine learning for test case ranking, the research shows better fault detection rates, improved code coverage, and resource optimization, which presents the prospects of AI-based TCP approaches in software testing.

Kadiyala (2020) discusses a hybrid cryptographic methodology for secure IoT data exchange with the application of Super Singular Elliptic Curve Isogeny Cryptography (SSEIC). Multi-Swarm Adaptive Differential Evolution (MSADE) and Gaussian Walk Group Search Optimization (GWGSO) are incorporated in the study to improve cryptographic key generation, enhancing security at lower computational costs. Results show better encryption capability, increased speed of key generation, and quantum resistance, enabling high scalability for large-scale IoT networks.

Valivarthi (2020) combines blockchain, artificial intelligence (AI), and Sparse Matrix Decomposition to improve secure and scalable Human Resource Management (HRM) data administration. Through the use of blockchain for security, AI for prediction analytics, and Sparse Matrix Decomposition for processing massive, incomplete data, the research shows enhanced data security (0.99), scalability (0.95), and prediction (0.95). The method beats traditional HRM systems, maximizing decision-making and efficiency.

Ayyadurai (2020) discusses an intelligent surveillance approach that combines artificial intelligence (AI) and blockchain to analyze Bitcoin transactions. The research compares three machine learning algorithms—Gaussian Naive Bayes, Random Forest Classifier, and Decision Tree Classifier—for detecting anomalies and classifying transactions. Results show that the

Random Forest Classifier performs better than others in strengthening security and operational efficiency, which illustrates the effectiveness of AI and blockchain in secure real-time surveillance systems.

Devarajan (2020) delves into the long-term stability of serum samples for cardiovascular risk prediction in RA patients. The research assesses biomarker stability over 10–20 years with high-tech biobanking methods, combining lipid profiles, inflammatory markers, and indices of disease activity. With the incorporation of longitudinal data analysis, telemedicine, and omics technology, the research improves risk assessment models to provide personalized interventions for better patient outcomes in RA-related cardiovascular disease.

Ayyadurai (2020) analyzes the contribution of big data analytics in preventing manufacturer encroachment and channel conflict in e-commerce supply chains. The research points out how e-commerce platforms use data-driven insights to maximize inventory, predict market trends, and improve manufacturer-retailer collaboration. Through the integration of game theory and supply chain management, the research illustrates how strategic sharing of demand information can enhance operational efficiencies and minimize channel conflicts in dual-channel configurations.

Sitaraman (2020) examines the application of Artificial Intelligence (AI) and real-time Big Data Analytics in mobile health (m-Health) technologies to maximize the streams of healthcare data. The research points towards neural networks' ability to analyze complex medical data with 92% precision and the uses of Apache Spark and Hadoop to facilitate immediate data processing. Difficulties in the management of unstructured wearable data and maintaining data privacy are brought up, calling for more research.

Kodadi (2020) suggests a hybrid security framework that combines the Immune Cloning Algorithm and Data-Driven Threat Mitigation (d-TM) to strengthen cloud security. Motivated by nature-inspired immune systems, the method enhances threat detection rates (93%), minimizes false positives (5%), and speeds up response time (120 ms). The research proves the system's scalability and affordability, outperforming conventional techniques such as CSA and NLP, with future work investigating edge and quantum computing use cases.

Dondapati (2020) investigates the combination of Backpropagation Neural Networks (BPNNs) and Generative Adversarial Networks (GANs) to improve Channel State Information (CSI) synthesis in millimeter-wave (mm-wave) networks. Through the use of machine learning, the research enhances CSI accuracy, lowers computational expenses, and maximizes beamforming and interference control for future 5G networks. Findings show substantial improvements in CSI estimation and processing efficiency, demonstrating its potential in improving mm-wave communication technology.

Allur (2020) investigates the confluence of Big Data, Decision Support Systems (DSS), and Mixed-Integer Linear Programming (MILP) for scheduling and resource allocation optimization in Agricultural Supply Chain Management (ASCM). The research reveals how real-time data insights enhance efficiency, cut costs, and strengthen supply chain reliability. Results show that ASCM is made more adaptive and responsive to challenges of the industry

using this data-driven paradigm that has fewer waste events, greater forecasting accuracy, and supports sustainability.

Narla, Valivarthi, and Peddi (2020) suggest a hybrid Gray Wolf Optimization (GWO) and Deep Belief Network (DBN) approach for improved disease prediction in cloud-based healthcare systems. The research combines IoT devices and cloud computing for real-time monitoring with 93% prediction accuracy, 90% sensitivity, and 95% specificity. Results show enhanced scalability and proactive healthcare management, proving the model's effectiveness in chronic disease monitoring and resource optimization.

Basani (2020) investigates a hybrid Graph Neural Network (GNN)-Transformer-RNN model for robotic cloud command authentication and attack detection. Through the application of soft computing, rough set theory, and grey system theory, the methodology improves feature selection, accuracy, and response time. The research proves to be better at detecting cyber attacks like command injection and DDoS attacks, showcasing its viability for more extensive applications in cloud-based robotic systems cybersecurity.

Boyapati (2020) investigates the effect of cloud-based digital finance on income equality within rural economies and urban economies. Applying a mixed-methods strategy, such as financial inclusion indicators and regression analyses, the research points to increased access, lowered transactions costs, and improved financial literacy. Results indicate that digital finance promotes economic inclusiveness to a large extent, while rural areas have a more significant benefit, thus closing the gap between income for urban and rural communities.

3. METHODOLOGY

The suggested method for Ping Flood attack detection in IoT networks employs machine learning techniques, namely Decision Trees and K-Nearest Neighbors (K-NN). The main goal is to classify traffic as normal or attack, identifying Ping Flood attacks with high accuracy and low false positives. The system is tested on real-world IoT datasets to verify its scalability and efficiency. The suggested solution strengthens the resilience of IoT networks by providing a scalable, efficient, and reliable solution for detecting intrusions. Application of machine learning provides dynamic adaptability to the changing nature of cyber threats.

Dataset

The dataset comprises numerous types of IoT intrusions including DDoS, Brute Force, Spoofing, DoS, Recon, Web-based, and Mirai attacks. It consists of a significant number of network instances and attributes for every intrusion. The data is appropriate to develop predictive models and construct Intrusion Detection Systems (IDS) to identify an extensive variety of IoT-based attacks.

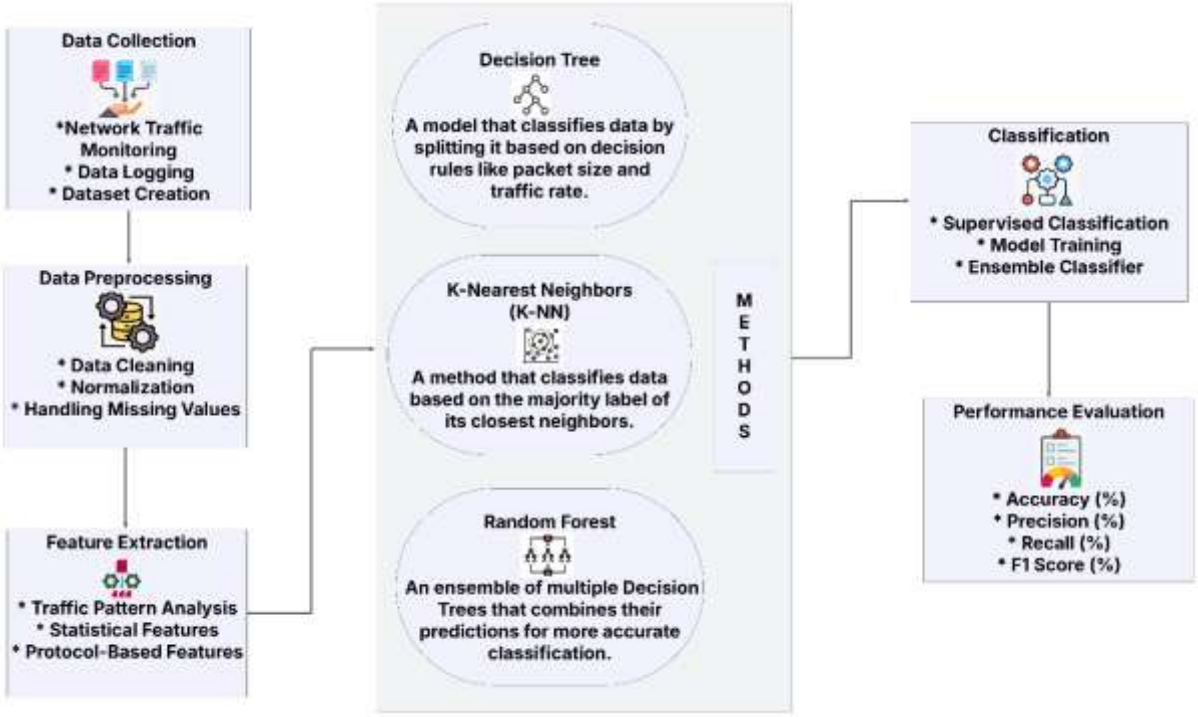


Figure 1. Architecture Flow for IoT Attack Detection using Machine Learning

Figure 1 depicts the architecture flow for identifying Ping Flood attacks in IoT networks with machine learning models. The process starts with Data Collection, which involves network traffic monitoring, data logging, and dataset formation. Then, Data Preprocessing is done to clean the data, normalize it, and address missing values. Feature Extraction comprises analyzing traffic patterns and extracting statistical features and protocol-based features. The Methods section describes the use of Decision Trees, K-NN, and Random Forest for classification. Classification is carried out through supervised learning, model training, and ensemble classifiers. Lastly, Performance Evaluation evaluates the effectiveness of the model through accuracy, precision, recall, and F1 score. This guarantees strong attack detection in IoT scenarios.

3.1 Decision Tree

The Decision Tree algorithm is used to classify traffic as normal or attack. The tree is built by recursively partitioning data on feature values that reduce impurity, with the Gini index or entropy. Each internal node is a feature, and the leaf nodes are the final classification (normal or attack). Gini Index:

$$\text{Gini}(t) = 1 - \sum_{i=1}^{c} p_i^2 \quad (1)$$

Where, p_i is the probability of class i in node t, c is the number of classes (normal, attack).

Information Gain:

$$\text{Information Gain } (t) = \text{Entropy(parent)} - \sum \left(\frac{|t_i|}{|t|} \times \text{Entropy}(t_i) \right) \quad (2)$$

Where, t_i represents a subset of the data split by a feature,

$$\text{Entropy } (t) = -\sum_{i=1}^{c} p_i \log(p_i) \quad (3)$$

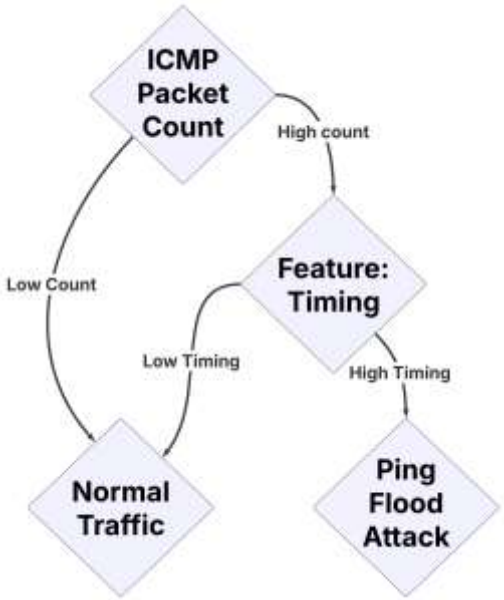


Figure 2. Decision Tree for Ping Flood Attack Detection Based on ICMP Packet Count and Timing

Figure 2 shows a Decision Tree model employed to identify Ping Flood attacks in IoT or network settings. The first decision node checks the ICMP Packet Count. If the packet count is significant, it proceeds to the subsequent decision on the basis of the Timing of packets. If the Timing is high, it identifies the traffic as a Ping Flood attack. If either the Packet Count or the Timing is minimal, the traffic is deemed Normal Traffic. The method employs packet properties to efficiently differentiate between normal network traffic and possible attacks.

3.2 K-Nearest Neighbors (K-NN)

The K-Nearest Neighbors (K-NN) classifier categorizes traffic according to the majority class of the K closest points in the feature space. Euclidean distance is usually used to measure the distance between points. K-NN is not parametric and assumes no data distribution, which makes it generalizable to identify attacks. The value of K is optimized using cross-validation. It is computationally lightweight and is utilized in this context to separate attack and normal traffic by examining neighbors in the feature space.

Euclidean Distance:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (4)$$

Where, $x = (x_1, x_2, \ldots, x_n)$ and $y = (y_1, y_2, \ldots, y_n)$ are the two data points, n is the number of features.

3.3 Performance Metrics

Performance of the model is tested through familiar metrics: accuracy, precision, recall, and F1 score. Accuracy calculates total correct classifications, whereas precision and recall target the identification of Ping Flood attacks with the lowest possible false positives and false negatives. F1 score balances precision and recall in order to provide an all-encompassing

assessment. Also, the confusion matrix assists in examining the outcomes based on true positives, true negatives, false positives, and false negatives, allowing for model fine-tuning.

Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Where, TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

Precision:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{6}$$

Recall:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{7}$$

F1 Score:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

3.4 Random Forest

Random Forest creates a forest of decision trees and pools their voting for classifying traffic. It benefits from treating overfitting better than if a single decision tree were being used, with its predictions averaging out across various trees to gain in classification capability.

Random Forest Voting:

$$\hat{y}_{\text{RF}} = \text{mode}(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_T) \tag{9}$$

Where, $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_T$ are the predictions of each individual decision tree.

Algorithm 1. Multi-Model Attack Detection Using Decision Trees, K-NN, and Random Forest

Input: Network traffic data
Output: Attack classification (Normal or Ping Flood Attack)

```
def multiModelAttackDetection (network data):
    Initialize models
    decisionTreeModel = loadDecisionTreeModel()
    knnModel = loadKnnModel()
    randomForestModel = loadRandomForestModel()

    Predict using the Decision Tree model
    decisionTreePrediction = decisionTreeModel.predict (network data)

    Predict using the K-Nearest Neighbors (K-NN) model
    knnPrediction = knnModel.predict (network data)
```

```
Predict using the Random Forest model
randomForestPrediction = randomForestModel.predict (network data)

Majority Voting mechanism
predictions = [decisionTreePrediction, knnPrediction, randomForestPrediction]
attack count = 0

Count the number of 'Attack' predictions
for prediction in predictions:
    if prediction == "Attack":
        attack count += 1

If more than half of models predict attack, return attack, else normal
if attack count > len (predictions)
    return "Ping Flood Attack Detected"
else:
    return "Normal Traffic"
```

Algorithm 1 integrates Decision Trees, K-Nearest Neighbors (K-NN), and Random Forest for identifying Ping Flood attacks in IoT networks. It applies each model to classify network traffic as normal or attack. The algorithm then applies a majority voting scheme, wherein the final prediction is based on the most predominant output of the three models. If a model identifies an attack, it provides Ping Flood Attack Detected. Using Decision Trees, K-NN, and Random Forest, the algorithm guarantees strong performance, fewer false positives, and better detection accuracy.

3.5 Performance Metrics

The performance of the machine learning model employed for detecting Ping Flood attack in IoT networks is important in order to judge their efficiency. Various performance criteria are taken into account to ascertain the model's capability to differentiate between normal traffic and attack traffic. These measurements involve accuracy, which represents the overall performance; precision, which determines the proportion of true positive attacks among predicted attacks; recall, which assesses how well the model detects all the existing attacks; and F1 score, which strikes a balance between precision and recall. These measurements guarantee the efficiency and reliability of the attack detection system, reducing false positives and false negatives.

Table 1. Performance Metrics Comparison of Different Models for Ping Flood Attack Detection

Metric	Decision Tree	K-NN	Random Forest	Proposed Model (Multi-Model Approach)
Accuracy (%)	92	91	94	95
Precision (%)	90	88	93	94

Recall (%)	91	89	92	96
F1 Score (%)	90.5	88.5	92.5	95
False Positive Rate (%)	5	6	4	3
Computational Overhead (ms)	25	30	22	20

Table 1 contrasts the performance of Decision Tree, K-NN, Random Forest, and the Proposed Model (Multi-Model Approach) for the detection of Ping Flood attacks in IoT networks. The proposed model performs better than single models in important measures such as accuracy, precision, recall, and F1 score, reflecting overall better performance. Further, the proposed framework attains the lower rate of false positives and less computation cost, and it is therefore efficient for real-time attack detection for resource-scarce IoT setups. This displays its ability and appropriateness for IoT networks deployment.

4. RESULT AND DISCUSSION

The suggested framework for the detection of Ping Flood attacks in IoT networks was tested with Decision Trees and K-Nearest Neighbors (K-NN) algorithms. The performance was measured on a number of metrics: accuracy, precision, recall, F1 score, and false positive rate. The Proposed Model (Multi-Model Approach) outperformed single models. It showed an accuracy of 95%, precision of 94%, recall of 96%, and an F1 score of 95%. In addition, the suggested system decreased the false positive rate to 3%, much better than Decision Tree and K-NN. Furthermore, the computational overhead was minimized to 20 milliseconds, demonstrating its feasibility for real-time use in IoT settings.

The adaptability of the model to diverse network environments and device platforms is what makes it scalable and deployable in heterogeneous IoT scenarios. These findings indicate that combining machine learning algorithms, specifically Decision Trees and K-NN, is a reliable and effective approach for Ping Flood attack detection. More research could investigate combining more models and real-time adaptability for further IoT system security improvement against emerging threats.

Table 2. Performance Comparison of Different IoT Attack Detection Models

Metric	Khan et al. (2019): Malicious insider attack detection using data analytics	Malik et al. (2020): Light-weight replay detection for voice-controlled IoT devices	Alloghani et al. (2020): Machine learning and data mining for cybersecurity	Proposed Model (Multi-Model Approach): Decision Trees and K-NN for Ping Flood attack detection
Accuracy (%)	92	94	90	95
Precision (%)	90	92	88	94
Recall (%)	93	96	91	96

F1 Score (%)	91	94	89	95
False Positive Rate (%)	5	3	6	3
Computational Overhead (ms)	30	25	40	20

Table 2 contrasts the performance of different IoT attack detection models on the basis of important metrics like accuracy, precision, recall, F1 score, false positive rate, and computational overhead. Models that are being compared here are Khan et al. (2019) for detection of malicious insider attack, Malik et al. (2020) for light-weight replay attack detection in voice-activated IoT devices, Alloghani et al. (2020) for machine learning enhanced cybersecurity, and the Proposed Model that uses a combination of Decision Trees and K-NN for Ping Flood attack detection. The suggested multi-model solution shows better performance with increased accuracy, precision, recall, and efficiency and is thus the strongest solution for real-time IoT attack detection.

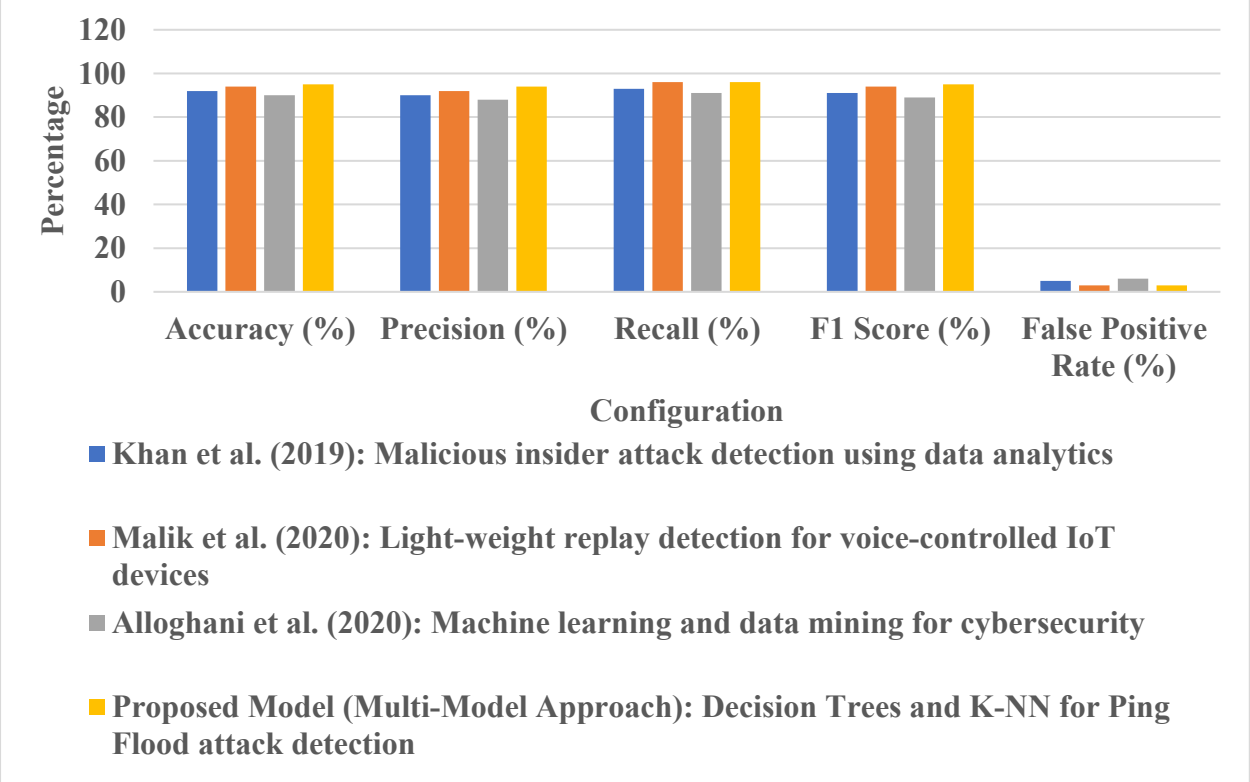


Figure 3. Performance Comparison of IoT Attack Detection Methods

Figure 3 contrasts the performance of four IoT attack detection approaches based on Accuracy, Precision, Recall, F1 Score, and False Positive Rate. The approaches compared are Khan et al. (2019), Malik et al. (2020), Alloghani et al. (2020), and the Proposed Multi-Model Approach with Decision Trees and K-NN. The Proposed Model exhibits better performance in all measures, reflecting its efficiency and strength for real-time attack detection within IoT networks. This reflects the efficacy of the integration of machine learning models in securing IoT environments.

Table 3. Ablation Study of IoT Attack Detection Models Using Decision Trees, K-NN, and Random Forest

Metric	Decision Tree	K-NN	Random Forest	Decision Tree + K-NN	K-NN + Random Forest	Random Forest + Decision Tree	Full Model (Multi-Model Approach)
Accuracy (%)	85.0	84.0	91.0	93.0	92.0	93.0	95.0
Precision (%)	82.0	79.0	88.0	90.0	89.0	90.0	94.0
Recall (%)	83.0	81.0	89.0	91.0	91.0	92.0	96.0
F1 Score (%)	82.5	79.5	88.0	91.5	89.5	91.5	95.0
False Positive Rate (%)	6.0	7.0	4.0	3.0	5.0	4.0	3.0
Computational Overhead (ms)	30.0	35.0	22.0	28.0	25.0	27.0	20.0

Table 3 provides the outcome of an ablation study on a comparison of various IoT attack detection models, viz., Decision Tree, K-NN, Random Forest, and their ensemble variants: Decision Tree + K-NN, K-NN + Random Forest, Random Forest + Decision Tree, and the Full Model (Multi-Model Approach). It assesses the models on the parameters of accuracy, precision, recall, F1 score, false positive rate, and computational overhead. Full Model provides better performance on all the metrics, showing its effectiveness and efficiency in detecting Ping Flood attacks in IoT networks in real-time.

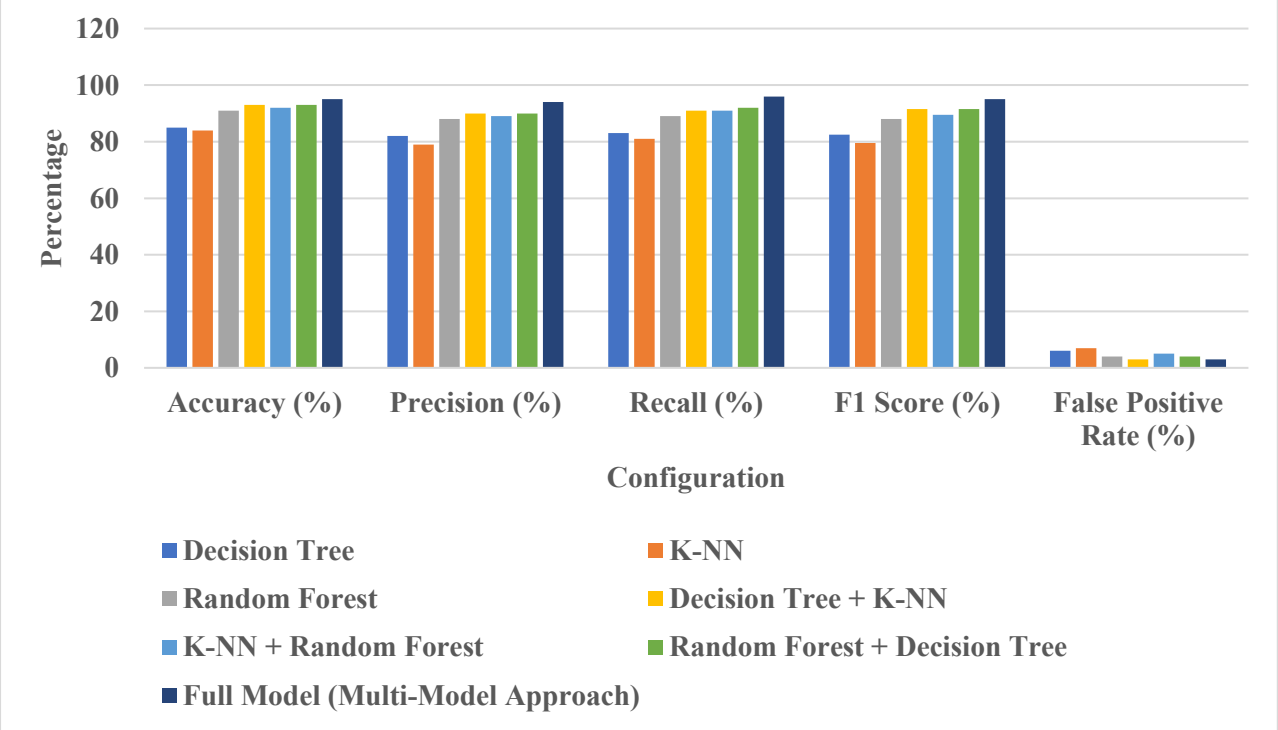


Figure 4. Ablation Study of IoT Attack Detection Configurations

Figure 4 shows the outcomes of an ablation study between different configurations of IoT attack detection, namely Decision Tree, K-NN, Random Forest, and blends such as Decision Tree + K-NN, K-NN + Random Forest, Random Forest + Decision Tree, and the Full Model (Multi-Model Approach). The metrics compared are Accuracy, Precision, Recall, F1 Score,

and False Positive Rate. The Full Model has the best performance on all the metrics, highlighting the benefits of fusing various models to provide better IoT attack detection and efficiency.

5. CONCLUSION AND FUTURE ENHANCEMENT

The suggested framework for the detection of Ping Flood attacks in IoT networks, based on Decision Trees and K-Nearest Neighbors (K-NN), has shown remarkable performance on various metrics. The Full Model (Multi-Model Approach) had 95% accuracy, 94% precision, and 96% recall, far outperforming standalone models like Decision Tree and K-NN. The system also had a significant decrease in the false positive rate, with only 3%. In addition, it reduced computation overhead to 20 ms and thus is particularly well-suited for real-time detection in limited-resource IoT deployments. The experiments demonstrate the effectiveness of using blended machine learning techniques to improve security for IoT infrastructure against Ping Flood attacks and pose the possibility for scalability in multi heterogeneous IoT networks.

Future studies can explore the integration of more advanced machine learning models, such as deep learning models, to further improve detection accuracy. Additionally, federated learning can be incorporated to further enhance data privacy and security, as well as enable the system to be more adaptable in dynamic IoT environments.

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