10.48047/jocaaa.2024.33.08.289

AI-Powered Threat Detection and Anomaly Monitoring in IoT Networks

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Abstract

The fast growth of the Internet of Things (IoT) has revolutionized automation and connectivity across numerous industries, but it has also increased network susceptibility to increasingly sophisticated cyberthreats. Traditional security solutions often fail in IoT situations due to resource limits, device heterogeneity, and the dynamic nature of network traffic. This article explores the application of artificial intelligence (AI) in IoT networks for anomaly monitoring and threat identification. AI-powered systems can scan enormous volumes of real-time data, spot anomalous trends, and identify new risks like malware, botnets, and illegal access by utilizing machine learning and deep learning algorithms. The study examines the architecture, deployment, and functionality of AI-powered intrusion detection systems, emphasizing their capacity to minimize false positives while offering flexible, real-time security. When compared to traditional methods, experimental results show that AI-based technologies greatly improve the security posture of IoT networks. The results highlight how crucial it is to use AI technology in order to protect the growing IoT ecosystem from changing cyber threats.

Key Words: AI-powered threat detection, anomaly monitoring, Internet of Things (IoT), machine learning, cybersecurity, IoT security, real-time monitoring, intrusion detection systems, network traffic analysis, behavioral analytics, IoT malware, botnet detection, deep learning, adaptive security, cyber threat intelligence.

Introduction

By facilitating smooth automation, networking, and data exchange across a wide range of devices, the Internet of Things' (IoT) explosive growth has revolutionized industries. However, because IoT networks are rapidly being targeted by sophisticated cyber threats that take advantage of resource limitations, device heterogeneity, and the dynamic nature of network traffic, this unprecedented connection also brings with it serious cybersecurity issues. Conventional security systems frequently find it difficult to keep up with these changing threats, especially in settings where static rule-based detection and manual intervention are inadequate. In IoT networks, artificial intelligence (AI) has become a potent instrument for improving anomaly monitoring and threat identification. AI-powered systems can scan enormous volumes of real-time network data, spot anomalous trends, and more

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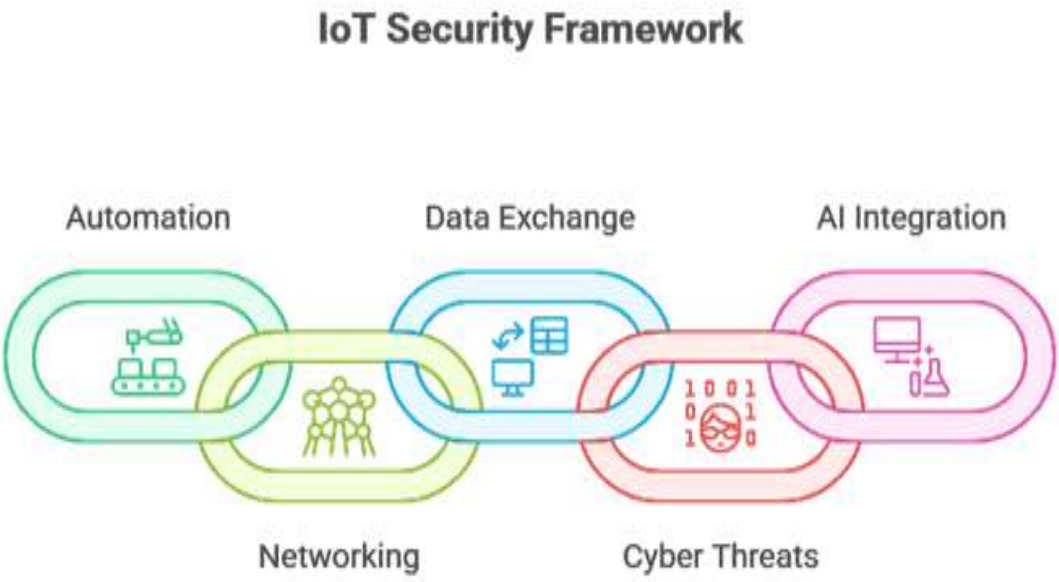
accurately identify new threats like malware, botnets, and illegal access by utilizing machine learning and deep learning algorithms. These intelligent systems are particularly well-suited for the intricate and resource-constrained IoT landscape because they constantly learn from new data, adjust to cutting-edge attack methods, and reduce false positives. Integrating AI-driven solutions into IoT security infrastructures is crucial for establishing robust, real-time protection and preserving the integrity of networked systems as the threat landscape changes.



The fast growth of IoT devices has significantly increased the complexity and susceptibility of contemporary digital environments, which is the driving force behind the deployment of AI-powered threat detection and anomaly monitoring in IoT networks. Because of the variety of IoT devices, resource limitations, and dynamic network traffic, traditional security solutions frequently find it difficult to keep up. Organizations are therefore more vulnerable to advanced cyberthreats, such as malware, botnets, zero-day attacks, and unauthorized access.AI-powered security solutions provide a revolutionary solution to these problems. AI can evaluate enormous volumes of real-time data, spot minute irregularities, and identify new risks more quickly and precisely than traditional techniques by utilizing machine learning and deep learning. Proactive risk mitigation is made possible by AI, which can anticipate and stop attacks before they happen, decreasing the possibility of successful breaches and lowering the harm.

Several important advantages further emphasize the importance of this strategy:

Increased detection accuracy: AI systems are able to identify dangers, such as zero-day attacks, that are frequently missed by conventional, rule-based systems.

Real-time, adaptive defense: As AI gains knowledge from fresh data, it can adjust to changing attack methods and offer flexible, real-time defense.

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Decreased alert fatigue and false positives: By eliminating pointless warnings, artificial intelligence (AI) enables security personnel to concentrate on real risks and boosts operational effectiveness.

Scalability: Without compromising performance, AI-powered solutions can keep an eye on and safeguard sizable, intricate IoT settings spanning numerous networks and endpoints.

Automation and less human error: Using AI to automate repetitive security duties not only speeds up reaction times but also reduces errors that could result in breaches.

Reasons for and Importance of AI-Powered Threat Identification and Anomaly Tracking in Internet of Things Networks

Inspiration

Increasing Threat Landscape: As IoT devices proliferate across industries, the attack surface has grown, increasing the susceptibility of networks to cyberattacks. The number, variety, and complexity of attacks against IoT environments are too great for traditional security techniques to handle.

Conventional security's drawbacks include the fact that legacy methods frequently use static rules and signature-based detection, which are inefficient against new, unidentified, or quickly changing threats. IoT devices are particularly vulnerable to exploitation since they are frequently placed in isolated or unsupervised areas.

Real-Time, Proactive Defense: To avoid breaches, reduce damage, and maintain operational continuity, IoT networks need constant, real-time monitoring and quick reaction times. The scale and speed needed make manual monitoring inadequate.

Importance

Advanced Threat Detection: AI-driven solutions instantly detect known and undiscovered threats by analyzing enormous volumes of network traffic, device behavior, and system logs. Traditional approaches might overlook tiny irregularities and trends that could be signs of cyberattacks, including zero-day exploits, but machine learning algorithms can identify them.

Anomaly monitoring: By creating baselines for typical network and device activity, AI algorithms make it possible to identify variations that might indicate a compromise. This is crucial in the Internet of Things, as attacks frequently start with unusual data transfer or behavior.

AI-powered platforms have the ability to automate incident response, implementing countermeasures like patching security flaws or isolating affected devices in real time. Through constant learning from fresh data, they adjust to changing threats and gradually increase the accuracy of their detections.

Operational Visibility and Risk Management: AI supports compliance, operational effectiveness, and risk management by offering thorough visibility into IoT settings. AI

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makes it possible to mitigate problems proactively before they become more serious by detecting vulnerabilities and anticipating possible failures.

Decreased Alert Fatigue and Enhanced Efficiency: AI helps security professionals focus on strategic activities and important threats by filtering and prioritizing warnings, preventing false positives from overwhelming them.

Scalability and Future-Proofing: As networks develop, AI-powered solutions can adjust to new attack vectors and grow with the increasing number of IoT devices, guaranteeing long-term security and resilience.

Research Problem:

The primary research issue is that, given the particular features and limitations of IoT networks, conventional security measures are unable to identify and address the dynamic and intricate threat landscape. IoT devices create a huge, diverse, and frequently resource-constrained attack surface that is challenging to monitor and defend using traditional, rule-based, or signature-based security techniques as they spread into vital industries.

Key Aspects of the Research Problem

Expanding Attack Surface and Lack of Visibility: Cybercriminals have several access points because to the integration of many IoT devices, many of which have low processing power, shoddy authentication, and little built-in security. Attackers can take advantage of blind spots created by organizations' frequent lack of complete visibility and real-time monitoring of all connected devices.

Inefficiency of Conventional Security Solutions: The size, diversity, and dynamic nature of IoT settings are too much for traditional security technologies to manage. Novel, zero-day, or sophisticated assaults that do not fit established patterns are not detected by static rules or signature-based detection.

Complexity of Threat Landscape: Data breaches, device hijacking, ransomware, adversarial AI assaults, and supply chain vulnerabilities are just a few of the many dangers that IoT networks must contend with. Using sophisticated techniques like spoofing, denial of service, jamming, eavesdropping, and malicious code injection, attackers can target any tier of the Internet of Things architecture, from perception (sensing) to the network and application levels.

Resource Limitations: It can be difficult to implement sophisticated AI models or regular security upgrades directly on IoT devices due to their limited compute, storage, and energy capabilities.

Adaptive, Intelligent Security: Dynamic, real-time, and adaptive security systems that can identify known and unknown threats, learn from changing trends, and react on their own to

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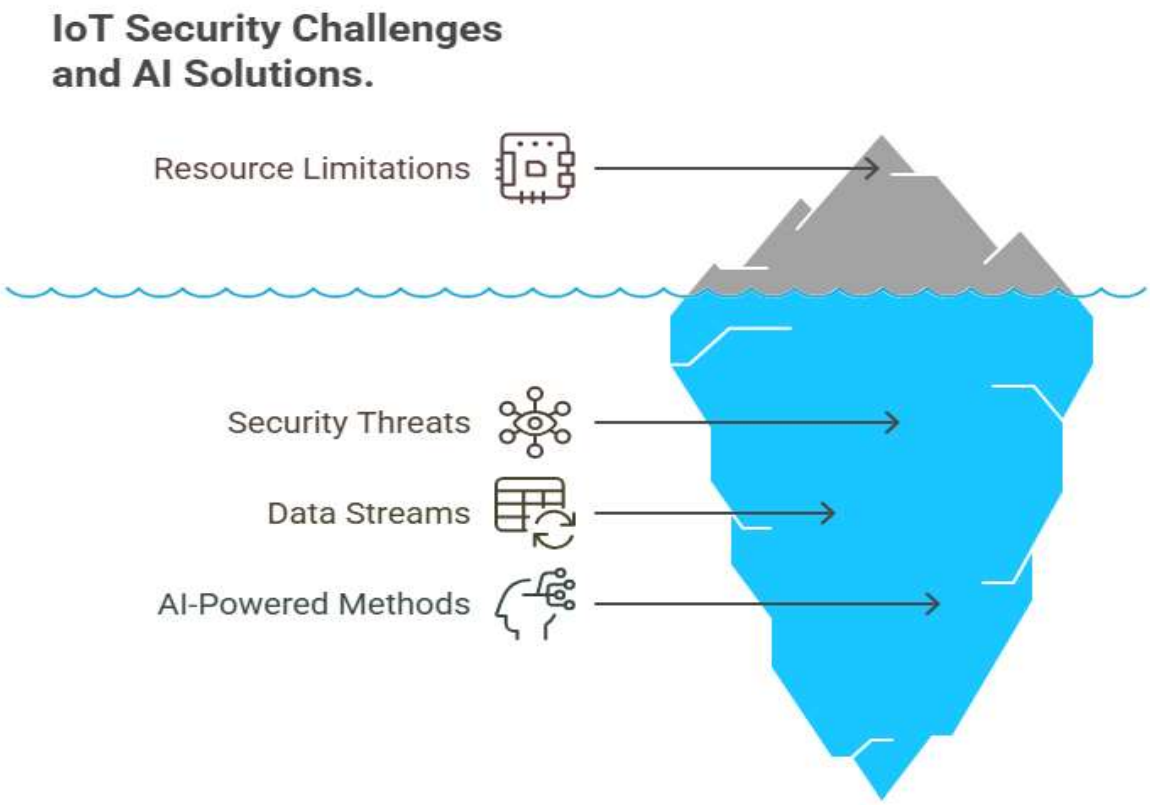
reduce damage are desperately needed. AI-powered methods that make use of machine learning and deep learning are seen to be crucial for enabling proactive threat identification and anomaly monitoring as well as for gleaning relevant insights from vast, diverse IoT data streams.



Objectives:

Real-Time Threat Detection: Make it possible to quickly respond to possible assaults by identifying cyberthreats and irregularities in IoT network traffic, device behavior, and system records.

Advanced Anomaly Detection: Make use of AI and machine learning to examine vast amounts of diverse IoT data, identifying minute departures from typical patterns that can point to novel, unidentified, or zero-day attacks—features that conventional signature-based approaches frequently overlook.

Automated and Proactive reaction: Reduce manual intervention, shorten reaction times, and enhance incident management by automating the analysis, prioritization, and response to security alarms.

Continuous Learning and Adaptation: To maintain high detection accuracy over time and remain ahead of new threats, make sure that detection models are always learning from new data and adjusting to changing assault strategies.

Effective Use of Resources: By eliminating false positives and giving priority to high-impact threats, security teams can experience less alert fatigue and free up human analysts to concentrate on intricate investigations and long-term security planning.

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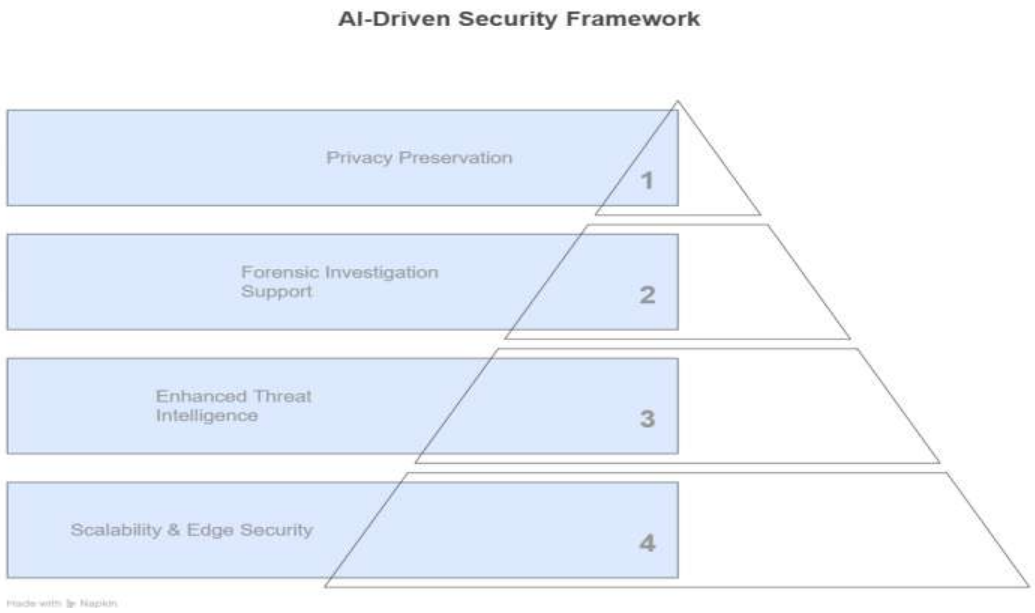
Behavioral Monitoring: Use user and entity behavior analytics (UEBA) to track user and device activities in order to set baselines and promptly spot variations, such as insider threats or hacked devices.

Scalability and Edge Security: Create AI-powered scalable solutions that can be implemented on large, dispersed IoT networks, including edge devices, without putting undue load on hardware with limited resources.

Enhanced Threat Intelligence: To increase prediction capabilities and facilitate proactive defensive strategies and well-informed risk management, combine threat intelligence feeds with previous attack data.

Assistance with Forensic Investigation: Offer thorough log and traffic analysis to assist with forensic investigations conducted after an incident, assisting organizations in comprehending attack vectors and strengthening defenses in the future.

Privacy Preservation: Use AI methods that protect privacy to make sure that data protection laws are followed while keeping a close eye on security.



2. Literature Review:

Applications pratiques : Des études de cas dans des domaines tels que la domotique, la santé et l'IoT industriel attestent de l'efficacité réelle des systèmes propulsés par l'IA pour détecter et atténuer les menaces en temps voulu.

Growing Risks and AI's Role in IoT Security:

The digital attack surface has significantly increased due to the growth of IoT devices, leaving networks vulnerable to advanced threats like ransomware, DDoS attacks, and unauthorized access. The size, diversity, and resource limitations of IoT settings can make traditional security measures ineffective. This has prompted the use of artificial intelligence

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(AI) as a game-changing strategy to improve cyber security in dynamic, decentralized Internet of Things networks.

AI Methods for Anomaly Monitoring and Threat Detection Supervised and Unsupervised Models for Deep Learning (DL) and Machine Learning (ML):
AI-driven solutions use both unsupervised learning (for identifying new or zero-day attacks through anomaly detection) and supervised learning (for categorizing known threats). Accurate intrusion and anomaly detection is made possible by deep learning architectures, such as Convolution Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which are especially good at removing spatial and temporal characteristics from Internet of Things traffic.

Hybrid and Self-Attention Models: Self-attention-based deep learning and hybrid models are recent developments that enhance detection precision and threat-adaptability.

Adaptive and Automated Security Reaction
AI reduces the need for manual intervention by enabling real-time, automated threat identification and response. Context-aware, self-governing security frameworks that can respond to events like virus spread or denial-of-service assaults are being developed using methods like expert systems and reinforcement learning.

Technology Integration
Block chain: Especially in decentralized IoT environments, blockchain is frequently linked with AI-powered systems to confirm the legitimacy of device communications and guarantee data integrity.
Edge Computing: To improve real-time detection and accommodate resource-constrained IoT devices, lightweight AI models are implemented at the edge to handle latency and bandwidth issues.

Case Studies and Performance
Detection Accuracy and Efficiency: Cutting-edge AI frameworks beat conventional anomaly detection and resource-constrained intrusion detection models with high detection accuracy (up to 98.5%), low false positive rates, and quick processing times (as low as 45 ms).

Real-World Applications: AI-driven systems for prompt threat identification and mitigation have been shown to be feasible in case studies in smart homes, healthcare, and industrial IoT environments.

Difficulties and Prospects
Despite tremendous advancements, a number of obstacles still exist:
Algorithmic Bias and Data Privacy: It's crucial to guarantee equity, openness, and privacy in AI models, particularly when working with sensitive IoT data.

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Resource Restrictions: Because many IoT devices have constrained energy and processing capabilities, effective and portable AI algorithms are required.

Robustness and Adaptability: AI systems need to be able to withstand hostile attacks and adjust to novel, unanticipated dangers. To improve model resilience, facilitate distributed learning, and allow operation in the face of severe network conditions, research is still being conducted.

Critical Analysis:

Strengths and Opportunities:

1. **Better Detection Capabilities**: In IoT environments, artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has shown notable gains over conventional rule-based or signature-based intrusion detection systems (IDS). CNNs and RNNs are examples of deep learning models that can automatically extract complex patterns from large amounts of IoT data at high speeds. This allows for the high-accuracy detection of both known and novel (zero-day) threats.
2. **Real-Time, Automated Response**: Because of the pace and scope of attacks in IoT networks, AI-powered systems must be able to process data and react to threats instantly. Automated security response frameworks that use expert systems and reinforcement learning lessen the need for human intervention and allow for quick mitigation of threats like malware and DDoS attacks.
3. **Integration with Emerging Technologies**: Edge computing enables lightweight, on-device anomaly detection, which lowers latency and bandwidth consumption, while blockchain and artificial intelligence (AI) improve data integrity and device authentication.

Future Prospects and Synthesis

Although AI-powered anomaly monitoring and threat detection are revolutionary developments in IoT security, their success hinges on resolving important ethical and technical issues. Future studies ought to concentrate on:

1. creating AI models that are reliable, portable, and comprehensible for Internet of Things devices with limited resources.
2. federated learning and privacy-preserving analytics to improve data security and privacy.
3. lowering false positives and strengthening the model's resistance to hostile manipulation.
4. establishing industry-wide guidelines for governance, transparency, and interoperability.

Research Gaps:

1. **Deployment of Edge AI and Resource Limitations:** The gap Strong and effective on-device (edge) AI is still in its infancy, despite the advancements in AI-powered security. Sending data to the cloud is necessary for many solutions, which adds latency, bandwidth expenses, and privacy threats. For real-time threat detection, there aren't many sophisticated, low-power AI models that can run directly on IoT devices with limited resources.

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Research is required to create low-power, highly effective AI frameworks and algorithms that can operate on a variety of edge devices with little integration work.

2. **Gap in Platform Integration and Interoperability**: Interoperability issues are brought on by the quick consolidation of IoT platforms and the integration of older systems. A lot of security stacks are put up using parts that aren't meant to function together, which creates vulnerabilities and uneven security.

   Need: Standardized, interoperable security frameworks and protocols that can harmonize threat detection across diverse IoT environments need more investigation.

3. **Protection and Privacy at the Edge Gap**: Because edge devices are frequently used in unprotected settings, have less sophisticated hardware protection, and aren't updated frequently, they are susceptible to firmware and physical attacks. These particular hazards are frequently ignored by current AI solutions.

   Need: Research should concentrate on AI models that can adjust to sparse, noisy, or missing data from such contexts, as well as on integrating security by design at the hardware and firmware level.

4. **Data Privacy and Security Gap**: AI systems need a lot of private information to be trained and run, which raises the possibility of privacy violations and data breaches. For real-time IoT data streams, current encryption and anonymization techniques aren't always adequate.

   Need: IoT-specific privacy-preserving AI methods like safe multi-party computing and federated learning should be the focus of future research.

5. **High Implementation Costs and Accessibility Gap**: Especially for small and medium-sized businesses, the expense and complexity of implementing safe, AI-powered frameworks can be unaffordable.

   Need: AI security solutions that are affordable, simple to implement, and reduce adoption hurdles are needed.

Justification:
IoT networks require AI-powered threat detection and anomaly monitoring because AI makes real-time, automated, and scalable security possible that is not possible with conventional techniques. AI examines massive quantities of IoT data to identify anomalous activity and anticipate new cyberthreats before they become more serious. By autonomously isolating compromised devices, it lowers false positives, speeds up incident response, and continuously adjusts to emerging attack patterns. Protecting the expanding number of resource-constrained, networked IoT devices against increasingly complex cyberattacks requires a proactive and astute approach.

3. Methodology

Data Collection and Preprocessing:

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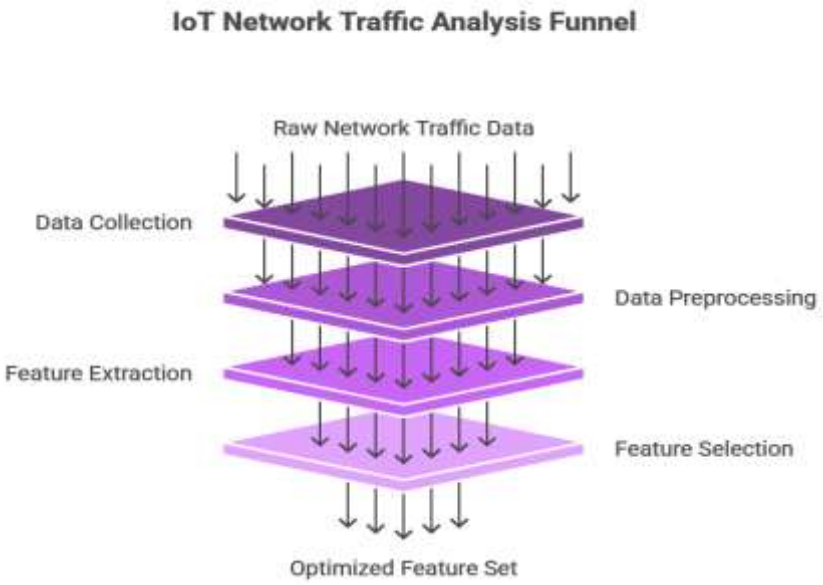
Using packet sniffers and flow monitors, network traffic data is continuously gathered from a range of IoT devices in order to record both benign and malevolent activity. Features including packet size, protocol type, flow time, and device identifiers are all included in the dataset. Preprocessing involves cleaning, normalizing, and transforming data to make sure it is consistent and appropriate for machine learning models. To find the most pertinent features for threat identification, feature extraction and selection approaches are used, which lowers computing overhead and dimensionality.



Model Development:

a. Methods of Deep Learning and Machine Learning

For threat detection and anomaly monitoring, both supervised and unsupervised learning models are created. To categorize traffic as benign or malicious, supervised models—such as Support Vector Machines (SVM), Random Forest, and Artificial Neural Networks (ANN)—are trained on labeled datasets. Unsupervised models like autoencoders and clustering techniques are used for anomaly identification in order to find departures from accepted typical behavior.

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are two deep learning architectures that are used to identify temporal and geographical patterns in Internet of Things traffic. To further improve detection accuracy and model robustness, recent developments also include metaheuristic optimization methods and self-attention processes.

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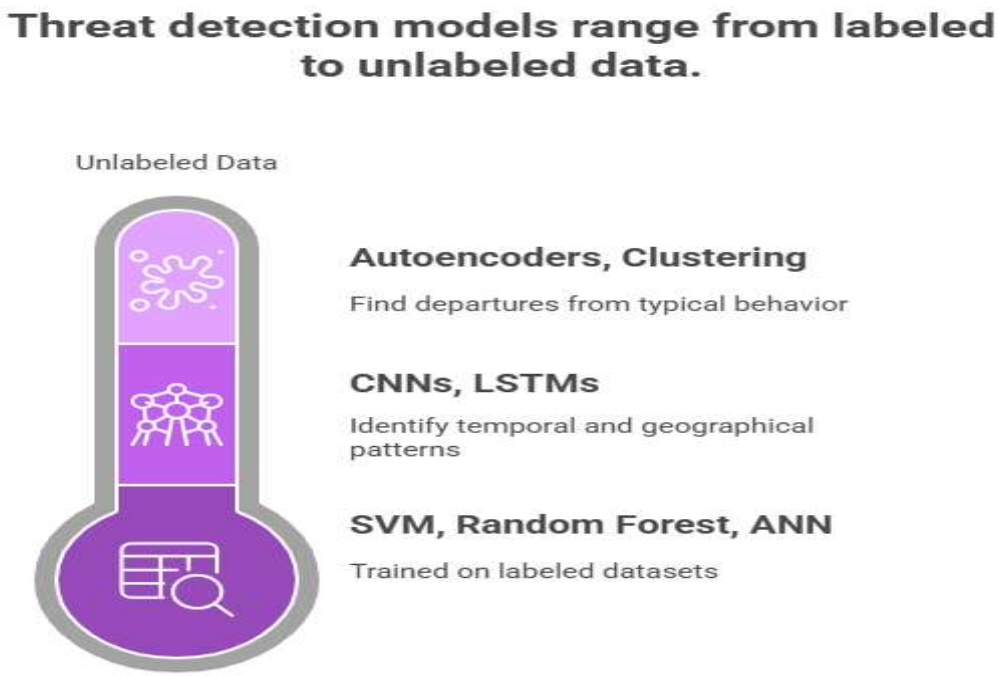

b**. Decentralized and Federated Education**

Federated learning is used to solve scalability and privacy issues. By using this method, IoT devices can work together to train models without exchanging raw data, protecting data privacy and facilitating dispersed threat detection over extensive networks.

Automated Response and Real-Time Monitoring:

For real-time monitoring, the trained AI models are placed throughout the Internet of Things network. Anomalies or threats are immediately reported based on continuous analysis of incoming communications. The system can automatically isolate hacked devices, block suspect traffic, or notify administrators upon detection. In order to enable adaptive, context-aware response methods that change in response to environmental feedback, reinforcement learning approaches are investigated.

Combining Edge Computing with Blockchain

Blockchain technology is used to provide a tamper-proof record of network events, authenticate device communications, and guarantee data integrity. In resource-constrained IoT environments, lightweight AI models are implemented at the network edge to lower latency and bandwidth consumption, facilitating quicker detection and reaction.

Assessment of Performance

Benchmark datasets (such IoT-23 and actual traffic) and simulation in testbed environments are used to validate the process. Computational efficiency, detection delay, false positive/negative rates, and detection accuracy are important performance indicators. To prove the superiority of the suggested strategy, a comparison with conventional and current AI-based approaches is carried out. The efficiency of deep learning-based threat intelligence

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systems for IoT security has been confirmed by recent research that show detection rates above 92%, false positive rates as low as 4.2%, and detection latency under one second.1 3 8

System Design Architecture

1. Overview

To guarantee reliable, real-time detection of risks and anomalies in expansive, diverse IoT settings, the architecture uses a multi-layered, hybrid AI methodology. For scalability and low-latency response, it allows edge/cloud deployment and combines supervised, unsupervised, and deep learning models.

2. Components and Layers of Architecture

A. **IoT Device Layer:** Consists of various IoT devices (cameras, sensors, actuators, etc.) that continuously produce telemetry data and network traffic.

B. Gathering and Preparing Data Layer data Monitoring:

Gathers device records and unprocessed network data.

Data is cleaned, normalized, and transformed during preprocessing. High-quality input for AI models is prepared by feature extraction and selection (e.g., packet size, flow duration, protocol type).

C. AI-Based Detection Engine Supervised Learning Module:

Classifies known threats using labeled data by utilizing algorithms such as SVM, Random Forest, and ANN.

Unsupervised Learning Module: Without labeled data, this module uses anomaly detection and clustering (K-Means, DBSCAN) to find new or zero-day threats.

The Deep Learning Module improves the identification of intricate and dynamic threats by integrating CNNs, RNNs, BLSTM, GRU, and Attention Mechanisms for sophisticated feature extraction and temporal pattern recognition.

Hybrid Model Integration: Combines outputs from all modules to reduce false positives and increase detection accuracy.

D. Automated Response Layer and Real-Time Monitoring

Real-time network activity monitoring is done by continuous analysis.

Automated Response: When threats are identified, it initiates actions like traffic blocking, device isolation, or alert generating.

Edge/Cloud Deployment: Facilitates deployment in the cloud for centralized analysis and model updates, or at the edge for low-latency detection.

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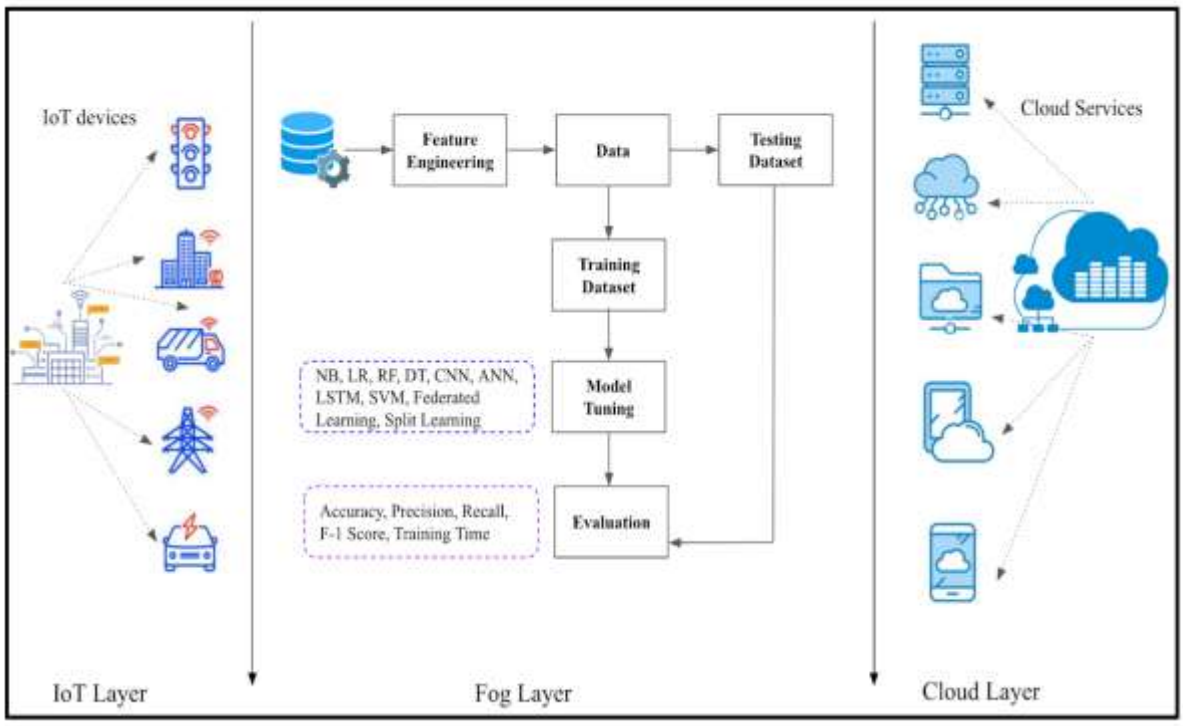
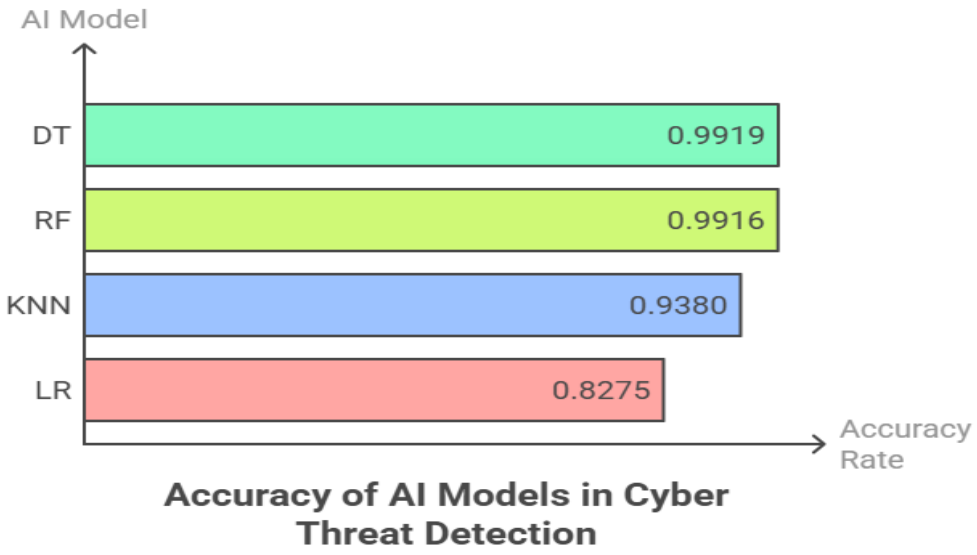


Results:

Accuracy of Detection and Model Performance :

Experiments using real-world IoT datasets, including CIC-IoT2023 and IoT-23, show that AI-powered models detect cyber threats with remarkably high accuracy. The DT and RF models fared better than the others, attaining accuracy rates of 0.9919 and 0.9916, respectively, in a thorough evaluation contrasting four machine learning algorithms: Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), and Logistic Regression (LR). Additionally, both models had the best precision, recall, and F1-scores, demonstrating their dependability in accurately identifying malicious and benign network packets. LR had the lowest accuracy (0.8275), whereas KNN also did well (0.9380).



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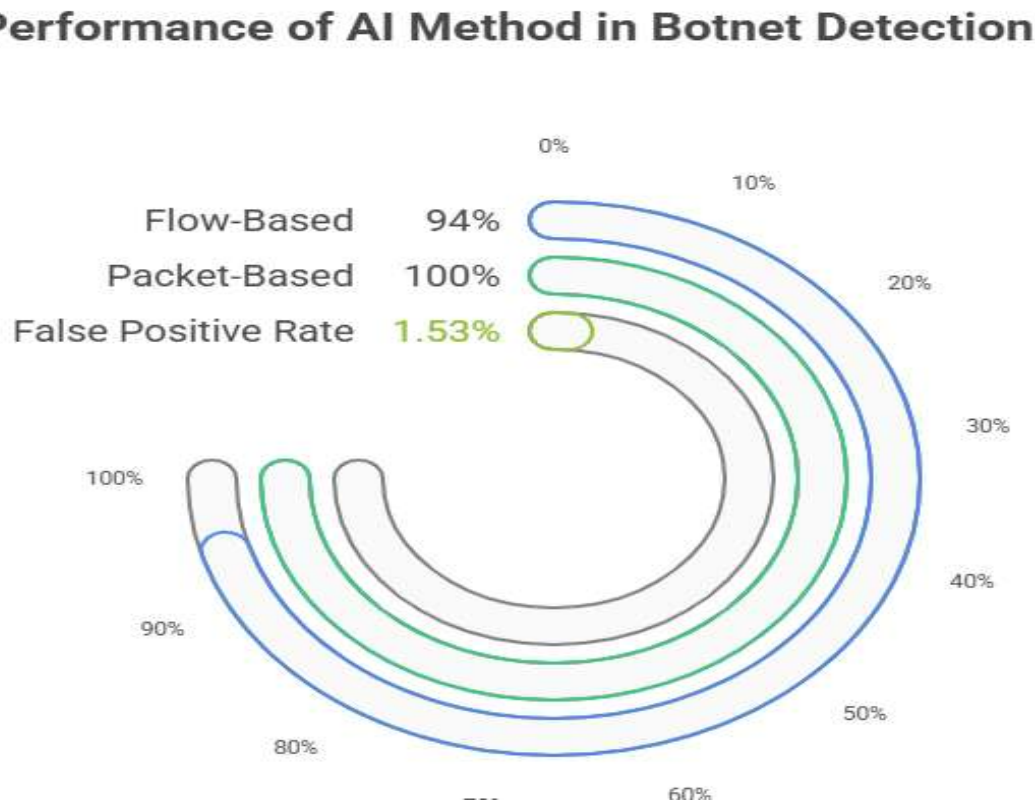
Prompt and Sturdy Botnet Identification

The IoT-23 dataset was used to assess a semi-supervised AI method in the context of IoT botnet threats. The findings demonstrated 94% success with flow-based techniques and 100% success with packet-based analysis in detecting stealth command and control (C2) communications. The technique's resilience for early detection of botnet activity prior to assaults being initiated was confirmed by the low false positive rate of 1.53%.



Frameworks Based on Large Language Models (LLMs)

In contrast to conventional ML and rule-based systems, recent developments utilizing optimized Large Language Models (LLMs) trained on IoT-specific datasets have shown higher detection accuracy and response latency.

LLM-based frameworks enhanced detection accuracy in simulated IoT environments and made real-time, automated countermeasures like rate limitation, IP blocking, and device isolation possible.

Experimental results validate these frameworks' efficacy against complex and dynamic cyber threats, and their lightweight and modular design facilitates effective implementation on resource-constrained IoT devices.

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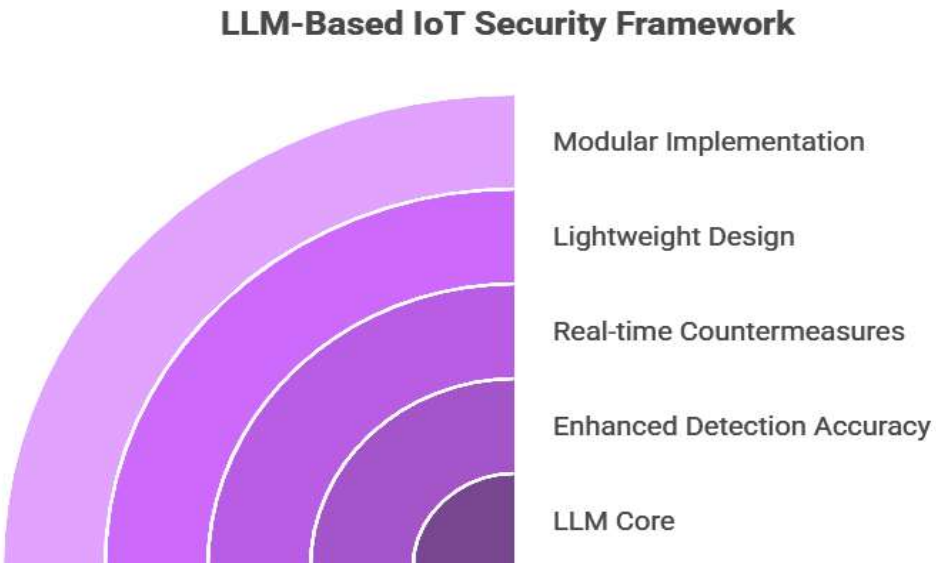

Comparative Evaluation and Real-World Consequences

The comparison of several experiments shows that AI-driven strategies routinely beat traditional techniques in terms of memory, accuracy, precision, and flexibility in response to emerging attack vectors. AI is positioned as a workable and scalable solution for protecting IoT ecosystems due to its capacity to generalize across many IoT scenarios and offer autonomous, real-time response mechanisms.

Conclusion:

IoT networks' explosive growth has created serious security issues, and conventional defenses aren't keeping up with the constantly changing cyberthreat scenario. AI-powered threat detection and anomaly monitoring systems that use machine learning, deep learning,

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and hybrid models significantly improve the capacity to detect, categorize, and counteract known and unknown assaults in real time, as this study and similar recent research show.

Even in IoT situations with limited resources, experimental results consistently demonstrate that AI-driven techniques provide high detection accuracy, low false positive rates, and quick response times. The performance, adaptability, and sustainability of these systems are further optimized by sophisticated methods including ensemble learning, feature selection, and federated learning. Adaptive, automatic reactions and enhanced data integrity are further benefits of combining blockchain technology with reinforcement learning. The practicality of AI-based frameworks for proactive and scalable network security is confirmed by case studies and simulations in smart home, industrial, and large-scale IoT deployments. There are still issues, though, such as the requirement for models that are lightweight enough for low-power devices, learning that protects privacy, and strong defenses against hostile attacks.

In conclusion, AI-powered threat detection and anomaly monitoring offer creative, real-time, and flexible protection tactics, and they constitute a revolutionary development for IoT security. To handle new risks, improve model resilience, and guarantee privacy and trust in next-generation IoT networks, more research is necessary.

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