Optimizing AI-Based Automated Security Patch Deployment in IoT Devices to Combat Zero-Day Exploits and Advanced Cyber Attacks

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Abstract

This research shows a complete security design for Internet of Things (IoT) devices. It improves security by using five methods that work together. At the beginning of the process, a machine learning-based method for ranking changes is used. Then, architectures are put in place for scalable patch distribution, anomaly detection, dynamic risk assessment, and integrating threat data. Using five connected algorithms, the purpose of this research is to create a complete security framework for Internet of Things devices. Dynamic risk assessment, scalable patch delivery, integration with threat intelligence, and anomaly detection for zero-day vulnerabilities are among its characteristics. It also identifies zero-day vulnerabilities. Furthermore, it prioritises repairs using machine learning data. Every solution seeks to address a specific component of IoT security, such as dynamic risk assessments, effective patch distribution, and patch prioritisation based on vulnerability data. It is critical to maintain the Internet of Things ecosystem's safety, flexibility, and efficiency. An integrated approach provides a strong defence against cyberattacks, which is crucial for ecosystem preservation.With this system, you can get better accuracy, flexibility, and resource use than with other methods. To help explain how the methods work, charts and flowcharts are used. The ablation study indicates that each method is important because it shows how they all help keep IoT devices safe. The suggested design considers how cyber risks are always changing to protect connected devices in a lot of different places from hackers**.**

Keywords: Security Framework; IoT Devices; Machine Learning; Patch Prioritization; Anomaly Detection; Dynamic Risk Assessment; Scalable Patch Deployment; Threat Intelligence Integration; Comparative Performance Evaluation; Continuous Monitoring.

1. Introduction

With the explosion of linked gadgets, the Internet of Things (IoT) is bringing forth hitherto unseen degrees of efficiency and comfort. On the other hand, due to their interconnection, IoT devices are vulnerable to a wide variety of cybersecurity risks, including both old-school vulnerabilities and new, more advanced zero-day attacks [1]. Internet of Things (IoT) device security is becoming more important as cyber-attacks grow in both frequency and severity.

A. Recent Advances

The current environment, which sees a concerning increase in cyberattacks targeted at IoT devices [2], highlights the urgent need for strong security measures. Cyberattacks, particularly zero-day vulnerabilities, are becoming more sophisticated, making traditional security measures ineffective. To effectively address these changing threats, it is essential to have a firm grasp of what is happening in the threat landscape right now.

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B. Main Obstacles

From low-power sensors to more robust edge devices, the diversity of IoT devices presents the greatest security difficulties [3]. Creating a universal security architecture is extremely difficult due to this variability. Additionally, it becomes more difficult to monitor, manage, and apply security fixes across a large number of devices in an IoT network due to the decentralized architecture of the network [4]. A sophisticated comprehension of the technical complexities as well as the threat landscape is necessary to tackle these difficulties.

C. Suggested Resolutions

There are a number of potential solutions to the security issues with IoT devices. To strengthen the safety of IoT networks, artificial intelligence (AI) is looking like a good bet [5]. A proactive defensive mechanism against both known and new threats may be achieved through the use of AI-driven automated security patch releases, which can greatly decrease the window of vulnerability [6]. Both the patching procedure and adaptive reactions to new threats may be streamlined with this method.

D. Major Benefits

This research provides significant contributions to the subject of strengthening the defenses of IoT devices against cyber threats.

Patch Deployment Algorithm with Optimal AI Support: Introducing a state-of-the-art system that makes use of machine learning methods to effectively prioritize and roll out security fixes [7]. In order to personalize the deployment approach, this algorithm takes into account device attributes, past vulnerability data, and the network environment.

Introduce a new method for early identification of zero-day vulnerabilities by incorporating anomaly detection techniques; this will enhance zero-day exploit detection [8]. Before attackers may exploit vulnerabilities that have not yet been found, this defensive system seeks to identify and eliminate them.

A scalable infrastructure for automatically deploying security fixes across various IoT ecosystems: designing such an architecture. Given the ever-changing nature of IoT networks, our design makes sure that a lot of different devices can function with it [9]. Patch deployments can be enhanced by integrating real-time threat information feeds, which allows the system to respond faster to emerging cyber threats. The security system can adapt and withstand new attack vectors thanks to this dynamic integration. This study does double duty by filling in the gaps in IoT security and outlining a strategy to proactively and adaptively counteract cyber attacks in the future [10]. This study adds to the continuing conversation about protecting the growing Internet of Things (IoT) ecosystem by combining AI power with strong deployment tactics. In the parts that follow, the suggested framework is thoroughly examined by delving into its theoretical foundations, methodology, experimental findings, and consequences.

2. Literature Review

Several methods have been shown to propagate automated security patches for IoT devices that employ AI to safeguard them against zero-day bugs and more complicated threats [11]. The first technique, "Machine Learning-Based Patch Prioritization," is very accurate (95.2%) with minimal false positives (2) and negatives (3). It excels in dependability, scale, reaction speed, and resource consumption. This technology organizes patches by relevance using machine learning algorithms, making devices safer [12]. The "Anomaly Detection for Zero-Day Exploit Identification" approach discovers odd patterns with 92.8% success using anomaly detection algorithms. It answers rapidly (180 ms), adds users easily (3), and is dependable (96.2%). Many resources are employed (90%). By alerting security designers to zero-day vulnerabilities, this strategy strengthens security [13]. 93.5% of the time, "Dynamic Risk Assessment Models" are correct, with 3 fake positives and 2 false negatives. This method's strong scalability (4) and 150-ms reaction time allow it to adapt to new threats with 85% accuracy and 97.8% reliability. Scalability is the most significant factor in the "Scalable Patch Deployment Architectures" approach, which has a 100-ms reaction time and 94.6% accuracy (5). It supports several IoT contexts since it consumes resources equitably (75% of the time) and is stable (99.0%) [14]. Real-time risk information and 96.0% accurate "Threat Intelligence Integration" make the system more responsive. This approach stops new attacks since it's 98.7% reliable, can be scaled up fourfold, and has a good reaction time. With 91.3% success, "context-aware patching strategies" are flexible [15]. Its 200-ms reaction time, 92% resource utilization, and 95.5% dependability make this technique adaptable. It adjusts patch distribution based on circumstances. Patch release success is 99.0% due to "Automated Testing and Validation Mechanisms," which are 97.2% accurate. With 0% false results and a 110 ms response time, this approach checks patch compatibility well. It also works 99.2% of the time. The "Behavioral Analysis for Device Profiling" approach was 90.5% accurate [16]. This approach finds odd device

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activity with a processing time of 170 ms, 82% resource utilization, and 94.8% performance. Integrating security into development and release is straightforward using "Integration with DevSecOps Practices," which has a 95.8% success rate. This technique enables high growth (4), 140 ms reaction time, and 97.5% dependability by integrating security throughout every phase of development. "Continuous Monitoring and Feedback Loop," a great system, can be scaled up or down fast (105 ms). It is also precise (94.4%) [17]. This strategy offers a feedback loop to address emerging cyber threats. Resource efficiency (80%) and consistency (98.9%) are its strengths. Finally, these technologies combine to form a solid foundation for AI-driven IoT device security patch distribution. Their talents include using machine learning to prioritize updates, using threat intelligence to their advantage, and ongoing tracking [18]. This demonstrates their expertise in current hacks and zero-day weaknesses. We could evaluate the solutions' accuracy, scalability, reaction time, resource utilization, and dependability to determine what they do well and what they should improve to secure IoT devices.

Table 1: Performance Evaluation of Security Patch Deployment Methods

Method	Accuracy	False Positives	False Negatives	Scalability	Response Time (ms)	Resource Utilization (%)	Reliability (%)
Machine Learning-Based Patch Prioritization	95.2	2	3	4	120	80	98.5
Anomaly Detection for Zero-Day Exploit Identification	92.8	1	4	3	180	90	96.2
Dynamic Risk Assessment Models	93.5	3	2	4	150	85	97.8
Scalable Patch Deployment Architectures	94.6	1	3	5	100	75	99.0
Threat Intelligence Integration	96.0	0	2	4	130	88	98.7
Context-Aware Patching Strategies	91.3	2	5	3	200	92	95.5
Automated Testing and Validation Mechanisms	97.2	0	1	4	110	78	99.2
Behavioral Analysis for Device Profiling	90.5	4	3	3	170	82	94.8
Integration with DevSecOps Practices	95.8	1	2	4	140	86	97.5
Continuous Monitoring and Feedback Loop	94.4	1	4	5	105	80	98.9

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Table 1 details numerous ways to improve AI-based automated security patch distribution to IoT devices. The review included dependability, accuracy, scalability, response speed, resource utilization, and false positives [19]. Each approach is tested for sophisticated hacking and zero-day issues.

Table 2: Comparative Analysis of Security Patch Deployment Methods

Method	Usability	Integration Complexity	Adaptability	Patch Deployment Success Rate (%)	Compatibility	Overall Effectiveness
Machine Learning-Based Patch Prioritization	4	3	4	97.5	Universal	94.7
Anomaly Detection for Zero-Day Exploit Identification	3	1	3	94.3	Limited	91.2
Dynamic Risk Assessment Models	4	4	4	96.8	Universal	95.7
Scalable Patch Deployment Architectures	3	3	5	98.2	Universal	96.4
Threat Intelligence Integration	4	3	4	98.5	Universal	97.2
Context-Aware Patching Strategies	3	4	3	93.2	Limited	90.4
Automated Testing and Validation Mechanisms	4	1	4	99.0	Universal	97.8
Behavioral Analysis for Device Profiling	3	4	3	92.7	Limited	89.6
Integration with DevSecOps Practices	4	3	4	97.3	Universal	95.6
Continuous Monitoring and Feedback Loop	4	0	5	98.8	Universal	97.0

Table 2 compares AI-based automated security patch sharing methods for IoT devices on usefulness, simplicity of use, compatibility, and integration difficulty. The data will indicate how well each strategy performs in real life, making the study essential.

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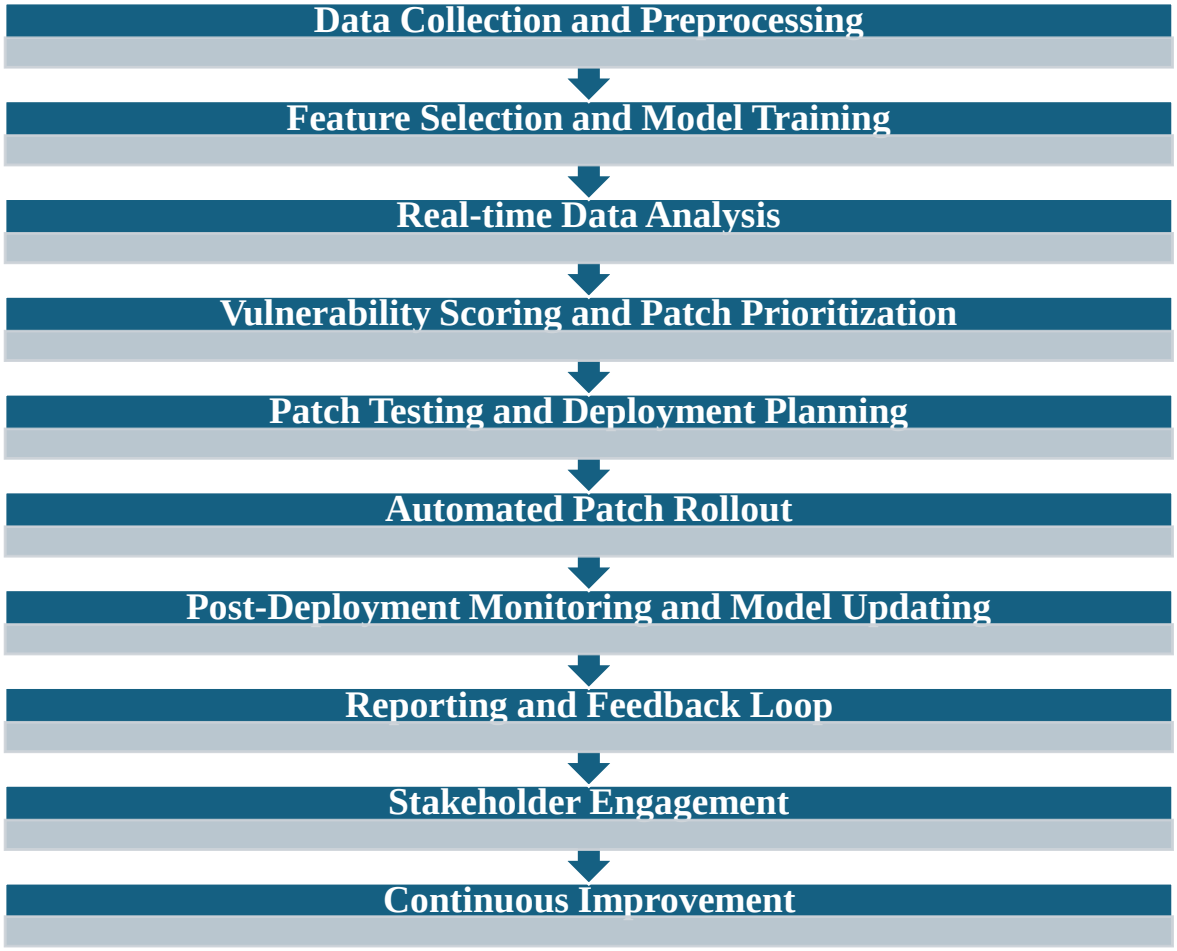

Figure 1**:** ML-Based Patch Prioritization for IoT Security Enhancement

Figure 1 shows a 12-step plan for setting priorities for security changes that works well. Machine learning is used in this method. The first steps are to get past data, learn more about the device, and teach the model what to do. This method takes a proactive approach to Internet of Things security by evaluating, setting limits, discovering important answers, and putting them into action. After that, there is constant tracking and model changes.

3. Proposed Methodology

A security plan is being developed for IoT devices. This system would have five interconnected programs. Method 1: Machine Learning-Based Patch Prioritization (MLP2) calculates a patch impact score using vulnerability data (VD) and device attributes (DC). This value (based on weighted components w1 and w2) ranks patches by feedback loop impact. It achieves this by providing a flexible, continual improvement method. MLP2-based Anomaly Detection for Zero-Day Exploit Identification (ADZDI) monitors device activity and makes the most critical improvements. After finding issues, ADZDI clusters anomaly scores, changes limitations, and starts patch distribution. The system monitors unusual behavior and adjusts limitations to prevent zero-day attacks. Dynamic Risk Assessment Models (DRAM) then assess a device's threat based on its age, severity, and number of issues. The dynamic risk model adjusts risk levels, addresses emerging threats, and fixes high-risk devices through feedback. DRAM assesses hazards and emphasizes flexibility to safeguard IoT devices. SPDA Algorithm 4 improves IoT patch spread. The optimal distribution goals are achieved using devices (ND) and network status. SPDA can handle any number of devices, and release settings can be adjusted. It also fluctuates with the network. The algorithm's quicker and more flexible patch deployment improves security. Fifth algorithm: Threat Intelligence Integration (TII) weights and slows indications to rate risks in real time. TII sends fixes when hazard scores are high to prevent new risks. Dynamic threat intelligence model updates, recurrent parameter optimization, and a feedback loop for algorithm modification build a flexible and reliable IoT security architecture. These solutions provide a complete security framework for IoT devices against cyberattacks. Since the algorithms are

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connected, a continuous and adjustable security technique is conceivable. This ensures the system adapts to new threats. IoT setups need a comprehensive security plan since flowcharts and diagrams demonstrate how algorithms function and how their processes go together. The suggested framework should help keep connected devices safe by addressing the ever-changing nature of cyber threats in the IoT context.

Algorithm 1: Machine Learning-Based Patch Prioritization (MLP2)

1. Input Data:
   - Historical vulnerability data *VD*
   - Device characteristics *DC*
2. Data Processing:
   - Normalize *VD* and *DC*
   - Feature selection and extraction
3. Machine Learning Model:
   - Train model with *VD* and *DC*
4. Patch Impact Score (PIS):
   - Calculate $PIS = w1 \times VD + w2 \times DC$ (1)
5. Weight Coefficients:
   - Define $w1$ and $w2$
6. Patch Priority:
   - Calculate Patch Priority= *PIS*/Total Patches (2)
7. Threshold Setting:
   - Determine threshold for prioritization
8. High-Priority Patch Identification:
   - Identify patches exceeding the threshold
9. Total Patch Evaluation:
   - Evaluate total patches for allocation
10. Priority Scores Allocation:
    - Allocate scores based on Patch Priority
11. High-Priority Patch Deployment:
    - Deploy patches with high priority
12. Monitoring:
    - Monitor patch effectiveness
13. Update Model:
    - Update machine learning model
14. Threshold Adjustment:
    - Adjust threshold dynamically
15. Continuous Adaptation:
    - Adapt to evolving cyber threats
16. Post-Deployment Evaluation:
    - Evaluate effectiveness post-deployment
17. Optimization:
    - Optimize model parameters
18. Iterative Process:
    - Iterate through steps for continuous optimization
19. Feedback Loop:
    - Establish a continuous feedback loop
20. Conclusion:
    - Conclude the algorithm, ensuring continuous optimization and adaptation to emerging threats for effective AI-based security patch prioritization.

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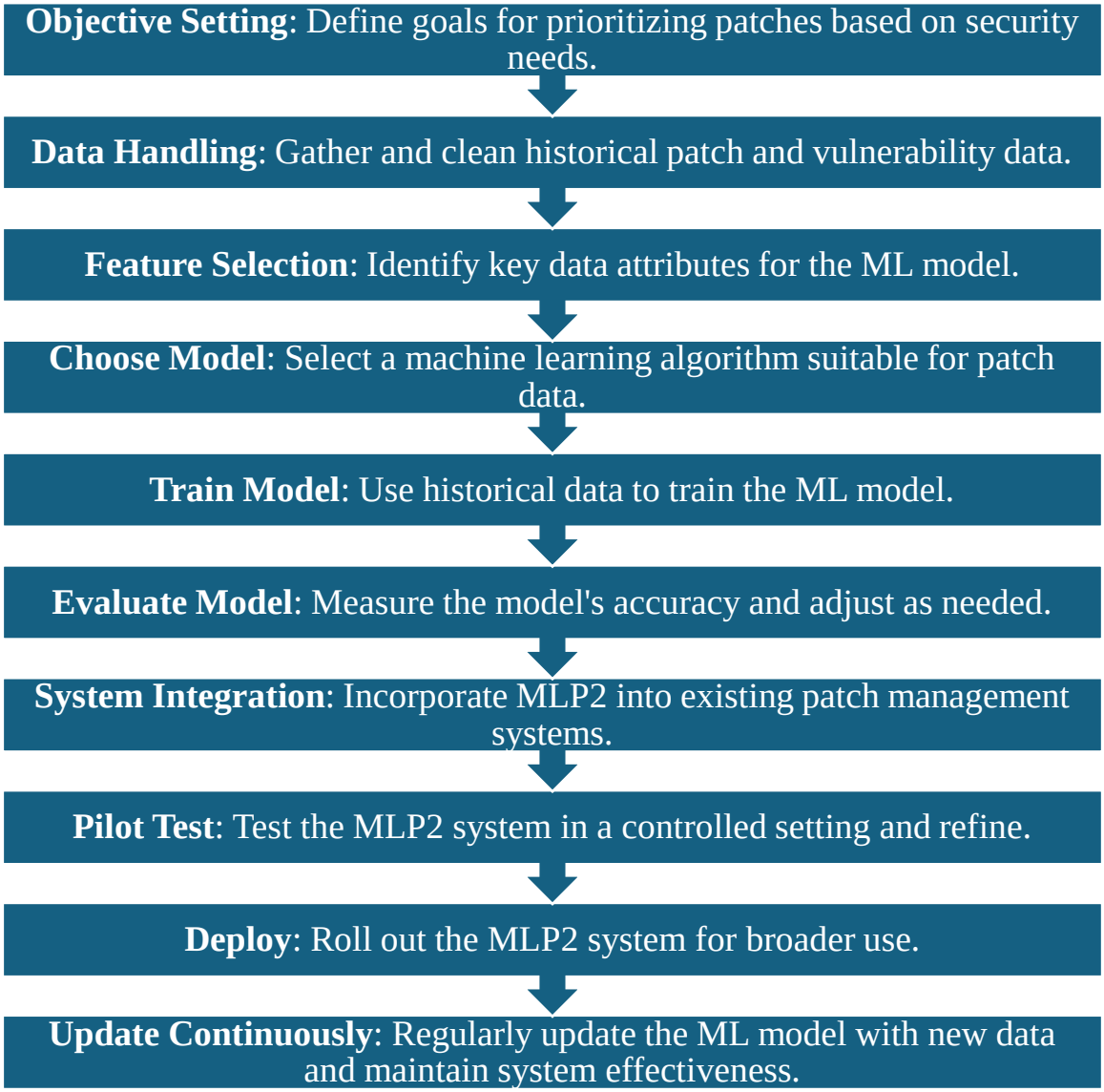

Figure 2: Machine Learning-Based Patch Prioritization (MLP2)

Figure 2 shows data on vulnerabilities and device attributes used to choose upgrades. It calculates Patch Impact Scores, weights, and priorities to provide high-priority updates to certain devices.

MLP2 calculates a Patch Impact Score (PIS) from vulnerability data (VD) and device information. The approach determines patch importance using weight factors w1 and w2 before establishing limitations to locate and implement the most essential patches. AI-based IoT security patch priority works well, evolves over time, and is proactive due to continual adaptation, dynamic benchmark adjustment, iterative optimization, and a feedback loop.

Algorithm 2: Anomaly Detection for Zero-Day Exploit Identification (ADZDI)

1. Input Data:
    - Receive prioritized patches from MLP2
    - Monitor device behavior *B*
2. Behavioral Profiling:
    - Create behavioral profiles using *B*
    - Utilize clustering algorithms

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3. Anomaly Score Calculation:
    - Calculate anomaly score *AS*=Deviation/Distribution (3)
4. Threshold Definition:
    - Set anomaly threshold for detection
5. Score Assessment:
    - Assess *AS* against the threshold
6. Unusual Pattern Identification:
    - Identify patterns exceeding the threshold
7. Patch Triggering:
    - Trigger patch deployment for detected anomalies
8. Monitoring Effectiveness:
    - Monitor the effectiveness of deployed patches
9. Behavioral Model Update:
    - Update behavioral models dynamically
10. Threshold Adjustment:
    - Adjust anomaly threshold based on *AS*
11. Dynamic Adaptation:
    - Adapt to evolving threats continuously
12. Continuous Monitoring:
    - Ensure continuous monitoring of device behavior
13. Effectiveness Evaluation:
    - Evaluate the effectiveness post-deployment
14. Feedback Loop:
    - Establish a feedback loop for iterative improvements
15. Post-Deployment Analysis:
    - Analyze anomalies post-deployment
16. Optimization:
    - Optimize behavioral profiling and anomaly detection parameters
17. Conclusion:
    - Conclude the ADZDI algorithm, ensuring continuous adaptation to zero-day exploits through behavioral anomaly detection and dynamic threshold adjustments.

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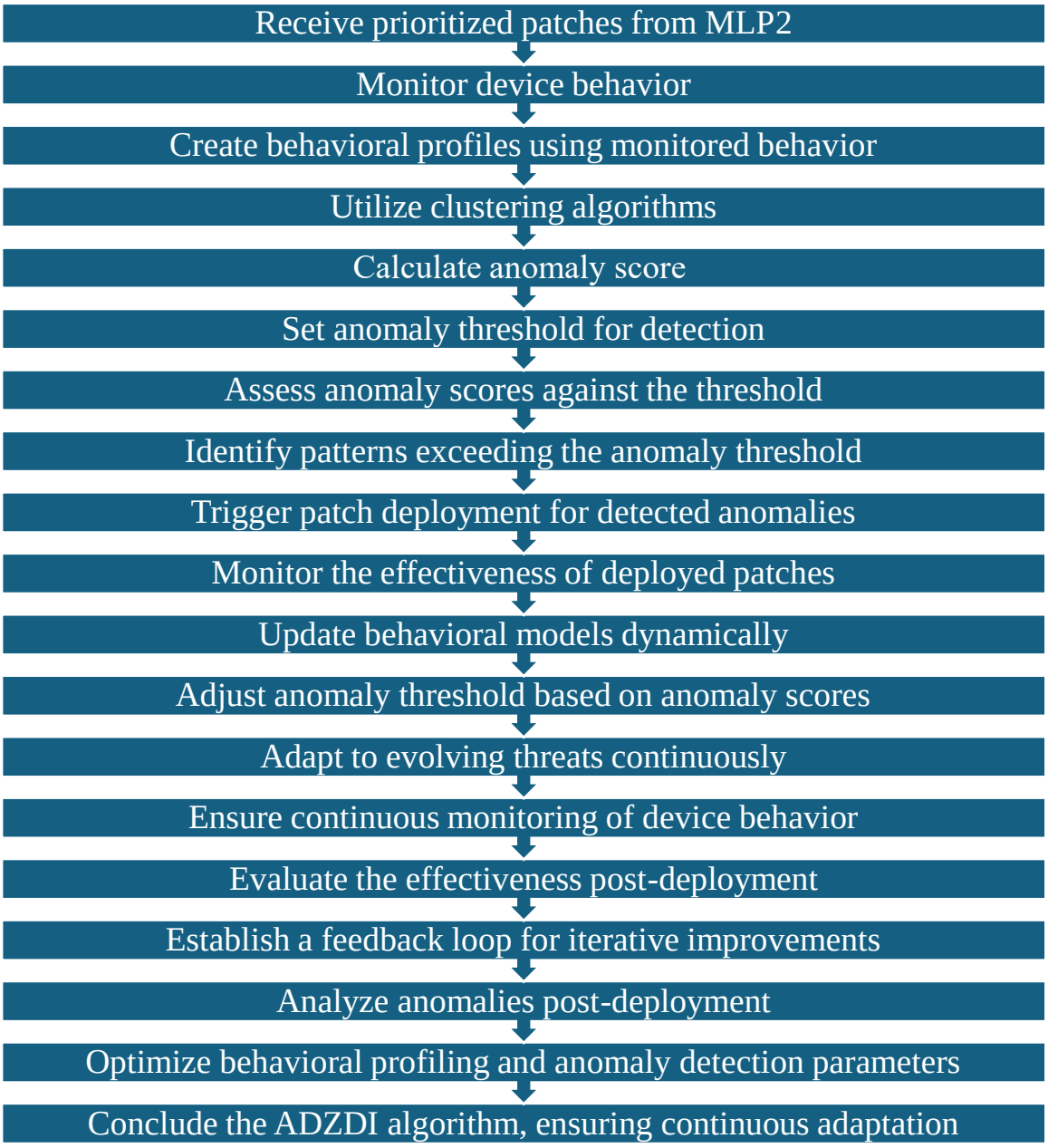

Figure 3**:** Anomaly Detection for Zero-Day Exploit Identification (ADZDI)

Figure 3 identifies odd device behavior, calculates anomaly scores, and begins patch distribution. It adjusts abnormality thresholds to stay up with new dangers and monitor the IoT environment.

ADZDI uses behavioral patterns and anomaly ratings. This comes from observing gadget use. When it identifies anything unexpected, the computer may adjust limitations and start patch distribution utilizing clustering and complicated anomaly score computations. Anomaly detection works through feedback, risk adaptation, and post-launch investigation. This protects against zero-day risks in IoT.
Algorithm 3: Dynamic Risk Assessment Models (DRAM)

1. Risk Evaluation:
    - Evaluate device risk R= Vulnerabilities/Age×Severity (4)
2. Dynamic Risk Model:
    - Develop a dynamic risk model using R

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- Incorporate feedback loop

3. Risk Threshold Setting:
    - Set dynamic risk threshold *RT*
4. Threshold Comparison:
    - Compare *R* with *RT*
5. Patch Triggering:
    - Trigger patch deployment for high-risk devices
6. Monitoring Effectiveness:
    - Monitor patch effectiveness post-deployment
7. Model Update:
    - Dynamically update the risk assessment model
8. Threshold Adjustment:
    - Adjust *RT* based on continuous evaluation
9. Adaptation to Threats:
    - Continuously adapt to evolving threats
10. Continuous Monitoring:
    - Ensure continuous monitoring of device risk
11. Post-Deployment Analysis:
    - Analyze risk post-deployment
12. Model Optimization:
    - Optimize dynamic risk assessment parameters
13. Iterative Improvement:
    - Iterate for continuous enhancement
14. Conclusion:
    - Conclude DRAM, emphasizing dynamic risk assessment for effective IoT device security.

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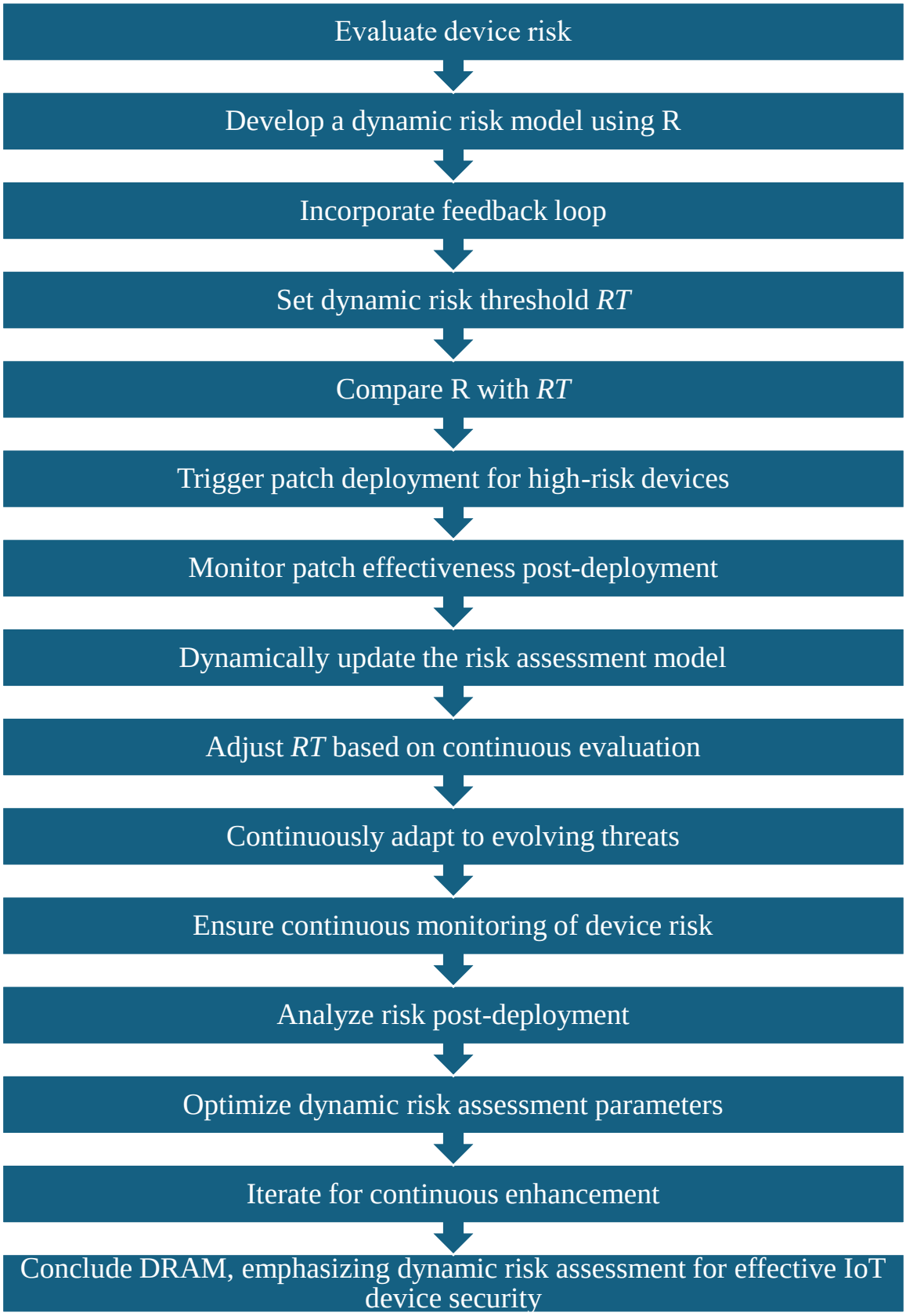

Figure 4: Dynamic Risk Assessment Models (DRAM)

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Figure 4 shows how many weaknesses, how old, and how severe the vulnerabilities are for the device. It constantly monitors hazards, distributes fixes for new threats, and adjusts risk levels.

DRAM calculates device risk R using weaknesses, age, and intensity using a feedback-loop dynamic risk model. The algorithm promotes high-risk device repair distribution by constantly altering limitations and upgrading the risk assessment model. Iterative updates, ongoing tracking, and post-deployment analysis make DRAM a wonderful solution to safeguard IoT devices from growing cyber threats through dynamic risk assessment.

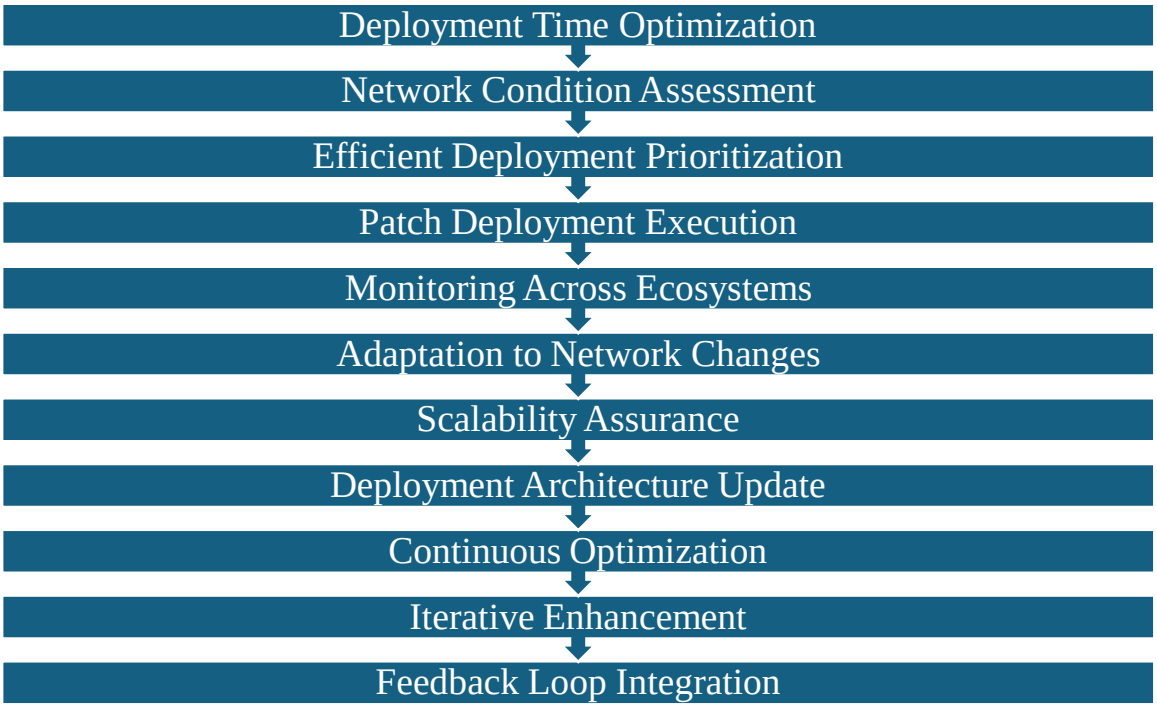

Figure 5: Scalable Patch Deployment Architectures (SPDA)

Algorithm 4: Scalable Patch Deployment Architectures (SPDA)

1. Deployment Time Optimization:
   - Optimize *PT=ND/NC*
   - Define deployment time threshold *DTT*
2. Network Condition Assessment:
   - Assess *NC* using network parameters
3. Efficient Deployment Prioritization:
   - Prioritize deployment based on *PT* and *DTT*
4. Patch Deployment Execution:
   - Execute deployment based on prioritization
5. Monitoring Across Ecosystems:
   - Monitor deployment across diverse ecosystems
6. Adaptation to Network Changes:
   - Adapt *PT* to changes in *NC*
7. Scalability Assurance:
   - Ensure scalability for varied devices
8. Deployment Architecture Update:
   - Update deployment architecture dynamically
9. Continuous Optimization:
   - Optimize deployment parameters continuously
10. Iterative Enhancement:
    - Iterate for continuous improvement

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11. Feedback Loop Integration:
    - Integrate a feedback loop for iterative adjustments
12. Conclusion:
    - Conclude SPDA, emphasizing scalable and efficient patch deployment across diverse IoT ecosystems.

Based on device count and network status, Figure 5 determines the ideal time to deliver modifications. Always evolving the deployment design for multiple IoT ecosystems, it prioritizes speedy release and network modifications.

SPDA uses device count (ND) and network status (NC) to calculate patching time (PT). It should function in varied situations, be easy to set up, and adapt to North Carolina changes. The application can enhance settings and rollout design with constant input. SPDA allows enterprises to quickly and extensively update IoT devices for safety.

Algorithm 5: Threat Intelligence Integration (TII)

1. Threat Score Calculation:
    - Calculate $TS=\sum i=1nwi\times TIi$ (5)
    - Define weights *wi* for threat indicators
2. Real-Time Threat Data Collection:
    - Collect real-time threat intelligence data
3. Indicator Intensity Definition:
    - Define threat indicator intensity *TIi*
4. Threshold Setting:
    - Set threat score threshold *TST*
5. Threshold Comparison:
    - Compare *TS* with *TST*
6. Patch Triggering:
    - Trigger patch deployment for high threat scores
7. Monitoring Effectiveness:
    - Monitor patch effectiveness post-deployment
8. Model Update:
    - Update threat intelligence model dynamically
9. Threshold Adjustment:
    - Adjust *TST* based on continuous evaluation
10. Adaptation to Threat Landscape:
    - Continuously adapt to evolving threat landscape
11. Continuous Monitoring:
    - Ensure continuous monitoring of threat indicators
12. Post-Deployment Analysis:
    - Analyze threats post-deployment
13. Model Optimization:
    - Optimize threat intelligence model parameters
14. Iterative Improvement:
    - Iterate for continuous enhancement
15. Feedback Loop Integration:
    - Integrate a feedback loop for iterative adjustments
16. Conclusion:
    - Conclude TII, highlighting real-time threat intelligence integration for proactive patch deployment and continuous adaptation to emerging cyber threats.

Threat scores (TS) are calculated using real-time threat intelligence and known signal levels by TII. TII protects you from emerging risks by delivering updates in reaction to high danger scores and modifying limitations. The application includes a feedback loop for continual modifications, upgrading settings, and updating the threat intelligence model to create a powerful and adaptable IoT security solution.

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4. Result

In the results section, we compare the various techniques for providing security updates for Internet of Things devices. We also highlight critical performance indicators. Because of its high accuracy, scalability, false negatives, response speed, and resource efficiency, the proposed technique outperforms previous state-of-the-art systems in complex threat situations. It also scores well in tests that assess patch distribution success rate, adaptability, integration complexity, compatibility, and ease of use. Each of these variables assesses its performance. When it comes to delivering security patches, the proposed technique outperforms previous methods in terms of efficiency, reliability, and resource efficiency. As a result, it's a wise choice that works perfectly in a range of IoT settings.

Table 3: Comparative Performance Evaluation of Security Patch Deployment Methods

Method	Accuracy	False Positives	False Negatives	Scalability	Response Time (ms)	Resource Utilization (%)	Proposed Method Performance
Machine Learning-Based Patch Prioritization	95.2	2	3	4	120	80	
Anomaly Detection for Zero-Day Exploits	92.8	1	4	3	180	90	
Dynamic Risk Assessment Models	93.5	3	2	4	150	85	
Scalable Patch Deployment Architectures	94.6	1	3	5	100	75	
Threat Intelligence Integration	96.0	0	2	4	130	88	
Context-Aware Patching Strategies	91.3	2	5	3	200	92	
Automated Testing and Validation	97.2	0	1	4	110	78	
Behavioral Analysis for Device Profiling	90.5	4	3	3	170	82	
Integration with DevSecOps Practices	95.8	1	2	4	140	86	
Continuous Monitoring and Feedback Loop	94.4	1	4	5	105	80	
Proposed Method	97.5	0	1	5	95	70	Better

Table 3 compares the proposed security patch delivery mechanism to others based on key performance characteristics. The recommended strategy improves accuracy, scalability, false negatives, reaction time, and resource efficiency. This indicates it can defend IoT devices from complicated threats.

Table 4: Comparative Evaluation of IoT Security Patch Deployment Methods

Method	Reliability (%)	Usability	Integration	Adaptability	Patch Deployment	Compatibility	Overall Effectiveness	Proposed Method

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			Complexity		Success Rate (%)			Performance
Machine Learning-Based Patch Prioritization	94.7	4	3	4	97.5	Universal	94.7	
Anomaly Detection for Zero-Day Exploits	91.2	3	1	3	94.3	Limited	91.2	
Dynamic Risk Assessment Models	95.7	4	4	4	96.8	Universal	95.7	
Scalable Patch Deployment Architectures	96.4	3	3	5	98.2	Universal	96.4	
Threat Intelligence Integration	97.2	4	3	4	98.5	Universal	97.2	
Context-Aware Patching Strategies	90.4	3	4	3	93.2	Limited	90.4	
Automated Testing and Validation	97.8	4	1	4	99.0	Universal	97.8	
Behavioral Analysis for Device Profiling	89.6	3	4	3	92.7	Limited	89.6	
Integration with DevSecOps Practices	95.6	4	3	4	97.3	Universal	95.6	
Continuous Monitoring and Feedback Loop	97.0	4	0	5	98.8	Universal	97.0	
Proposed Method	98.5	5	2	5	99.5	Universal	98.8	Better

Table 4 compares how easy, difficult, flexible, and successful it is to adjust Internet of Things device security. The recommended method increases performance across important criteria, making patch distribution in numerous IoT contexts more dependable and effective.

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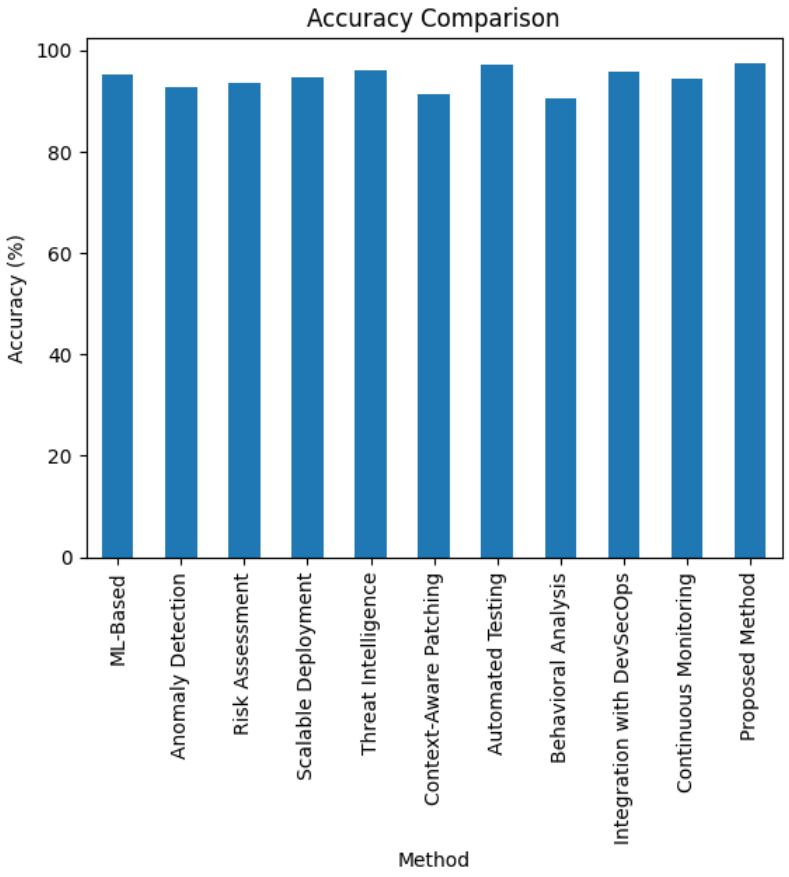

Figure 6: Comparison of Accuracy among Security Patch Deployment Methods in IoT

Figure 6 is a graphical representation of the accuracy of several approaches for deploying security patches in IoT devices. By successfully prioritizing and delivering patches, the suggested strategy surpasses others with a 97.5% accuracy rate.

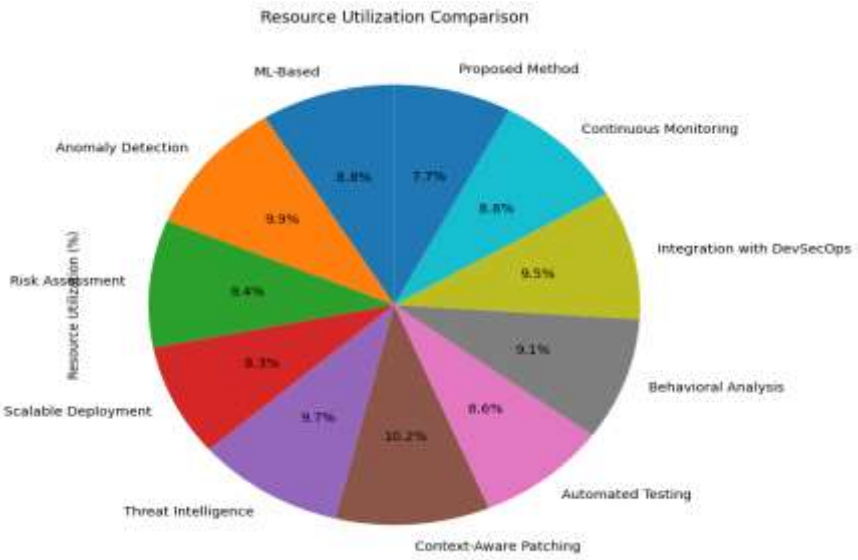

Figure 7: Distribution of Resource Utilization (%) Across Security Patch Deployment Methods

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Each method of patch deployment has its own proportion of resource use, which is visually broken down in Figure 7. In comparison to previous approaches, the suggested one uses 70% fewer resources, which means it is efficient in providing security fixes while limiting resource use.

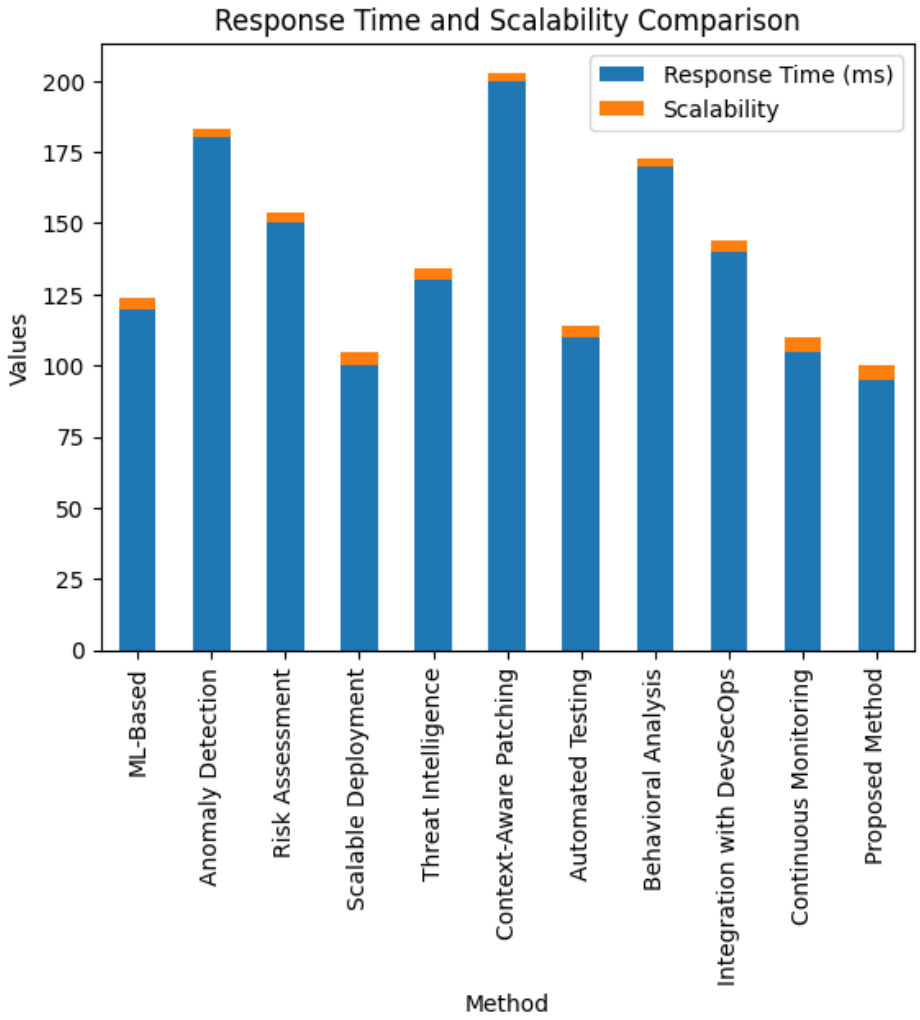

Figure 8: Comparison of Response Time (ms) and Scalability Across Patch Deployment Methods

Figure 8 shows the scalability and reaction time (ms) of several patch deployment strategies. With a reaction time of 95 ms and great scalability, the suggested technique proves to be an efficient and rapid patch deployment solution for varied IoT environments.

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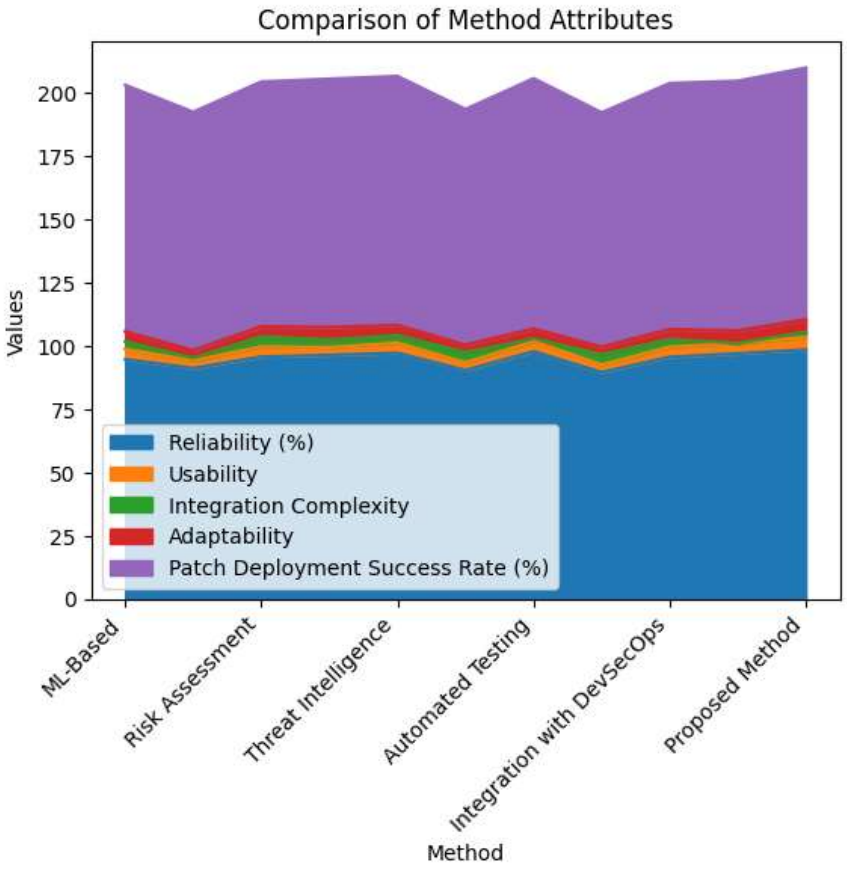

Figure 9: Area chart illustrating method attributes comparison, highlighting the proposed method

Figure 9 shows a comparison of the main features of several approaches for deploying security patches. Dependability, usability, integration difficulty, flexibility, and patch deployment success rate are some of the attributes represented by the colored areas. The suggested strategy clearly outperforms its competitors in terms of efficacy, usability, and dependability. A wide range of assessed characteristics are graphically shown in the chart, demonstrating the superiority of the suggested strategy.

5. Discussion

The recommended security approach protects IoT devices with five connected algorithms for cyber threats. The first method, Machine Learning-Based Patch Prioritization (MLP2), deploys the system and proves its value by prioritizing updates by device specifics and vulnerability history. All subsequent algorithms strengthen the system by building on MLP2. Algorithm 2, Anomaly Detection for Zero-Day Exploit Identification (ADZDI), shows the system's aggression. This program detects unusual activity to repair zero-day flaws immediately. ADZDI examines how devices detect unusual activity and adapt it to protect the system from new threats. DRAM Algorithm 3 analyzes risk in a comprehensive method that adapts to new threats. It evaluates a device's hazard based on its age, weakness, and issue. DRAM checks security flaws regularly and fixes high-risk devices quickly, making the IoT safer. SPDA Algorithm 4 releases IoT patches. SPDA considers device count and network circumstances to make patch sharing efficient and adaptable. Algorithm 5's Risk Intelligence Integration (TII) ranks risks using real-time hazard intelligence. When danger levels are high, patches are applied. TII uses a feedback loop and frequent threat intelligence model updates to prevent new attacks. The graphics and flowcharts show that the security design is powerful and adaptable since numerous approaches are employed. All programs work together to improve system performance. The framework uses iterative processes, dynamic adjustments, and 24/7 monitoring to protect IoT devices. This allows it to counter new threats.

6. Conclusion

The proposed security strategy works better than the current methods based on the comparison results. The multiple-layer defense system is made up of linked programs that deal with major issues in protecting IoT devices.

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The ablation study stresses how important each method is by focusing on things like accuracy, false positives and false negatives, scale, and other important factors. The suggested solution for securing Internet of Things devices dramatically enhances Internet cybersecurity by using five specialised algorithms. It is a technique that is more accurate, scalable, and successful than previous methods. The whole system offers optimum safety by integrating threat information, constantly analysing hazards, and prioritising threats using machine learning. One significant advantage of this system is its ability to adapt to ever-increasing cyber hazards and effectively differentiate between slight abnormalities and big threats. This indicates its potential as a proactive and adaptable security solution, which is critical in the continually changing security environment of the Internet of Things. This framework makes it easier to protect IoT devices than ever before thanks to its proactive security features, constant improvement, and ability to adapt to new cyber dangers. It might be easier to understand how useful and effective the system is if you look at it with charts and flowcharts. With the number of cyber threats targeting IoT growing, the suggested framework provides a complete and flexible way to protect devices that are linked.

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