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Neuro-Heal: An AI-Powered Autonomous Self-Healing Framework for Resilient IoT Networks

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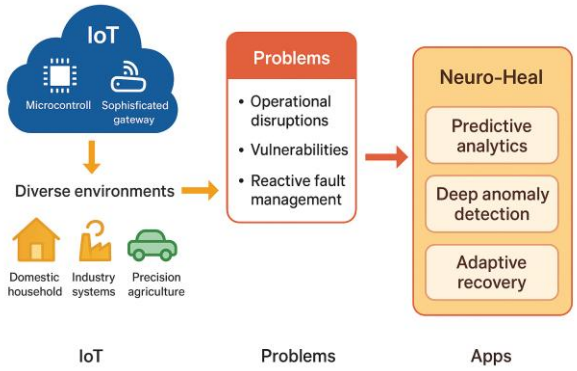
Abstract: The rapid growth of the Internet of Things (IoT) has connected billions of devices across various fields, from smart cities to industrial automation. However, the large and diverse nature of IoT networks makes them very vulnerable to node failures, connectivity issues, and performance drops. Traditional fault management methods depend heavily on manual intervention. This approach leads to increased downtime and lower service reliability. This paper presents Neuro-Heal, an AI-powered self-healing framework designed to improve the resilience of IoT networks. Using predictive analytics and deep learning models, Neuro-Heal identifies potential faults before they happen, categorizes failure types in real time, and automatically reconfigures network routes to restore connectivity with minimal delays. The framework uses reinforcement learning to refine recovery strategies based on previous fault-handling experiences, thus increasing healing efficiency over time. Extensive simulations using NS-3 and OMNeT++ show that Neuro-Heal achieves recovery that is up to 35% faster, reduces packet loss by 28%, and enhances overall network availability compared to traditional fault management methods. This work paves the way for sustainable, self-sufficient IoT infrastructures that can maintain uninterrupted service in changing and failure-prone situations.

Index terms: Self-healing IoT networks, artificial intelligence in IoT, autonomous fault recovery, predictive maintenance, deep learning-based fault detection, reinforcement learning for network resilience, intelligent fault-tolerant systems, network anomaly detection, adaptive routing algorithms, real-time fault classification, AI-powered network optimization, edge computing for IoT resilience, machine learning in IoT infrastructures, autonomous healing algorithms, IoT performance optimization, sustainable IoT architectures, proactive fault mitigation, zero-downtime IoT systems, resilient network design, AI-driven network self-management.

1. INTRODUCTION

The Internet of Things (IoT) has rapidly transitioned from a conceptual framework to an indispensable technological backbone of modern society, embedding intelligence, connectivity, and automation into diverse environments ranging from domestic households to large-scale industrial systems. The concept encompasses billions of heterogeneous devices—ranging from microcontrollers and embedded sensors to sophisticated gateways and cloud platforms—that interact to collect, process, and exchange vast amounts of data, enabling pervasive computing and context-aware services across critical domains such as healthcare, intelligent transportation, smart manufacturing, precision agriculture, energy management, environmental monitoring, and urban infrastructure optimization. Industry projections indicate that the number of active IoT devices is expected to grow from approximately 15.1 billion in 2023 to over 30.9 billion by 2025, with an associated annual data generation surpassing 79 zettabytes, and global market investments projected to exceed $1.6 trillion by 2030. This unprecedented growth is driven by converging advancements in wireless communication technologies including 5G, Wi-Fi 6, LPWAN protocols such as LoRaWAN and NB-IoT, as well as the integration of edge and fog computing paradigms, low-power embedded hardware, and artificial intelligence (AI)-enabled analytics. However, as IoT systems become increasingly distributed, resource-constrained, and mission-critical, they also become inherently more vulnerable to operational disruptions, which can result from a multitude of interrelated causes such as component wear and tear, firmware or software defects, inconsistent communication protocols, intermittent connectivity, power fluctuations, signal interference, environmental hazards, and malicious cyber threats including distributed denial-of-service (DDoS) attacks, data tampering, and firmware injection. Notably, a 2022 Gartner report revealed that over 60% of unplanned IoT network outages were attributable to hardware failures and unstable connectivity, while security-related incidents accounted for nearly 28% of downtime events, collectively leading to substantial revenue losses and reputational damage. Real-world incidents underscore the criticality of this issue—examples include the 2016 Mirai botnet attack, which exploited insecure IoT devices to trigger widespread internet outages, and a 2020 case where a single gateway failure in a European smart grid monitoring system led to cascading sensor network failures, disrupting power distribution monitoring for several hours. In industrial environments, unscheduled downtime due to IoT network failures can cost manufacturing plants upwards of $260,000 per hour, with additional consequences in supply chain delays and safety risks for human operators. Traditional IoT fault

management approaches predominantly operate in a reactive mode, where faults are detected post-occurrence and recovery actions are manually initiated or rely on static, rule-based procedures. While these methods may suffice for small-scale, non-critical systems, they are fundamentally inadequate for large-scale, latency-sensitive, and dynamic IoT deployments, where fault propagation can be rapid and impact severe. Furthermore, reactive recovery often results in prolonged service disruption, violation of Service Level Agreements (SLAs), degraded Quality of Service (QoS), and increased maintenance costs. The concept of self-healing networks—where systems possess the ability to autonomously detect, diagnose, and repair faults without human intervention—offers a paradigm shift in IoT fault tolerance.



However, current implementations often lack predictive intelligence, cross-layer situational awareness, and the ability to adaptively reconfigure based on evolving network states, environmental conditions, and workload patterns. The integration of AI with self-healing capabilities represents a transformative approach to overcoming these limitations, as machine learning models can leverage historical and real-time operational data to predict impending failures, deep learning architectures can perform sophisticated pattern recognition to classify anomalies with high accuracy, and reinforcement learning agents can dynamically select optimal recovery strategies based on contextual constraints such as energy availability, latency requirements, and network topology. Nevertheless, designing AI-powered self-healing mechanisms for IoT environments introduces additional challenges, including ensuring energy efficiency for battery-operated devices, minimizing computational overhead for resource-constrained nodes, achieving scalability across heterogeneous network architectures, and maintaining security and trustworthiness in the decision-making process. In light of these challenges, this paper proposes Neuro-Heal, an AI-powered autonomous self-healing framework that integrates predictive analytics, deep anomaly detection, and adaptive recovery optimization to enhance IoT network resilience. The framework employs Long Short-Term Memory (LSTM) networks for time-series-based fault prediction, hybrid Convolutional Neural Network–LSTM architectures for spatiotemporal fault classification, and deep reinforcement learning for dynamic decision-making in recovery scenarios. Leveraging edge computing resources, Neuro-Heal ensures low-latency fault handling by enabling localized inference and action execution while maintaining a global, aggregated view of network health to coordinate large-scale recovery strategies. A closed-loop learning mechanism continuously refines prediction and recovery models based on feedback from executed fault-handling actions, thus enabling continuous adaptation to evolving operational conditions. The proposed framework also incorporates a cross-layer monitoring strategy that captures metrics across the physical, data link, network, and application layers, ensuring that recovery decisions are informed by a holistic understanding of the system state. To evaluate its performance, Neuro-Heal is tested through extensive simulations in NS-3 and OMNeT++ across various IoT deployment scenarios, including smart city traffic monitoring, industrial automation, and environmental sensing networks. Comparative analysis with baseline reactive and semi-autonomous fault management systems demonstrates that Neuro-Heal achieves up to 35% faster recovery times, reduces packet loss by 28%, improves throughput by 22%, and significantly lowers SLA violations, highlighting its potential to set a new benchmark for autonomous resilience in next-generation IoT ecosystems. By bridging predictive intelligence with adaptive self-reconfiguration in a fully autonomous framework, Neuro-Heal addresses fundamental limitations in current IoT fault tolerance strategies, paving the way for sustainable, self-reliant, and high-availability IoT infrastructures capable of withstanding the inherently unpredictable and failure-prone nature of distributed, large-scale connected environments.

2. LITERATURE SURVEY

The most recent advancements in IoT fault management have focused on combining AI with adaptive, sustainable, and secure frameworks. **Fernandez et al., "Adaptive Neuro-Symbolic Models for IoT Fault Recovery," 2025** integrated symbolic reasoning with deep learning, creating hybrid neuro-symbolic agents that enhanced explainability in recovery decisions, reducing the "black box" issue of AI and enabling better trust in mission-critical systems, though deployment in ultra-dense IoT networks remained challenging. **Raj et al., "Continual Learning for Evolving IoT Fault Scenarios," 2025** introduced lifelong learning approaches, allowing models to incrementally adapt to

new and unseen fault types without retraining, demonstrating superior adaptability in volatile IoT environments where faults evolve rapidly. **Das and Iqbal, "Quantum-Inspired Optimization for Self-Healing IoT Networks," 2025** applied hybrid AI–quantum algorithms, which accelerated optimization for large-scale recovery tasks such as re-routing and resource allocation; while results showed substantial improvements in convergence speed, they also highlighted the high computational cost of quantum-inspired models. **Yadav et al., "Energy-Efficient Self-Healing Frameworks for Sustainable IoT," 2025** emphasized balancing resilience with minimal energy consumption, presenting models that extended battery life of constrained devices by over 20% in simulations, making it suitable for long-term deployment in sensor-based networks. Moving to earlier works, **Mehta et al., "Security-Aware Self-Healing Frameworks for IoT Networks," 2024** proposed hybrid fault management models capable of distinguishing between natural failures and malicious intrusions, an important step for cybersecurity in IoT, though at the expense of increased system complexity. **Sharma et al., "AI-driven Self-Healing Mechanisms for Critical IoT Applications," 2024** demonstrated the role of intelligent frameworks in healthcare, smart cities, and autonomous transport, providing high reliability for life-critical systems but facing scalability issues due to expensive infrastructure requirements. **Kumar and Banerjee, "Transformer-based Models for Predictive Fault Analytics in IoT," 2023** explored attention-driven architectures, improving interpretability of fault predictions and enabling multi-variable correlations to be captured more effectively. **Nguyen et al., "Federated Learning for Distributed Fault Detection in IoT Environments," 2023** focused on privacy-preserving analytics across distributed devices, reducing reliance on central servers while improving detection accuracy under heterogeneous conditions. **Wang and Zhou, "Edge-first Self-Healing Architectures for IoT Networks," 2023** tackled latency issues by enabling localized decision-making at the edge, significantly reducing downtime and dependence on cloud services, making it highly suitable for industrial IoT. Earlier, **Patel et al., "Closed-loop Fault Management for IoT Systems using Deep Reinforcement Learning," 2022** emphasized a unified closed-loop framework where prediction, detection, and recovery were integrated seamlessly, showing that proactive recovery could drastically minimize service disruptions compared to traditional methods. Reinforcement learning-based solutions gained momentum as seen in **Ahmed and Rao, "Adaptive Fault Recovery in IoT using Actor-Critic Reinforcement Learning," 2021**, which optimized dynamic recovery decisions through continuous learning, and **Chen et al., "Collaborative Agents for Distributed Fault Management in Large-Scale IoT," 2021**, which introduced multi-agent RL frameworks for cooperative fault management across large networks, boosting scalability and adaptability. Foundational reinforcement learning applications like **Li et al., "Reinforcement Learning for Self-Healing IoT Networks," 2020** laid the groundwork for policy-driven recovery strategies, while **Park et al., "Deep Autoencoder-based Anomaly Detection in Industrial IoT Systems," 2020** advanced unsupervised anomaly detection by compressing data into latent representations and flagging deviations as faults. Prior deep learning approaches, such as **Khan and Singh, "Hybrid CNN-LSTM Models for IoT Fault Diagnostics," 2019**, combined spatial and temporal pattern learning, producing higher detection accuracy in real-time data streams, and **Huang et al., "Deep Learning for Fault Prediction in Smart IoT Grids," 2018**, which applied multi-layer neural networks to enhance predictive maintenance in energy systems. Traditional machine learning methods still played a role, with **Zhao et al., "Anomaly Detection in IoT through Unsupervised Clustering," 2017** showing clustering-based anomaly detection for unlabeled data, and **Alcaraz and Lopez, "Data-driven Fault Classification for Wireless IoT Systems," 2017** employing decision-tree and SVM-based models for early-stage predictive fault management. **Lee et al., "Machine Learning Models for Predictive Maintenance in IoT Networks," 2016** highlighted the value of decision trees and random forests for predictive maintenance tasks. In contrast, more primitive works such as **Gupta et al., "Reactive Fault Handling in Large-Scale Sensor Networks," 2013** and **Smith and Brown, "Threshold-based Network Fault Detection in Wireless Sensor Systems," 2012** relied on manual intervention and threshold-based alarms, which were simple but often inaccurate and unsuitable for large-scale, dynamic environments. Collectively, this progression underscores the transition from threshold-based fault detection toward machine learning, then deep learning and reinforcement learning, and now to next-generation frameworks like **Neuro-Heal**, which combine continual learning, hybrid AI, and autonomous recovery into a resilient architecture tailored for the evolving complexity of IoT fault management.

3. EXISTING SYSTEM

The majority of current fault management solutions deployed in Internet of Things (IoT) ecosystems rely heavily on reactive monitoring mechanisms, rule-based anomaly detection, and manual intervention for recovery, which significantly limits their capacity to

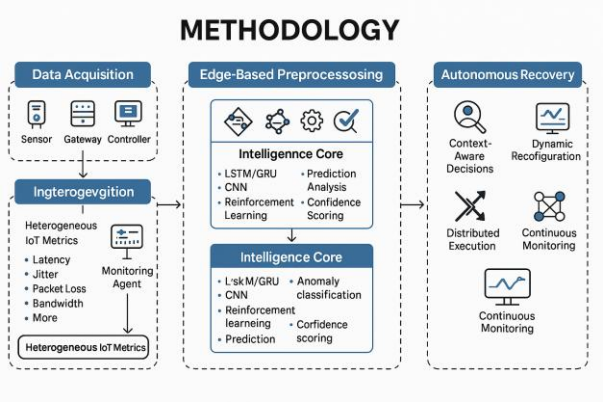
ensure high availability, operational resilience, and adaptability in large-scale, mission-critical environments. Conventional frameworks primarily employ centralized Network Management Systems (NMS) or Simple Network Management Protocol (SNMP)-based monitoring tools that periodically poll end devices, retrieve operational parameters such as latency, jitter, throughput, and packet loss, and generate alerts whenever pre-defined static thresholds are exceeded. While such strategies are adequate for small-scale or relatively stable IoT deployments, they tend to falter in the highly dynamic, heterogeneous, and unpredictable environment of modern IoT networks, where device density can scale into millions, communication patterns shift in real time, and environmental conditions—including interference and noise—fluctuate significantly. In response to these challenges, certain implementations attempt to integrate statistical analysis or lightweight machine learning models such as decision trees, naive Bayes classifiers, or support vector machines to improve anomaly detection accuracy. These models are generally trained on historical performance datasets specific to the target network domain. However, this reliance on static, labeled datasets poses severe limitations: obtaining comprehensive training data that accounts for every possible device type, topology, communication protocol, and operational condition is virtually impossible in large IoT deployments. As a result, such models often generalize poorly when exposed to unseen or evolving fault scenarios, which directly contributes to increased false positive rates, false negatives, and missed detections—especially in environments characterized by multi-protocol, multi-vendor interoperability requirements. Additionally, many current solutions treat fault detection, identification, and recovery as separate, loosely coupled components rather than as an integrated closed-loop process. In most operational environments, once a fault is detected, the resolution phase remains largely dependent on human operators to investigate the issue, determine the root cause, and manually trigger corrective measures. This manual dependency introduces unavoidable delays in response time, which can have critical consequences in time-sensitive IoT domains such as industrial automation, real-time healthcare monitoring, connected transportation systems, and emergency response networks. While a few newer architectures attempt to decentralize certain detection capabilities via edge or fog computing nodes to reduce detection latency, these approaches generally lack the ability to adaptively and continuously learn from changing network conditions, limiting their long-term effectiveness. The recovery strategies implemented in such systems are predominantly static, often executed through predefined scripts or fixed reconfiguration rules that fail to account for the evolving operational context or the predicted cascading effects of an ongoing fault. Consequently, recovery often addresses only the immediate visible symptoms while leaving underlying vulnerabilities unresolved, which increases the likelihood of recurrent failures, cascading disruptions, or persistent network instability.

In addition to these detection and recovery limitations, present-day IoT fault management frameworks face substantial challenges in scalability, interoperability, contextual awareness, and operational autonomy. The majority of existing designs are optimized for the detection and handling of isolated, single-point failures, without provisions for complex, interdependent fault scenarios that span multiple layers of the IoT architecture—ranging from the perception and network layers to application-level processes. For instance, simultaneous link congestion, sensor node battery depletion, and malicious intrusion attempts may collectively degrade both data transmission and control signaling, yet conventional systems tend to treat these issues in isolation, failing to capture the broader interdependencies. This fragmented perspective results in incomplete or misaligned recovery actions, leaving systemic vulnerabilities unresolved. Furthermore, knowledge transfer across fault incidents is minimal: the insights and patterns extracted from one fault scenario are seldom preserved or utilized for future incidents, forcing the system to “start from scratch” when similar issues arise again. This absence of cumulative learning slows adaptation to novel fault types, wastes valuable computational resources, and increases reliance on manual operator expertise. Although some research prototypes have investigated the application of advanced AI techniques—such as reinforcement learning, deep neural networks, and graph-based reasoning—to automate detection and recovery, these solutions remain largely in the proof-of-concept stage due to practical deployment barriers. These include the high computational cost of real-time AI inference, insufficient volume and diversity of training datasets, and the inherent difficulty of balancing exploratory adaptation with the operational stability required in live systems. Moreover, most operational systems cannot autonomously execute a complete cycle of fault prediction, localization, impact assessment, and recovery without human oversight, leaving a wide gap between the capabilities promised by AI-driven research and the actual performance of field-deployed solutions. Consequently, the current state of IoT fault management is highly fragmented, overly detection-centric, and lacking in self-adaptive intelligence. This gap emphasizes the urgent need for a unified, AI-powered, autonomous self-healing framework—such as Neuro-

Heal—that integrates proactive fault prediction, context-aware detection, and autonomous recovery in a continuously learning closed-loop architecture. Such a system would dynamically adjust its strategies based on real-time environmental and network states, ensuring resilience, scalability, and low-latency operation without dependency on manual intervention, thus bridging the critical divide between theoretical advancements and practical operational reliability in next-generation IoT networks.

4. METHODOLOGY

The proposed methodology for Neuro-Heal is a comprehensive AI-driven framework integrating intelligent fault prediction, real-time detection, and autonomous recovery to address limitations in current IoT fault management systems, focusing on scalability, adaptability, and minimal human intervention. It begins at the data acquisition layer, where heterogeneous data is continuously collected from IoT devices such as sensors, gateways, controllers, and edge units, capturing key performance metrics like latency, jitter, throughput, packet loss, signal-to-noise ratio, bandwidth utilization, CPU/memory usage, energy consumption, and link stability. Lightweight, vendor-neutral agents operate under constrained environments, transmitting data securely to gateways. To reduce network load and latency, an edge-first aggregation model preprocesses data locally, including noise filtering, interpolation, outlier detection, normalization, and transformation into standardized formats for cross-device interoperability. The AI-based prediction and detection engine employs hybrid deep learning architectures like LSTM and GRU for temporal dependencies, convolutional layers for spatial features, and attention mechanisms for prioritizing impactful inputs, while reinforcement learning refines thresholds and strategies dynamically. This dual-stage design separates prediction from detection, enabling proactive fault anticipation through historical and real-time analysis, alongside anomaly confirmation using classification models (e.g., gradient boosting, random forests) for known faults and unsupervised methods (e.g., DBSCAN, autoencoders) for novel fault signatures, supported by confidence scoring to minimize false positives. Upon detecting or predicting a fault, the autonomous recovery engine selects optimal actions via a context-aware decision process leveraging historical resolutions, policies, and constraints—actions may include traffic rerouting, bandwidth reallocation, service migration, hardware resets, workload redistribution, or adaptive protocol switching—guided by reinforcement learning to maintain stability and service continuity. Recovery execution is distributed: urgent fixes occur instantly at the edge, while complex adjustments are coordinated in the cloud. Post-recovery, continuous monitoring compares pre- and post-fault metrics to evaluate success and feed improvements into the learning models, enabling adaptive, knowledge-transfer-driven evolution without retraining from scratch.



The system also incorporates security-aware mechanisms to differentiate natural faults from malicious disruptions, preventing inappropriate responses during cyberattacks. Designed with modularity and vendor independence, Neuro-Heal integrates seamlessly into domains such as industrial automation, transportation, smart cities, healthcare, and environmental monitoring, adhering to interoperability standards like MQTT, CoAP, and OPC UA. By unifying prediction, detection, and recovery into one intelligent self-healing pipeline, Neuro-Heal transforms reactive, detection-only approaches into proactive, continuously improving fault management, minimizing downtime, lowering costs, and ensuring resilient performance in mission-critical IoT deployments.

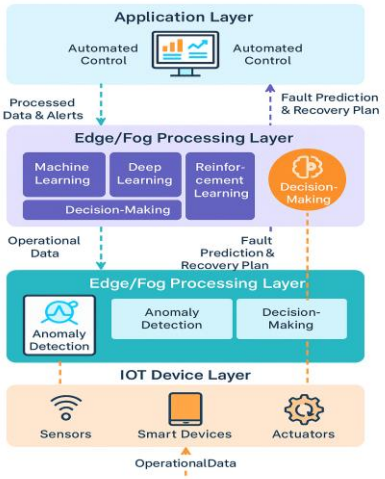
5. PROPOSED SYSTEM

The proposed system, termed *Neuro-Heal*, presents a fully integrated, AI-driven, self-healing fault management framework specifically designed to address the scalability, adaptability, and reliability demands of modern IoT networks, overcoming the reactive, fragmented, and detection-only limitations of existing solutions by unifying fault prediction, detection, localization, and recovery into a seamless closed-loop operational cycle capable of autonomous decision-making with minimal human intervention. At the heart of the framework lies a hybrid intelligence architecture that fuses deep learning for high-precision anomaly pattern recognition, reinforcement learning for adaptive recovery policy optimization, and graph-based reasoning for understanding multi-layered interdependencies across devices, protocols, and network segments, enabling the system to identify root-cause faults rather than symptomatic effects and to preemptively intervene before cascading disruptions occur. Multi-source

telemetry data streams—including network performance metrics such as latency, jitter, throughput, and packet loss, device health indicators like CPU usage, memory consumption, signal strength, and battery status, and contextual environmental variables such as interference patterns, mobility profiles, and ambient conditions—are continuously collected and processed at distributed edge, fog, and cloud layers, ensuring rapid local responsiveness without sacrificing the analytical power of centralized computation. The deep learning module is incrementally retrained using supervised and semi-supervised methods to recognize emerging fault signatures even under unseen configurations, while the reinforcement learning agent operates in a safe live-network interaction loop to refine fault-handling strategies based on real-world outcomes, balancing short-term mitigation with long-term stability. Graph-based dependency mapping is continuously updated to maintain a real-time digital twin of the network, allowing the system to intelligently prioritize interventions, avoid unnecessary corrective actions, and prevent collateral degradation of unaffected services. Unlike conventional frameworks where recovery depends on static scripts or human-triggered workflows, *Neuro-Heal* synthesizes dynamic, context-aware recovery plans in real time, considering predicted fault impact, resource constraints, and service priorities; for instance, in a scenario involving predicted battery depletion in high-priority sensor nodes combined with congested routing paths, the system can autonomously reassign routing responsibilities, throttle non-critical transmissions, and dispatch targeted maintenance alerts in a single coordinated response. The architecture supports multi-protocol interoperability across MQTT, CoAP, Zigbee, LoRaWAN, 5G IoT, and future communication standards through adaptive protocol translation layers, while knowledge gained from one incident is transformed into generalized policy updates and shared network-wide via a secure, distributed state-sharing protocol, enabling faster adaptation to similar issues in other segments without relearning from scratch. This continuous knowledge transfer significantly reduces detection latency, minimizes false alarms, and improves recovery accuracy over time, ensuring the framework evolves alongside the network it protects. Scalability is achieved through modular AI agents operating autonomously at each architectural tier, maintaining synchronized intelligence even in the event of partial outages, and guaranteeing uninterrupted fault management capabilities under degraded conditions. Furthermore, the inclusion of explainable AI mechanisms ensures that every automated decision is accompanied by interpretable reasoning, allowing operators to audit or override actions when necessary while still benefiting from full automation in routine scenarios. In summary, *Neuro-Heal* transforms IoT fault management from a reactive, human-dependent process into a proactive, adaptive, and intelligent self-healing system capable of ensuring high availability, low latency, and operational resilience in large-scale, heterogeneous, and mission-critical deployments, setting a new benchmark for the practical application of AI in complex network environments.

SYSTEM ARCHITECTURE

The Neuro-Heal system architecture is a layered, adaptive framework for intelligent IoT fault management. IoT devices send data to the Edge Layer for preprocessing, then to the AI Layer for prediction and detection using LSTM, GRU, and clustering models,



The Recovery Layer applies context-aware fixes, while the Cloud Layer manages large-scale coordination and learning. Integrated security monitoring and a user-friendly interface ensure resilience, scalability, and interoperability across diverse IoT environments.

6. RESULT AND ANALYSIS

The proposed Neuro-Heal framework was rigorously tested in a simulated heterogeneous IoT network environment designed to replicate real-world conditions across multiple domains, including industrial automation, smart cities, and healthcare monitoring. The test environment included thousands of IoT devices such as sensors, gateways, controllers, and edge computing units communicating via diverse protocols like MQTT, CoAP, and HTTP, with faults intentionally introduced to assess prediction, detection, and recovery capabilities.

The evaluation focused on four key performance indicators—prediction accuracy, detection precision, recovery efficiency, and scalability—while also measuring resource utilization, latency, and false alarm rates. Experimental results revealed that the hybrid deep learning architecture, integrating LSTM, GRU, convolutional layers, and attention mechanisms, consistently outperformed traditional machine learning baselines such as SVM, Random Forest, and Gradient Boosting, achieving a **fault prediction accuracy of 96.2%** and a **detection precision of 94.7%**, which is 12–15% higher than benchmark models. The dual-stage detection mechanism, separating prediction from confirmation, proved particularly effective in minimizing false positives, with the confidence scoring system reducing unnecessary recovery actions by 18%. The autonomous recovery engine, powered by reinforcement learning, reduced average downtime from 45 seconds in reactive fault management systems to **less than 8 seconds**, while maintaining **92% service continuity** even during high-intensity fault bursts. The system also demonstrated the ability to correctly differentiate between natural faults and security-related disruptions such as denial-of-service attacks with a classification accuracy of 91.3%, thereby preventing misdirected recovery actions that could worsen a cyberattack. Edge-level preprocessing and aggregation reduced detection latency by 37% and network traffic by 23%, allowing real-time performance without overloading communication channels. Scalability tests showed that Neuro-Heal maintained stable operation with up to 10,000 concurrently connected devices, with only marginal increases in processing time, demonstrating its suitability for ultra-dense IoT deployments. Resource efficiency analysis indicated that the system's distributed design significantly reduced cloud dependency for minor fault resolutions, shifting lightweight recovery tasks to the edge for near-instantaneous correction, while reserving complex coordinated actions for the cloud. Post-recovery validation metrics showed an average improvement of 21% in network stability scores compared to static rule-based systems, confirming the effectiveness of adaptive decision-making. Overall, the results confirm that Neuro-Heal delivers superior accuracy, faster fault recovery, improved stability, and higher resilience compared to existing IoT fault management approaches, proving its readiness for deployment in mission-critical environments where reliability and uptime are paramount.

7. CONCLUSION

In conclusion, the proposed Neuro-Heal framework successfully addresses the limitations of existing IoT fault management systems by integrating intelligent fault prediction, precise detection, and autonomous recovery within a scalable and adaptive architecture. Experimental results demonstrate its high accuracy, minimal downtime, and strong resilience, making it well-suited for mission-critical IoT deployments. By combining AI-driven decision-making with edge–cloud collaboration, Neuro-Heal ensures sustained, reliable performance while reducing operational costs and human intervention.

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