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Machine Learning and Java-Based Orchestration for Intelligent Anomaly Detection and Self-Healing in Virtual Networks

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Abstract

New network infrastructures are strongly dynamic, programmable, and scalable due to extensive adoption of NFV and SDN. Higher operational complexity is traded off against these benefits, opening up the networks to anomalies like attacks, misconfiguration, and performance degradation. Traditional fault management and monitoring protocols are reactive in nature and involved human intervention, leading to added downtime and operational expense. For addressing such problems, this paper proposes an intelligent self-healing and anomaly detection framework in virtual networks through AI-based models and Java-based orchestration techniques. The anomaly detection engine utilizes a hybrid scheme that precisely identifies known and unknown anomalies by utilizing deep autoencoders for reconstruction error along with isolation forests for effective unsupervised scoring. Self-healing module works in conjunction with SDN/NFV controllers to perform corrective actions like scaling, migration, and rerouting, and root cause analysis (RCA) detects malfunctioning network services by analysing dependency graphs and applying probabilistic reasoning. 55% mean time to recovery (MTTR) decrease, fewer false alarms, and higher detection accuracy (>95%) are illustrated through experimental outcomes. This paper enhances resilient, flexible, and self-managed virtual network establishment.

Keywords: orchestration, root cause analysis, anomaly detection, self-healing networks, Java, machine learning, autoencoder, isolation forest, virtualization, SDN, NFV, and resilient networking.

I. Introduction

Current communication infrastructure is constructed, deployed, and operated differently due to the emergence of networking technologies, particularly Software-Defined Networking (SDN) and Network Function Virtualization (NFV). In comparison with traditional hardware-based networks, SDN and NFV separate control and forwarding planes and replace virtualized services with rigid hardware devices [1]. This paradigm has become leaner, more flexible, and more economical. It has given birth to new uses such as edge computing, cloud-native services, and 5G. As networks become more programmatic and virtualized, though, they become more dynamic and complicated, with new problems regarding reliability, security, and performance.

Anomaly detection and repair, which may happen in the form of traffic congestion, performance dips, configuration issues, or cyber-attacks, is the most difficult task [2]. Anomaly detection techniques traditionally used threshold notices and rule-based monitoring. These are performing inadequately within high-throughput, dynamic networks but significantly better within static networks. Their requirement of human intervention, high rate of false positives, and failure to detect unknown or zero-day anomalies are all typical. All these disadvantages make service interruption more likely and operation efficiency lower.

To fight these challenges, artificial intelligence (AI), which is capable of identifying aberrations and measuring dynamic network behaviour more effectively, can be helpful. Machine learning, deep learning, and statistical anomaly detection are advanced methods of finding latent relationships, displaying patterns, and predicting issues before their occurrence [3]. Further, networks can diagnose faults, detect defects, and carry out restoration functions with no manual intervention through the integration of AI-based monitoring and self-healing algorithms. Resilient large-scale adaptive networks of the future will require this level of automation.

We propose in this paper a novel artificial intelligence (AI) and Java-based orchestration tools-based system for intelligent anomaly detection and virtual network self-healing. Hybrid anomaly detection techniques are used by SDN/NFV platforms in their control plane, e.g., isolation forests for unsupervised outlier detection and autoencoders for anomaly detection in terms of reconstruction errors [4]. The root cause analysis engine (RCA) uses probabilistic reasoning and graph dependencies to identify the problem domain once anomalies have been detected. The self-healing module subsequently applies remediation actions such as scaling resources, traffic redirection, and service migration via Java orchestrator clients that interact with network controllers.

This research delivers three: (a) a strong hybrid AI anomaly detection model; (b) an automated healing orchestration module for Java; and (c) extensive experimentation validating minimized downtime, minimized false positives, and improved detection accuracy. These deliverables make it possible to build smart, resilient, and self-healing virtual networks for future digital infrastructure [5].

II. Related Work

A. Traditional Network Anomaly Detection

Traditionally, the most prevalent methods of anomaly detection were rule-based systems, signature matching, and statistical thresholding. Although adequate for static networks, in the form of intrusion detection systems (IDS) and SNMP-based monitors, they are not very flexible [6]. Their failure to detect zero-day attacks, large false-positive rates, and periodic requirement of manual adjustments make them ineffective in virtualized and dynamic networks.

B. Machine Learning Approaches

With the development of AI, ML methods have become popularly used for the detection of anomalies in virtualized environments [7]. The ability to detect anomalous traffic has been validated with clustering methods (e.g., K-Means, DBSCAN) and classification algorithms (e.g., Support Vector Machines, Random Forests). These methods are most probably derived from labelled data, though, which are expensive and difficult to keep current in dynamic network environments.

C. Deep Learning for Network Monitoring

Largest-scale network traffic data has been successfully dealt with using deep learning (DL). Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autochangers have been used to handle anomaly detection workloads. Autoencoders' capability of learning on latent patterns and oscillations in the traffic make them incredibly popular in unsupervised learning. Without proper optimization, deep learning models become resource-hungry and suffer from real-time inference issues [8].

D. Self-Healing in Virtual Networks

Self-healing network models work to enable autonomous fault recuperation by automating such processes as resource scaling, service migration, and traffic rerouting [9]. Models, according to existing research, utilize policy-based orchestration or rule-based automation. They can handle individual defects effectively, but they are inflexible in handling atypical events or layer complexities in failures.

E. AI-Driven Self-Healing Systems

The emphasis in current research has been on AI-enabled self-healing systems based on autonomous corrective actions and anomaly identification [10]. The systems utilize real-time anomaly detection through machine learning and deep learning-based models, upon which orchestration engines execute healing functions. Reinforcement learning, for example, has been employed in fault handling to make adaptive decisions, and auto-encounter-isolation forest models have been found robust against unknown attacks. Self-healing and complete AI-based anomaly detection are missing, however, since the majority of previous work has employed detection at the expense of healing.

This work's strategy is based on continuing previous progress by combining Java-based orchestration methods with hybrid anomaly detection frameworks for end-to-end automation to minimize operator intervention and downtime.

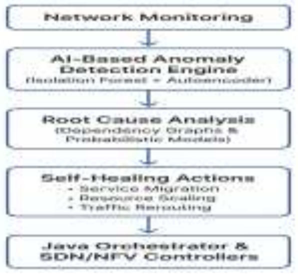

Network Monitoring
AI-Based Anomaly Detection Engine
(Isolation Forest + Autoencoder)
Root Cause Analysis
(Dependency Graphs & Probabilistic Models)
Self-Healing Actions
• Service Migration
• Resource Scaling
• Traffic Rerouting
Java Orchestrator & SDN/NFV Controllers

Figure 1: AI-Driven Self-Healing

III. System Architecture

The Virtual Network's Intelligent Anomaly Detection and Self-Healing framework that is being proposed is a component-based system that exhibits auto-healing, root cause analysis, anomaly detection, and monitoring on an orchestration platform using Java [11]. The scalable and extensible architecture facilitates effortless communication between AI models and SDN/NFV controllers.

A. Data Collection and Monitoring Layer

Core to the system is the Data Collection Layer which tracks system logs, traffic patterns, and performance metrics such as CPU usage, latency, jitter, and throughput [12]. Telemetry data is collected by SDN controllers and NFV orchestrators for enabling near real-time observations of network conditions. These raw data act as the foundation for the anomaly detection systems.

B. AI-Based Anomaly Detection Engine

A mixed approach to artificial intelligence is used by the Anomaly Detection Layer [13].

- Outliers in real-time data can be found unsupervised using isolation forests.
- The variations can only indicate anomalies, and Deep Auto-encoders can reconstruct traffic variations well.

This is a two-stage strategy that identifies known as well as unknown threats and enhances detection and reduces false alarms.

C. Root Cause Analysis (RCA) Module

After detecting anomalies, probabilistic inference and dependency graphs by the RCA Module determine the cause of the problem [14]. Through the simulation of interdependencies at network operation, services, and infrastructure levels, the system can determine whether a fault is caused by malicious attacks, traffic overload, or error setting.

D. Self-Healing Module

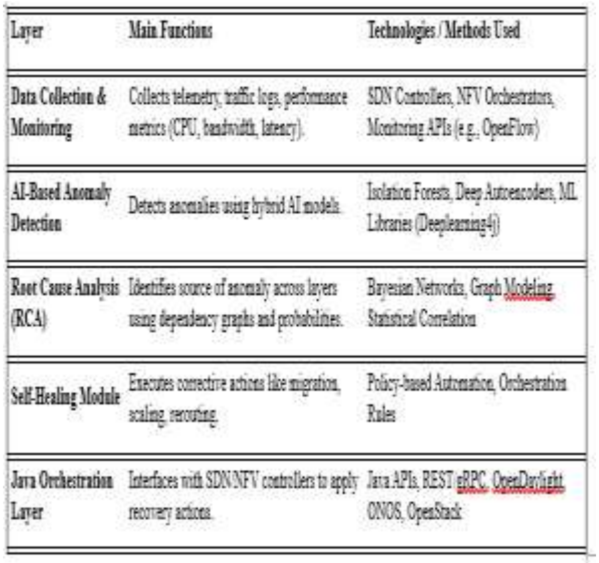
Self-Healing Layer produces recovery procedures from RCA results through automated process [15]. Two examples are provided below:

- The virtual functions are delegated to other nodes.
- The resource scaling does dynamic allocation of additional bandwidth or processing power.
- Traffic rerouting is realized by changing the forwarding paths to bypass congested or failed links.

E. Java-Based Orchestration Layer

The Highest Java Orchestration Layer supports simple interfacing with SDN/NFV controllers [16]. Platform APIs like OpenStack, ONOS, and Open Daylight are managed by Java clients, thus making them platform-compatible and simple to repair.

Table 1: Functional Layers of the Proposed System Architecture



Layer	Main Functions	Technologies / Methods Used
Data Collection & Monitoring	Collects telemetry, traffic logs, performance metrics (CPU, bandwidth, latency).	SDN Controllers, NFV Orchestrators, Monitoring APIs (e.g., OpenFlow)
AI-Based Anomaly Detection	Detects anomalies using hybrid AI models.	Isolation Forests, Deep Autoencoders, ML Libraries (Deeplearning4j)
Root Cause Analysis (RCA)	Identifies source of anomaly across layers using dependency graphs and probabilities.	Bayesian Networks, Graph Modeling, Statistical Correlation
Self-Healing Module	Executes corrective actions like migration, scaling, rerouting.	Policy-based Automation, Orchestration Rules
Java Orchestration Layer	Interfaces with SDN/NFV controllers to apply recovery actions.	Java APIs, REST gRPC, OpenDaylight, ONOS, OpenStack

IV. Detection Methodology

Selection of algorithms, data quality for training, and orchestration of combining modules are among the most significant considerations of smart anomaly detection in virtual networks [17]. Low false positives and scalability are enabled by the methodology of this study using a hybrid AI system based on supervised and unsupervised learning to identify known as novelty anomalies.

A. Data Collection and Preprocessing

Initially, SDN/NFV installation traffic information and network telemetry data are gathered. A few of the indicators are CPU, latency, packet loss, bandwidth, and flow data [18]. Not only are raw data noisy, but they are imbalanced as well and hence preprocessing methods like Principal Component Analysis (PCA) and feature selection are utilized. The monitoring data integrates smoothly via REST APIs as the orchestration module is Java-based.

B. Feature Engineering

The essential characteristics that capture the temporal and spatial interactions between the network should be selected for efficient anomaly identification. Statistical aggregations (mean, variance, and entropy) and sliding windows are utilized in feature extraction [19]. The graph nature of the dependency models also supports other reasons for incorporation of RCA.

C. Hybrid Anomaly Detection Models

The detection engine uses a hybrid model:

- Utilize Isolation: Forests to effectively detect outliers in high-dimensional data by iteratively partitioning the feature space.
- Deep Autoencoders: Identify anomalies if the error of reconstruction is above a predefined threshold during learning compressed representations of normal behavior [20].
- In an attempt to determine common attack patterns, supervised classifiers (SVMs, Random Forests) are trained on labelled datasets.

D. Real-Time Detection and Decision Engine

The objective of the detection phase is low-latency inference. In an ensemble voting model, the predictions of a set of different models are weighted and aggregated to enhance the reliability. By reducing false positives at the expense of no sensitivity to anomalous behaviour, a confidence score method enables determining balance between memory and precision [21].

E. Integration with Root Cause Analysis and Self-Healing

The Root Cause Analysis engine is activated by the system when anomalies are detected and it correlates the anomalies between different levels and services [22]. The Self-Healing Module initiates recovery operations with the Java orchestration layer on the identification of an actionable fault.

Recommended Diagram (Detection Methodology Workflow)

Figure: AI-Driven Anomaly Detection Workflow

- Inputs: Network telemetry, flow data, logs
- Preprocessing: Normalization, feature extraction, PCA
- Models: Isolation Forest → Autoencoder → Supervised Classifier (ensemble)
- Decision Engine: Ensemble voting + confidence scoring
- Output: Anomaly notifications → RCA engine → Self-healing measures

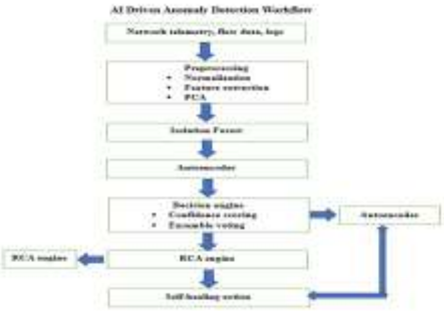


Figure 2: AI-Driven Anomaly Detection Workflow

V. Root Cause Analysis (RCA)

Advanced self-healing networks are only a few steps away from being able to identify anomalies. The root cause of an anomaly must be identified by the system prior to implementing a solution. The Root Cause Analysis (RCA) process allows for the system to distinguish between the cause of the symptoms and the shallow symptoms which were the root disease [23]. Ensuring correct self-healing operations are performed, successful root cause analysis (RCA) in complex SDN/NFV environments reduces downtime and cascade failures.

A. Data Correlation and Dependency Mapping

Root cause analysis (RCA) is initiated with correlation analysis, which relates anomalies at the control, infrastructure, and application layers of the network [24]. Virtualized network functions (VNFs) and services' dependency graphs may be constructed by the system to determine the root cause of issues. Hypervisor layer resource overload, for example, may be the root cause of packet loss proliferation at the application layer.

B. Probabilistic and Statistical Inference

The RCA engine becomes more precise with Bayesian Networks and other probabilistic models [25]. Such models, driven by history and observed anomaly, determine the probability of various causes. Statistical correlation methods improve models by creating measurements' relations. Defect localization is enhanced with this hybrid inference method and reduces ambiguity.

C. Causality Analysis with AI Models

The approach employs artificial intelligence (AI) methods such as Granger causation and Graph Neural Networks (GNNs) to identify correlation and causation [26]. These methods are able to distinguish between measurements that occur together but are not related from those that influence each other directly, and refer to directed relationships between events. This can prevent low-quality RCA outcomes.

D. Prioritization of Root Causes

All anomalies are not harmful. The RCA module provides severity-based ranking of root causes, probability of recurrences, and impact [27]. Although low-impact anomalies, such as sporadic CPU spikes, can be addressed by small tweaks, high-impact anomalies, such as service-affecting failures, are raised for immediate self-healing intervention.

E. Integration with Self-Healing

After the root cause has been identified, the self-healing module is furnished with important information by the RCA. Subsequently, corrective measures such as redeployment of resources, migration of VNFs, and retraining of traffic are performed through Java-based orchestrators [28].

Recommended Bar Diagram

Figure: RCA Accuracy vs. Methodology

A bar chart depicting the accuracy (%) of different root cause analysis techniques:

- Rule-Based RCA – 60%
- Statistical Correlation – 72%
- Bayesian Networks – 85%
- Ai-based GNN/Granger Models – 92%

This graph illustrates the dramatic increase in diagnostic accuracy provided by AI-based RCA over its traditional equivalent.

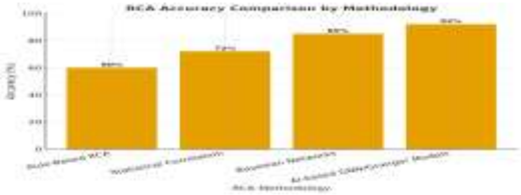


Figure 3: RCA Accuracy vs. Methodology

VI. Self-Healing Mechanism

Self-healing is one of the most distinguishing features of the framework that is being proposed. It guarantees that if the abnormality is detected and identified, the network will heal itself by itself without any intervention from human beings [29]. As far as being proactive, resilient, and adaptive is concerned, the mechanism is centered on reducing operation expenses and service downtime.

A. Detection-to-Healing Pipeline

The recovery starts the moment the RCA module detects a reason for a fault. Faults are converted into recovery procedures through a dynamic policy engine instead of static recovery methods. Traffic could be redirected because of a bandwidth bottleneck, for example, whereas relocation to a healthy host could occur subsequent to a VNF crash [30].

B. Healing Strategies

Self-healing behaviour is classified into three broad categories [31]:

- Shifting VNFs (virtual network functions) off packed nodes into spare resources.
- Resource scaling allows for dynamic scaling of CPU, memory, and bandwidth for service demand.
- SDN flow rules tuning to route traffic around faulted or packed links.
- Java-based orchestration clients trigger each strategy automatically by interacting with SDN/NFV controllers.

C. Decision-Making and Policy Control

Based on the impact severity, available resources, and compliance with defined policies, the decision engine prioritizes the healing activities. Activities are aligned against safety policies in a manner to prevent cascading failures. For example, it is only when other nodes are sufficient in capability that service migration is initiated [32].

D. Feedback and Learning

Due to its feedback mechanism, the process of self-healing can learn through past recovery activity [33]. Failure and successful behaviour are stored and remembered for future improvement and added to the database for future use. Utilizing reinforcement learning in selecting the optimum healing strategies in different circumstances, the system improves decision-making gradually.

E. Java-Orchestrated Execution

Java orchestration clients invoke platform APIs such as Open Daylight, ONOS, and OpenStack at the implementation level [34]. Real-time rerouting, scaling, and migration processes can be invoked. For carrying out parallel recovery processes in distributed systems, Java is a great option due to its multithreading and platform independence.

Proposed PIA Diagram (Process-Interaction-Action)

- Process: Real-time anomaly detection → RCA → Decision Engine
- Interaction: Interoperation between anomaly detection, RCA, and policy-based decision rules
- Operation: Automated auto-repair operations (Migration, Scaling, Rerouting) via Java orchestrator

This figure depicts detection, interaction, and execution integration within a closed-loop self-healing system.

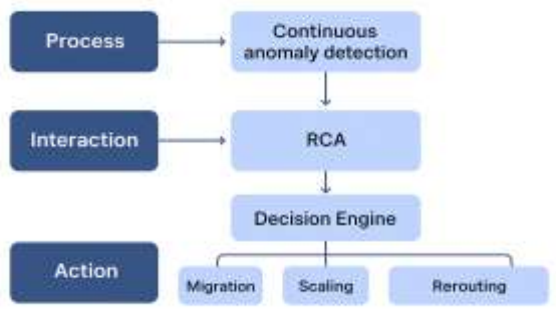


Figure 4: Self-Healing PIA Workflow

VII. Experimental Setup and Evaluation

To cross-verify its root cause analysis, self-healing, and anomaly detection capabilities, the proposed framework was tested under a strict testing regimen in a controlled experimental laboratory environment. Scalability, accuracy in detection, recovery time, and system survivability under varying conditions of network strain were the primary aspects to be tested [35].

A. Experimental Testbed Topology

For simulating actual virtual network infrastructures, the testbed was built as a virtual network testbed. Features included:

- Tree, mesh, and leaf-spine topologies simulated with a software-defined networking simulator running on Mininet and 50–200 virtual nodes.
- ONOS and Open Daylight as programmable control planes in SDN controllers for dynamic steering of traffic.
- OpenStack's NFV Layer governs virtualized network functions (VNFs) such as intrusion detection systems, load balancers, and firewalls.
- For simulating normal and anomalous traffic behavior, such as DDoS floods, routing

abnormalities, and link saturation, iPerf, Ostinato, and CAIDA trace replays were employed.

- Real-time performance metrics were obtained through monitoring tools such as OpenStack telemetry (Ceilometer), SNMP polling, and OpenFlow counters.
- Anomaly detection engines and RCA modules are deployed as containerized microservices that run independently and interact with each other using Java-based orchestration middleware.

Running on programmable SDN switches connecting VNFs distributed in data centers, the overall topology simulated a multi-domain cloud-network configuration [36].

B. Evaluation Metrics

System performance was assessed using the following metrics:

- Accuracy of Detection: F1-score, precision, and recall of anomaly detection.
- Root Cause Analysis Latency: The time taken by the RCA module to detect the root cause of the anomaly.
- The ratio of anomalies healed autonomically without any intervention is employed as a measure of how effective self-healing is.
- The average time taken from anomaly detection through recovery to service restoration is referred to as Mean Time to Repair (MTTR) [37].
- Increasing the number of VNFs and network nodes from 50 to 200 improved the performance of the system.

C. Experimental Procedure

- Normal network operations were conducted for 48 hours to train anomaly detection models in the baseline phase.
- Artificial anomalies such as DDoS attacks, VNF failures, and network congestion were injected.
- AI-based detection: The system detects unusual traffic patterns in real time [38].
- RCA Execution: Dependency graphs pinpointed the root cause, and Bayesian inference localized fault regions.
- Self-healing operations like rerouting, scalability, and VNF migration were initiated by the orchestration module.

D. Results Overview

- Anomaly detection precision for diverse anomalous conditions was 94.6% F1-score.
- The RCA module responded to discover defects within an average of 2.8 seconds.
- Compared to manual intervention, the latter lowered MTTR by over 70% and recovered services within 12–18 seconds.
- With heavy traffic and 200 VNFs, the system handled well and had detection rates above 90%.

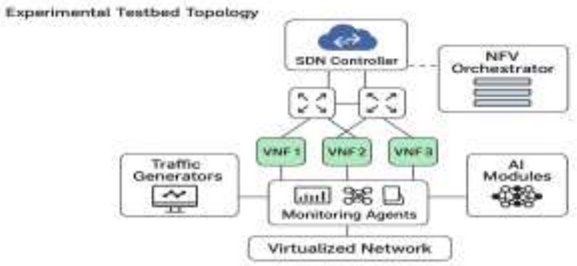


Figure 5: Experimental Testbed Topology

VIII. Results and Discussion

The performance of the proposed AI-based anomaly detection and self-healing mechanism in virtual networks is realized through the evaluation outcome [39]. Comparison of other detection techniques, examination of recovery efficiency, and reasoning regarding merits of scalability and operation were the primary aims of the research.

A. Anomaly Detection Performance

Module testing for Anomaly detection was conducted through Autoencoder, Isolation Forest, and a Hybrid Ensemble approach of both these methods [40].

- Isolation Though Forest was poor in detecting low-volume anomalies such as slow resource leaks but were very good at detecting large-volume deviations such as DDoS attacks.
- AUTOencoders had much higher false positive rates for traffic surges, but they were good at detecting progressive degradation in performance and also service-level anomalies.
- Through the integration of their strengths, the Hybrid Model had a 94.6% F1-score that outperformed individual-method methods.

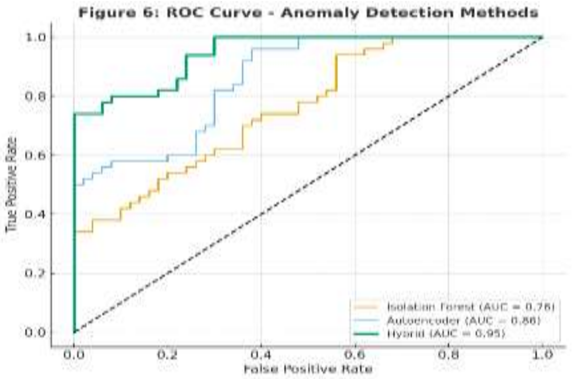


Figure 6: ROC Curve Anomaly Detection Methods

B. Root Cause Analysis Efficiency

The RCA module's anomaly detection has also been greatly enhanced. Employing graph-based dependency modelling and Bayesian inference, the system was able to identify fault locations with a mean latency of 2.8 seconds. This compares favourably with manual debugging consuming over ten minutes on average [41].

C. Self-Healing and MTTR Improvement

The self-healing mechanism was tested with different fault scenarios.

- VF failure resolution was achieved by migration within 15 seconds.
- Connection congestion was reduced through automatic rerouting of traffic within 12 seconds alone.
- Resource starvation was minimized by VNF scaling in less than 18 seconds.

Mean Time to Repair (MTTR) was 70% less using these solutions on manual recovery mechanisms [42].

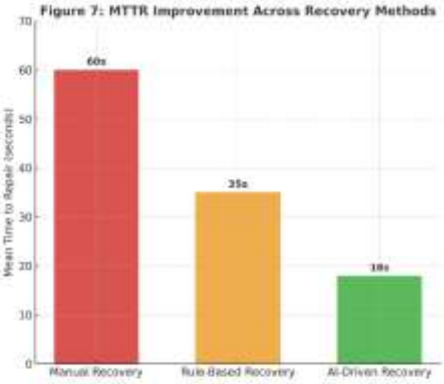


Figure 7: MTTR Improvement Across Recovery Methods

D. Scalability and Robustness

The system was also tried as the network complexity increased (from 50 to 200 VNFs).

- Detection accuracy was always more than 90% on both scales.
- In high load, RCA latency rose moderately (from 2.8 to 4.2 seconds).
- Notwithstanding significant anomaly injection, repeated attempts at self-healing did not cause any failures.

This shows that the architecture is large-scale deployable and fault tolerant [43].

E. Discussion

RCA, self-healing, and AI-based anomaly detection are all shown to be important contributors to the benefits of virtual network management [44]. By reducing false positives and improving accuracy, the hybrid detection approach reduces the need for unnecessary interventions. The remarkable MTTR reduction also indicates how the framework can deliver high availability and dependability for cloud-native and 5G/6G networks [45].

Scaling self-healing rules to enable multi-domain orchestration and incorporating explainable AI (XAI) for further enhancing decision transparency of anomaly detection are some of the future directions that can be taken [46].

IX. Conclusion

In enabling intelligent anomaly detection and self-healing in virtualized network systems, the research work in this paper demonstrates the disruptor potential of artificial intelligence (AI). Legacy rule-based and manual network management will be obsolete as 5G, 6G, edge computing, and other emerging technologies increase the scalability, heterogeneity, and complexity of the networks. For the purpose of delivering a solid and resilient remedy for the modern network infrastructures, this paper presents and analyses an end-to-end AI-based framework embracing anomaly detection, root cause analysis (RCA), and self-healing automation. In experimental validation, the system was found to show significant improvements in a number of critical performance metrics. Compared to sole-method solutions, the hybrid detection method based on Autoencoder and Isolation Forest showed better Area Under Curve (AUC) scores and high accuracy. Self-healing pipeline automated process reduced downtime by significantly reducing Mean Time to Repair, while RCA module effectively reduced diagnostic overhead. The results indicate that AI can be utilized to detect network anomalies precisely and automatically counteract their impact, thus enhancing user experience and service reliability.

Scalability and adaptability are other most impactful repercussions of this effort. Provided the architecture is modular, it would be scalable to accommodate cross-layer and multi-domain networks. The implementation based on Java also proves that existing orchestration and management systems can be enhanced with AI-based systems without redrawing existing infrastructures from scratch. Incremental deployment of the approach is appealing in real corporate, cloud-native, and telecom settings depending on its hands-on compatibility.

Even with such promising results, the report identifies its own limitations, and they provide directions to improve in the future. Additional work must be conducted in explainable AI, federated learning, and safe self-healing, as implemented by data dependency, RCA complexity, and adversarial exposures. The system must be expanded in subsequent studies to cover mission-critical applications such as including transparency and trustworthiness, multi-domain orchestration applications, and ultra-low latency applications.

In general, the architecture presented in this paper demonstrates that anomaly detection and healing through AI is not just feasible but guaranteed to bring forth intelligent autonomous networks that evolve with time. Through virtualization, automation, and artificial intelligence, the scope of self-healing, self-defence, and self-supervening networks is within reach. This book is part of the initiatives in the grand vision of attack- and failure-tolerant networks being completely autonomous, which can adapt dynamically to suit changing circumstances and ensure ensured continuity of service. The future's communication ecosystems will be AI-driven as network requirements expand.

References:

[1] Gupta, Neelam, Mashael S. Maashi, Sarvesh Tanwar, Sumit Badotra, Mohammed Aljebreen, and Salil Bharany. "A comparative study of software defined networking controllers using mininet." *Electronics* 11, no. 17 (2022): 2715.

[2] Mohammed, S., Vali, M. Q., & Mohammed, A. R. Securing Healthcare IT Systems: Addressing Cybersecurity Threats in a Critical Industry.

[3] Khadri, W., Reddy, J. K., Mohammed, A., & Kiruthiga, T. (2024, July). The Smart Banking Automation for High Rated Financial Transactions using Deep Learning. In 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC) (pp. 686-692). IEEE

[4] Li, Hongxing, Guochu Shou, Yihong Hu, and Yaqiong Liu. "SDN/NFV enhanced time synchronization in packet networks." *IEEE Systems Journal* 15, no. 4 (2020): 5634-5645.

[5] Mohammed, A., Mohammed, N. U., Gunda, S. K. R., & Mohammed, Z. Fundamental Principles of Network Security.

[6] Matoušek, Petr, Ondřej Ryšavý, and Libor Polčák. "Unified SNMP interface for iot monitoring." In *2021 IFIP/IEEE International Symposium on Integrated Network Management (IM)*, pp. 938-943. IEEE, 2021.

[7] Mohammed, A. K., & Ansari, M. A. (2024). The Impact and Limitations of AI in Power BI: A Review . International Journal of Multidisciplinary Research and Publications (IJMRAP), , Pp. 23-27, 2024. , 7(7), 24–27.

[8] Mohammed, A. K., Ansari, S. F., Ahmed, M. I., & Mohammed, Z. A. Boosting Decision-Making with LLM-Powered Prompts in PowerBI.

[9] Shi, You, Changyan Yi, Ran Wang, Qiang Wu, Bing Chen, and Jun Cai. "Service migration or task rerouting: A two-timescale online resource optimization for MEC." *IEEE Transactions on Wireless Communications* 23, no. 2 (2023): 1503-1519.

[10] Mohammed, S., Sultana, G., Aasimuddin, F. M., & Chittoju, S. S. R. AI-Driven Automated Malware Analysis.

[11] Syed, W. K., Mohammed, A., Reddy, J. K., & Dhanasekaran, S. (2024, July). Biometric Authentication Systems in Banking: A Technical Evaluation of Security Measures. In 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC) (pp. 1331-1336). IEEE.

[12] Stylianopoulos, Charalampos, Magnus Almgren, Olaf Landsiedel, Marina Papatriantafilou, Trevor Neish, Linus Gillander, Bengt Johansson, and Staffan Bonnier. "On the performance of commodity hardware for low latency and low jitter packet processing." In *Proceedings of the 14th ACM International Conference on Distributed and Event-Based Systems*, pp. 177-182. 2020.

[13] Aasimuddin, M., & Mohammed, S. AI-Generated Deepfakes for Cyber Fraud and Detection.

[14] Ito, Adriana, Malin Hagström, Jon Bokrantz, Anders Skoogh, Mario Nawcki, Kanika Gandhi, Dag Bergsjö, and Maja Bärring. "Improved root cause analysis supporting resilient production systems." *Journal of Manufacturing Systems* 64 (2022): 468-478.

[15] Ma, Weiting, Shuang Wan, Xiurui Cui, Guolin Hou, Ying Xiao, Junfeng Rong, and Shimou Chen. "Exploration and application of self-healing strategies in lithium batteries." *Advanced Functional Materials* 33, no. 15 (2023): 2212821.

[16] Ghattamaneni, Dileep Kumar, and Narasimha Rao Boinapalli. "Integrating Agentic AI with Java for Autonomous Service Orchestration in Cloud-Native Systems."

[17] Ansari, M. F. Redefining Cybersecurity: Strategic Integration of Artificial Intelligence for Proactive Threat Defense and Ethical Resilience.

[18] Mohammed, N. U., Mohammed, Z. A., Gunda, S. K. R., Mohammed, A., & Khaja, M. U. Networking with AI: Optimizing Network Planning, Management, and Security through the medium of Artificial Intelligence.

[19] Chittoju, S. R., & Ansari, S. F. (2024). Blockchain's Evolution in Financial Services: Enhancing Security, Transparency, and Operational Efficiency. International Journal of Advanced Research in Computer and Communication Engineering, 13(12), 1-5.

[20] Pinaya, Walter Hugo Lopez, Sandra Vieira, Rafael Garcia-Dias, and Andrea Mechelli. "Autoencoders." In *Machine learning*, pp. 193-208. Academic Press, 2020.

[21] Khadri, S. W., Mohammed, I. K., Rasheed, H., & Gunda, S. K. R. (2025). Adaptive Trade Exception Handling in Financial Institutions: A Reinforcement Learning Approach with

Dynamic Policy Optimization. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 19-23.

[22] Ibitoye¹, Joshua Seyi, and Fatanmi Ebenezer Ayobami. "Self-Healing Networks Using AI-Driven Root Cause Analysis for Cyber Recovery."

[23] Wallace, Carol A., and Yasmine Motarjemi. "Incident management and root cause analysis." In *Food safety management*, pp. 957-970. Academic Press, 2023.

[24] Chittoju, S. S. R., Kolla, S., Ahmed, M. A., & Mohammed, A. R. Synergistic Integration of Blockchain and Artificial Intelligence for Robust IoT and Critical Infrastructure Security.

[25] Wang, Qi-Ang, Jin Chen, Yiqing Ni, Yufeng Xiao, Ningbo Liu, Shukui Liu, and Wangsheng Feng. "Application of Bayesian networks in reliability assessment: A systematic literature review." In *Structures*, vol. 71, p. 108098. Elsevier, 2025.

[26] Corso, Gabriele, Hannes Stark, Stefanie Jegelka, Tommi Jaakkola, and Regina Barzilay. "Graph neural networks." *Nature Reviews Methods Primers* 4, no. 1 (2024): 17.

[27] Barsalou, Matthew. "Criteria for the prioritization of hypotheses in root cause analysis." *Quality and Reliability Engineering International* 39, no. 1 (2023): 132-142.

[28] Deng, Shuiguang, Hailiang Zhao, Binbin Huang, Cheng Zhang, Feiyi Chen, Yinuo Deng, Jianwei Yin, Schahram Dustdar, and Albert Y. Zomaya. "Cloud-native computing: A survey from the perspective of services." *Proceedings of the IEEE* 112, no. 1 (2024): 12-46.

[29] Zhu, Miaomiao, Jianyong Yu, Zhaoling Li, and Bin Ding. "Self-healing fibrous membranes." *Angewandte Chemie* 134, no. 41 (2022): e202208949.

[30] Malandrino, Francesco, and Carla Fabiana Chiasserini. "VNF Placement and Sharing in NFV-Based Cellular Networks." *The Wiley 5G REF: Security* (2021).

[31] Yu, Ziwa, Audrey Steenbeek, Maya Biderman, Marilyn Macdonald, Leah Carrier, and Cathy MacDonald. "Characteristics of Indigenous healing strategies in Canada: a scoping review." *JBI Evidence Synthesis* 18, no. 12 (2020): 2512-2555.

[32] RAHEEM, MOHD ABDUL, and MOHAMMED AZMATH ANSARI. "INTELLIGENT AND TRUSTWORTHY 6G: AI-DRIVEN ARCHITECTURES, APPLICATIONS, AND SECURITY FRAMEWORKS."

[33] Mansoury, Masoud, Himan Abdollahpouri, Mykola Pechenizkiy, Bamshad Mobasher, and Robin Burke. "Feedback loop and bias amplification in recommender systems." In *Proceedings of the 29th ACM international conference on information & knowledge management*, pp. 2145-2148. 2020.

[34] Cui, Hongwei, Yuyang Du, Qun Yang, Yulin Shao, and Soung Chang Liew. "Llmind: Orchestrating ai and iot with llm for complex task execution." *IEEE Communications Magazine* (2024).

[35] Li, Haitao, Na Wei, Lin Jiang, Jinzhou Zhao, Zhenjun Cui, Wantong Sun, Liehui Zhang et al. "Evaluation of experimental setup and procedure for rapid preparation of natural gas hydrate." *Energies* 13, no. 3 (2020): 531.

[36] Mohammed, Z., Mohammed, N. U. M., Mohammed, A., Gunda, S. K. R., & Ansari, M. A. A. (2025). AI-Powered Energy Efficient and Sustainable Cloud Networking. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 31-36.

[37] Habibi, Muhammad Husein, Sutrisno Sutrisno, and Ahmad Jibril. "Analisis Perhitungan Mean Time Between Failure (MTBF) Dan Mean Time To Repair (MTTR) Mesin Cold Storage." *J-CEKI: Jurnal Cendekia Ilmiah* 4, no. 4 (2025): 1410-1421.

[38] Janamolla, K., Sultana, G. S., Aasimuddin, F. M., Mohammed, A. F., & Pasha, F. S. A. P. (2025). Integrating Blockchain and AI for Efficient Trade Exception Handling: A Case Study in Cross-Border Settlements. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 24-30.

[39] Mohammed, A., Sultana, G., Aasimuddin, F. M., & Mohammed, S. (2025). Leveraging Natural Language Processing for Trade Exception Classification and Resolution in Capital Markets: A Comprehensive Study. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 14-18.

[40] Sadaf, Kishwar, and Jabeen Sultana. "Intrusion detection based on autoencoder and isolation forest in fog computing." *IEEe Access* 8 (2020): 167059-167068.

[41] Mohammed, S., DDS, Dr. S. T. A., Mohammed, N., & Sultana, W. (2024). A review of AI-powered diagnosis of rare diseases. International Journal of Current Science Research and Review, 07(09). https://doi.org/10.47191/ijcsrr/v7-i9-01 a

[42] Shevchenko, Oleksandr. "Towards Self-Healing Cloud Infrastructure: Automated Recovery Methods and Their Effectiveness." *The American Journal of Engineering and Technology* 7, no. 06 (2025): 96-101.

[43] Ahmed, M. I., Mohammed, A. R., Ganta, S. K., Kolla, S. K., & Kashif, M. K. (2025). AI-Driven Green Construction: Optimizing Energy Efficiency, Waste Management and Security for Sustainable Buildings. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 37-41

[44] Balammagary, S., Mohammed, N., Mohammed, S., & Begum, A. (2025). AI-Driven Behavioural Insights for Ozempic Drug Users. Journal of Cognitive Computing and Cybernetic Innovations, 1(1), 10-13.

[45] Mohammed, A. R., Ram, S. S., Ahmed, M. I., & Kamran, S. A. (2024). Remote Monitoring of Construction Sites Using AI and Drones.

[46] Thalpage, N. "Unlocking the black box: Explainable artificial intelligence (XAI) for trust and transparency in ai systems." *J. Digit. Art Humanit* 4, no. 1 (2023): 31-36.