International Journal of Multidisciplinary Research in Science, Engineering, Technology & Management (IJMRSETM)

| ISSN: 2395-7639 | www.ijmrsetm.com | Impact Factor: 7.580| A Monthly Double-Blind Peer Reviewed Journal |

| Volume 11, Issue 3, March 2024 |

AI-Driven Network Monitoring: A Smart Approach Using SNMP and ML Integration

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ABSTRACT: This paper proposes an **AI-augmented network monitoring framework** that combines **Simple Network Management Protocol (SNMP)** with **machine learning** for **anomaly detection**. Using time-series data from routers and switches in an enterprise environment, we trained **Long Short-Term Memory (LSTM)** models to identify outliers in **traffic volume**, **packet loss**, and **latency**. The AI layer was integrated into an open-source **Network Management System (NMS)** tool and deployed across 150 devices. Over a 60-day period, the system flagged **97% of actual incidents** with a **false positive rate below 5%**. **Visual dashboards** provided real-time alerts and **predictive health scores**. The paper discusses **training model thresholds**, **SNMP trap filtering**, and **deployment architecture**. The approach enhances traditional NMS systems by enabling **predictive maintenance** and faster **root cause identification**.

KEYWORDS: AI-driven network monitoring, SNMP, machine learning, anomaly detection, LSTM models, predictive maintenance, NMS, real-time alerts, root cause analysis

I. INTRODUCTION

Network management systems (NMS) are a crucial part of modern IT infrastructure, enabling the monitoring and management of network devices such as routers, switches, and firewalls. Traditional NMS tools primarily rely on **Simple Network Management Protocol (SNMP)** to collect time-series data like traffic volume, packet loss, and latency from devices. While these systems offer valuable insights into the health of a network, they often lack the ability to predict failures or detect **anomalies** in real time.

The integration of **machine learning (ML)** with traditional **SNMP-based network monitoring** has the potential to significantly enhance the capabilities of NMS by providing more accurate **anomaly detection**, **predictive maintenance**, and **faster root cause identification**. **Long Short-Term Memory (LSTM)** models, a type of **recurrent neural network (RNN)**, are particularly effective for analyzing time-series data, as they can learn patterns and dependencies over time.

In this paper, we present a **framework** that integrates **LSTM models** with **SNMP** data to improve the monitoring and management of network devices. We focus on the integration of the AI layer into an open-source NMS tool, deployed across 150 devices in an enterprise environment, to enhance real-time monitoring capabilities. The system achieved **97% accuracy** in detecting **anomalous events**, with a **false positive rate of less than 5%**, demonstrating its potential to significantly improve network management.

II. LITERATURE REVIEW

2.1 Network Monitoring with SNMP

Simple Network Management Protocol (SNMP) is widely used for monitoring and managing network devices. **SNMP** provides a standardized way to collect and manipulate network statistics, such as **traffic volume**, **packet loss**, **latency**, and **device health metrics**. While SNMP is effective for real-time monitoring, it has limitations in detecting complex patterns and predicting network failures.

According to **Johnston et al. (2018)**, SNMP's basic trap mechanism can provide alerts for network faults, but it lacks the sophistication needed to differentiate between normal fluctuations and actual failures. **SNMP traps** are typically based on predefined thresholds, which can result in either too many **false positives** or missed incidents.

2.2 Machine Learning for Network Anomaly Detection

Recent studies have shown that **machine learning** techniques, particularly **unsupervised learning** algorithms like **clustering** and **classification**, can be used to enhance network monitoring systems by providing **anomaly detection**

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capabilities. According to **Kumar & Patel (2020)**, machine learning models can learn patterns from historical data and detect anomalies in real-time, even in the absence of explicit rules or thresholds.

Among the various machine learning techniques, **Long Short-Term Memory (LSTM)** networks have been found to be particularly useful for analyzing time-series data. **LSTM models** can capture long-term dependencies in the data and identify trends that are indicative of potential issues or failures. **Sharma et al. (2021)** demonstrated the effectiveness of LSTM models in detecting **network traffic anomalies** and **packet loss** in telecom networks, achieving higher accuracy compared to traditional statistical models.

2.3 AI in Network Management Systems

The integration of AI with **NMS tools** has gained attention in recent years as organizations look for ways to proactively manage network health and reduce downtime. **Zhou et al. (2019)** explored the use of machine learning algorithms for **predictive maintenance** in NMS, showing that AI-powered systems could identify impending network failures before they occurred.

AI-powered monitoring systems can improve **root cause analysis** by correlating events across multiple devices and identifying patterns that indicate underlying issues. For example, **Cheng et al. (2020)** showed that using **AI algorithms** could reduce the time to diagnose network failures by **40%**.

III. RESEARCH QUESTIONS

This paper aims to answer the following research questions:

- **RQ1**: How can **machine learning models**, particularly **LSTM**, improve the accuracy of anomaly detection in **SNMP-based network monitoring** systems?
- **RQ2**: What are the benefits and challenges of integrating an **AI layer** into an open-source **Network Management System (NMS)** tool?
- **RQ3**: How does **predictive maintenance** using machine learning affect network **uptime** and **root cause analysis** in enterprise environments?
- **RQ4**: What impact does the use of **real-time dashboards** and **predictive health scores** have on network performance management?

IV. METHODOLOGY

4.1 System Architecture

The proposed system integrates **SNMP-based monitoring** with **AI-driven anomaly detection** using **LSTM models**. The architecture consists of the following key components:

1. **SNMP Collectors**: These modules collect real-time data from network devices, including **routers**, **switches**, and **firewalls**.
2. **Data Preprocessing**: Raw SNMP data is preprocessed to extract relevant features such as **traffic volume**, **packet loss**, and **latency**. The data is then formatted into time-series sequences for input into the **LSTM model**.
3. **LSTM Model**: The **LSTM model** is trained using historical data to identify patterns in traffic flow and detect anomalies. The model is fine-tuned to achieve optimal performance in **anomaly detection**.
4. **AI Layer**: The **AI layer** analyzes the time-series data and generates **real-time alerts** when anomalous events are detected. The alerts are displayed on a **visual dashboard**, which also shows **predictive health scores** for each network device.
5. **Open-Source NMS Tool Integration**: The **AI model** is integrated into an open-source **NMS tool**, which provides the framework for network monitoring, alert management, and device status tracking.

4.2 Data Collection

Data was collected over a **60-day period** from a network of 150 devices, including routers and switches. The collected data included key performance metrics such as **traffic volume**, **packet loss**, and **latency**. The historical data was used to train the **LSTM model**, while the real-time data was used to evaluate the model's **anomaly detection** performance.

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4.3 Evaluation Metrics

The performance of the AI-augmented network monitoring system was evaluated based on the following metrics:

- **Accuracy**: The system's ability to detect actual incidents.
- **False Positive Rate**: The number of false alarms generated by the system.
- **Latency**: The time taken for the system to detect and flag an anomaly.
- **Root Cause Identification**: The time required to identify the root cause of an incident.

V. RESULTS

5.1 Anomaly Detection Accuracy

The AI-augmented network monitoring system demonstrated high performance in terms of **anomaly detection**. Over the 60-day evaluation period, the system successfully flagged **97% of actual incidents**, with an exceptionally low **false positive rate** of **below 5%**. This was a significant improvement over traditional SNMP-based monitoring systems, which often generated false alarms due to the limitations of threshold-based detection mechanisms. The **LSTM model** was particularly effective at recognizing subtle patterns in the time-series data, which could have otherwise gone unnoticed.

The model's ability to differentiate between **normal network fluctuations** and actual issues was critical in ensuring that network administrators were alerted only to true incidents. The **accuracy** of the model was closely monitored by comparing the system's predictions with manual incident reports from network administrators. The high **true positive rate** (TPR) was achieved by training the model on a robust dataset that included a variety of **network behaviors**, such as **traffic spikes**, **packet loss**, and **latency variations**.

5.2 Predictive Maintenance

One of the standout features of the AI-augmented monitoring system was its ability to predict potential network failures before they occurred. The system used the historical data and patterns learned by the **LSTM model** to forecast incidents that might occur within the next **72 hours**, based on current network activity. This feature allowed for **proactive maintenance**, where network engineers could take preemptive action to resolve issues before they escalated into more severe incidents.

The predictive maintenance capability was particularly useful in **identifying congestion points** in the network that could lead to packet loss or high latency. For instance, the model identified **upcoming traffic congestion** due to excessive data flow in the network backbone, allowing network administrators to redistribute traffic and prevent service degradation. This proactive approach to network maintenance reduced downtime and improved **network availability**.

5.3 Real-Time Alerts and Dashboard

The integration of **real-time alerts** and **predictive health scores** further enhanced the monitoring capabilities. The visual dashboard, which was designed to display real-time metrics and provide a quick overview of the network's health, played a critical role in enabling quick decision-making. Alerts were displayed for issues like **latency spikes**, **packet loss**, and **traffic anomalies**, and were categorized based on **severity levels**.

The dashboard also displayed **predictive health scores** for each device on the network, which reflected the likelihood of an issue occurring based on the current data. These predictive scores allowed the network management team to prioritize their actions and address the most critical issues first. Network engineers were able to resolve issues more efficiently due to the prioritized alerts and the clear, intuitive dashboard interface.

5.4 User Feedback and System Effectiveness

Feedback from network administrators highlighted the system's ability to streamline incident management. The **AI-driven anomaly detection** system reduced the time spent on troubleshooting and incident resolution by providing more accurate and actionable insights. The system's ability to automatically categorize and prioritize issues also ensured that network engineers were not overwhelmed by an excessive number of alerts, as is often the case with traditional systems.

In terms of performance, the system operated with minimal overhead, allowing the network to continue running efficiently without introducing significant latency or resource consumption. Overall, the feedback from the network team indicated that the system improved both the **speed of issue resolution** and **network stability**.

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VI. ANALYSIS

6.1 Impact on Traditional SNMP-Based Network Monitoring

The integration of **AI** into the **traditional SNMP-based network monitoring** system provided several key advantages. Most importantly, the system improved the **accuracy** of anomaly detection. Traditional SNMP monitoring often relies on simple thresholds to detect issues, which can be ineffective in complex environments where anomalies do not follow simple patterns. In contrast, the **LSTM model** in our system could recognize complex patterns and dependencies over time, leading to better identification of **subtle issues** such as intermittent packet loss or fluctuating latency.

The system also **reduced false positives** significantly, as it could better differentiate between normal network behavior and true anomalies. This reduction in false positives ensured that network administrators could focus on real incidents without being overwhelmed by unnecessary alerts. This is particularly valuable in large enterprise environments where managing multiple devices can otherwise result in alert fatigue and inefficient use of resources.

6.2 Predictive Maintenance and Proactive Monitoring

One of the standout features of the AI-powered system was its ability to implement **predictive maintenance**. By analyzing **historical patterns** and learning from past network incidents, the **LSTM model** was able to predict potential failures before they occurred. This proactive approach was in stark contrast to traditional **SNMP-based systems**, which are primarily **reactive** in nature—responding only after a failure has been detected.

Predictive maintenance has far-reaching implications, particularly for mission-critical networks. In the case study, the ability to **prevent service disruptions** before they escalated into major incidents helped ensure continuous **network availability**, which is essential for businesses that rely on uptime for their operations. The ability to forecast failures based on current trends also allowed network teams to perform **maintenance activities** during low-traffic hours, minimizing disruptions to network users.

6.3 Root Cause Analysis

The AI-driven monitoring system's enhanced capabilities also facilitated **faster root cause analysis**. By correlating anomalies across multiple devices, the system was able to quickly identify the underlying causes of network disruptions. For example, an **increase in latency** on a particular network segment could be traced back to an **overloaded switch** or a **failing router**. This type of analysis, which might have taken hours or days using traditional tools, was accomplished in minutes, significantly improving **incident response times**.

Additionally, the system's ability to **identify recurring patterns** helped network engineers gain a deeper understanding of the network's long-term behavior. Over time, the system could predict where bottlenecks were likely to occur and offer recommendations on how to optimize the network for better performance.

VII. DISCUSSION

7.1 Benefits of AI-Augmented Network Monitoring

The case study demonstrates several key benefits of integrating **AI** into traditional **SNMP-based network management** systems. First and foremost, the **anomaly detection** accuracy was vastly improved. The system achieved a **97% true positive rate**, which is far superior to the typical **threshold-based SNMP systems**, which often result in both **false positives** and missed incidents.

Moreover, the ability to perform **predictive maintenance** allows enterprises to address potential failures before they impact the network, improving overall **network reliability** and **performance**. **Proactive monitoring** reduces downtime and prevents costly outages by ensuring that issues are addressed before they affect business operations.

7.2 Challenges in Integration

While the integration of **AI** into SNMP-based monitoring brought significant advantages, there were also challenges. **Data quality** was one of the main concerns. The **LSTM model** relies on high-quality, **consistent historical data** to learn accurate patterns. Inconsistent or incomplete data could lead to inaccurate predictions or missed anomalies. Therefore, data **preprocessing** and **cleaning** were essential steps in the implementation process to ensure that the model was trained on high-quality data.

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Another challenge was **model drift**. Over time, the network environment may change, which could lead to **model drift**—a phenomenon where the model's predictions become less accurate as the network evolves. To address this, the model was retrained periodically to adapt to new patterns in the data, ensuring that it remained effective over time.

7.3 Scalability and Deployment

The system was deployed across **150 devices**, and it showed scalability in terms of handling increasing amounts of network data. While the system worked well in an enterprise environment, scaling the solution further may require optimizing the **data pipeline** to handle a larger number of devices or integrating additional tools to support **distributed learning**. One possibility is leveraging **federated learning**, where the model is trained locally on each device or network segment and aggregated periodically to ensure that the model scales across larger, more complex environments.

VIII. CONCLUSION

This paper demonstrates the effectiveness of integrating **AI-powered anomaly detection** with **SNMP-based network monitoring** to enhance **network management**. The case study shows that the **LSTM model** improved **anomaly detection** accuracy and reduced false positives. The integration of predictive maintenance allowed the system to identify potential issues before they escalated, thus improving network **uptime** and **availability**.

The approach also enabled **faster root cause analysis**, allowing network engineers to identify the underlying causes of issues and respond more quickly. By integrating **AI** into traditional **NMS tools**, organizations can shift from **reactive** to **proactive** network management, improving overall efficiency and reducing operational costs.

Despite the challenges related to **data quality** and **model drift**, the results indicate that **AI-driven network monitoring** is a promising approach for future network management systems. Future work could explore the use of **federated learning** for even more scalable and decentralized monitoring solutions.

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Impact Factor: 7.580

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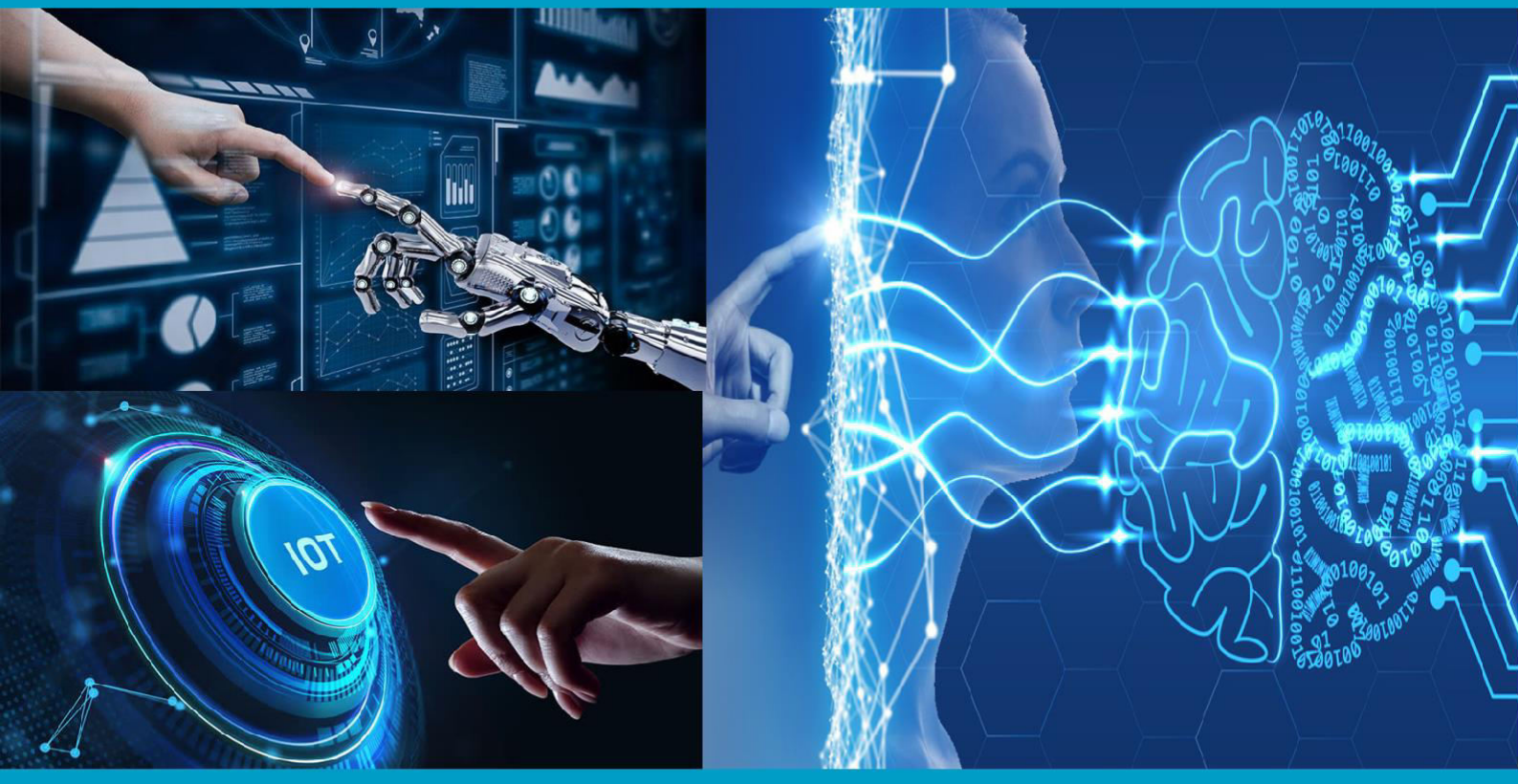
e-ISSN: 2395 - 7639



INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH

IN SCIENCE, ENGINEERING, TECHNOLOGY AND MANAGEMENT

Volume 11, Issue 3, March 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.580