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Enhanced Healthcare Data Security Through MI-Based Cyberattack Detection in SDN

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***Abstract*—** It is critical to protect sensitive data against hackers in the healthcare industry. Although they are used for effective resource management and security, software-defined networks, or SDNs, are susceptible to many types of assaults. A machine learning-based cyberattack detector (MCAD) designed specifically for healthcare systems is presented in this research. Enhancing network security, the system uses an adapted layer three (L3) learning switch application to collect and analyze normal and anomalous traffic, and then deploys MCAD on the Ryu controller. Many machine learning algorithms, such as Random Forest, Gradient Boosting Machines, Support Vector Machines, K Nearest Neighbors, Isolation Forest, Deep Neural Networks, Convolutional Neural Networks and XGBoost, are used in the study to assess MCAD's performance. The outcomes show how MCAD may enhance network efficiency, boost throughput, and lower latency and jitter, thereby bolstering the security of healthcare applications.

***Index Terms*—Cybersecurity, machine learning, healthcare security, SDN security, anomaly detection, network intrusion detection, deep learning,**

I. INTRODUCTION

In the rapidly evolving healthcare sector, the protection of sensitive patient data and the integrity of healthcare applications have become critical concerns. Healthcare systems are increasingly relying on digital platforms for managing patient records, appointments, billing, and communication. As a result, the amount of sensitive data being processed, stored, and transmitted has significantly increased, making healthcare networks a prime target for cyberattacks. Data breaches, unauthorized access, and disruption of services can have severe consequences, including compromised patient privacy, financial losses, and damaged trust in healthcare providers.

To address these growing security challenges, Software-Defined Networks (SDNs) have emerged as a promising solution. SDNs provide centralized control over network traffic, making them highly flexible and scalable, which is essential for managing the complex and dynamic nature of healthcare networks. However, despite their benefits, SDNs are also vulnerable to various forms of cyberattacks. These include traditional attacks like SQL Injection (SQLi) and Cross-Site Scripting (XSS), as well as more sophisticated threats targeting the underlying SDN architecture itself.

This research introduces a **Machine Learning-Based Cyberattack Detection (MCAD)** system, specifically designed for healthcare networks built on SDN infrastructure. The goal is to enhance the security of healthcare data by deploying machine learning models to detect and thwart cyberattacks in real time. The MCAD system is integrated into the SDN framework, leveraging an adapted Layer 3 (L3) learning switch to monitor and analyze network traffic. Various machine learning algorithms, such as Random Forest, Gradient Boosting Machines, and Convolutional Neural Networks (CNN), are employed to classify normal and anomalous network traffic, identifying potential threats.

Traditional security mechanisms such as firewalls, intrusion detection systems (IDS), and encryption have been effective to some extent but are often insufficient to protect against advanced and unknown cyber threats. To fill this gap, machine learning (ML) techniques have gained prominence in the field of cybersecurity, particularly for anomaly detection and real-time threat identification. Machine learning algorithms have the ability to analyze large datasets, recognize patterns, and adapt to new types of threats, making them highly suitable for detecting sophisticated cyberattacks in dynamic network environments.

II. RELATED WORK

Several research efforts have explored the application of machine learning in cybersecurity, particularly for anomaly detection in Software-Defined Networks (SDNs) and healthcare systems. Prior studies have demonstrated the effectiveness of ML-based techniques in identifying and mitigating cyber threats.

Smith et al. [1] provided a comprehensive review of machine learning-based cybersecurity solutions, highlighting various ML approaches, datasets, and evaluation metrics for network intrusion detection. Their work emphasized the advantages and

limitations of supervised and unsupervised learning models in detecting sophisticated cyberattacks.

M. Jarschel et al. (2014) discuss the fundamental aspects of Software-Defined Networking (SDN) by analyzing its interfaces, attributes, and use cases. The study provides a structured understanding of SDN, serving as a guide for researchers and practitioners in the field. It highlights the importance of SDN's decoupled control and data planes, which allow for greater network flexibility and programmability. The paper further explores various SDN applications and their potential benefits in improving network performance, scalability, and management. The research emphasizes SDN's role in enabling more efficient resource utilization and automation within modern network infrastructures.

W.Meng et al. (2018) investigate the implementation of Bayesian-based trust management to counter insider threats in healthcare Software-Defined Networks (SDN). The study addresses the growing security challenges faced by healthcare networks due to insider attacks, which are often difficult to detect using traditional security mechanisms. By leveraging Bayesian probability models, the proposed framework dynamically assesses trust levels to identify potential malicious activities. The research demonstrates that the trust-based approach enhances network security by reducing false positives and improving response mechanisms against insider threats. The study also highlights the importance of continuous monitoring and adaptive security strategies in healthcare SDN environments.

This study highlights the advantages of machine learning over traditional cybersecurity methods, particularly in its ability to analyze large volumes of network traffic and detect complex attack patterns in real time. However, existing ML-based security solutions face challenges such as high false-positive rates, model interpretability, and the need for continuous retraining to handle evolving cyber threats.

Building on these findings, our research explores the integration of machine learning techniques, including deep learning and ensemble learning, to enhance the accuracy, efficiency, and scalability of cyberattack detection in SDN-based healthcare networks.

J. T. Kelly et al. (2020) explore the impact and implications of the Internet of Things (IoT) in healthcare delivery. The study examines how IoT-enabled medical devices and sensors contribute to patient monitoring, remote healthcare services, and real-time data collection. The authors discuss the benefits of IoT in enhancing healthcare efficiency, reducing hospital visits, and improving patient outcomes. However, they also highlight significant challenges,including data privacy concerns, cybersecurity risks, and interoperability issues among different IoT platforms. The paper underscores the need for robust regulatory frameworks and security measures to mitigate risks associated with IoT in healthcare.

The 2022 study on networked medical devices presents an analysis of security and privacy threats associated with the increasing connectivity of medical systems. The research identifies key vulnerabilities in medical devices, including inadequate encryption, weak authentication mechanisms, and susceptibility to cyberattacks. The paper discusses real-world security breaches affecting healthcare institutions and emphasizes the importance of proactive security measures. It also explores solutions such as intrusion detection systems, secure communication protocols, and continuous security assessments. The findings highlight the critical need for healthcare organizations to prioritize cybersecurity in networked medical devices to prevent potential threats to patient safety and data integrity.

P. A. Williams and A. J. Woodward (2015) analyze cybersecurity vulnerabilities in medical devices, focusing on the complexity and multifaceted nature of security challenges in the healthcare sector. The study examines risks posed by interconnected medical devices, which can be exploited by cybercriminals to manipulate device functionality or access sensitive patient data. The authors discuss various attack vectors, including malware infections, unauthorized access, and data breaches. The paper emphasizes the need for collaboration among healthcare providers, device manufacturers, and cybersecurity experts to develop more secure medical technologies. It also advocates for stringent security policies, regulatory compliance, and the adoption of advanced encryption techniques to enhance the resilience of medical devices against cyber threats.

Their research highlights how adversarial inputs can manipulate machine learning models, leading to misclassification or failure in detecting cyber threats. They also discuss defense mechanisms, such as adversarial training and anomaly detection, to enhance the robustness of ML-based security systems. However, ensuring model resilience remains a significant challenge, particularly when dealing with evolving attack patterns.

Building upon these findings, our research aims to incorporate robust machine learning techniques and adversarial defense mechanisms to improve the reliability and security of cyberattack detection in SDN-based healthcare networks.

III. ALGORITHMS AND METHODOLOGY

A. Data Collection and Preprocessing

Data collection is a crucial step in building an effective machine learning-based cyberattack detection system for healthcare SDNs. The accuracy and reliability of the model depend on the quality and diversity of the network traffic data used for training and evaluation. The system gathers traffic data from multiple sources, including:

- **Normal Traffic Data:** Network traffic is collected from routine healthcare operations, such as patient data requests, medical device communication, and

electronic health record (EHR) access. This ensures that the model learns typical network behavior in a healthcare setting.

- **Attack Traffic Data:** Various cyberattacks, including SQL Injection (SQLi), Cross-Site Scripting (XSS), Denial-of-Service (DoS), and Distributed Denial-of-Service (DDoS), are simulated in the SDN environment. These simulations generate labeled datasets containing both normal and malicious traffic patterns, which are essential for training the machine learning models.

B. Feature Extraction

- ***Feature Extraction:***
  Relevant network traffic features, such as packet size, transmission time, request frequency, protocol types, and source/destination IP addresses, are extracted from raw network data.
- ***Traffic Tokenization:***
  Network traffic data is segmented into smaller components, such as packet headers, payloads, and protocol identifiers.
- ***Traffic Normalization:***
  Variations in network traffic, such as inconsistent timestamps, duplicate packet entries, and irrelevant metadata, are standardized.
- ***Non-Security Features:***
  Certain routine network requests that do not contribute to cyberattack detection, such as periodic system pings or authentication handshakes, may be filtered out.
- ***Handling Imbalanced Data:***
  Cyberattack datasets often have significantly fewer malicious traffic samples compared to normal traffic. To address this imbalance, techniques such as oversampling (duplicating attack samples) and undersampling (reducing normal samples) are applied.
- *Since machine learning models require numerical input, network traffic data is converted into numerical representations using encoding techniques like one-hot encoding, frequency encoding, and feature embeddings.*
- *Advanced methods, such as graph-based representations (e.g., network flow graphs) and time-series embeddings, are utilized to capture complex traffic patterns.*

Once the preprocessed dataset is ready, it is divided into training, validation, and test sets to ensure effective model learning and evaluation. These steps enhance the accuracy, efficiency, and generalization capability of the machine learning model for detecting cyberattacks in SDN-based healthcare networks.

C.Machine Learning Model Training

The selection of an appropriate machine learning model is crucial for accurately detecting cyberattacks in healthcare SDNs. Various algorithms are evaluated based on their effectiveness in handling classification tasks in network security. Ensemble learning methods like **Random Forest (RF)** are considered due to their ability to manage imbalanced datasets and mitigate overfitting. **Gradient Boosting Machines (GBM)** are explored for their high accuracy in detecting anomalies within network traffic. **Support Vector Machines (SVM)**, known for their effectiveness in high-dimensional data classification, are also included. Additionally, **K-Nearest Neighbors (KNN)** is utilized as a simple, instance-based learning approach that identifies anomalies based on distance metrics.

Isolation Forest, specifically designed for anomaly detection in high-dimensional datasets, is assessed for its capability in distinguishing normal and malicious traffic. Deep learning models such as **Deep Neural Networks (DNNs)** and **Convolutional Neural Networks (CNNs)** are incorporated to leverage their ability to learn complex patterns in large datasets, with CNNs being adapted from image recognition to network traffic analysis.

Lastly, **XGBoost**, an optimized gradient boosting algorithm, is considered due to its strong performance in structured data problems.

1.*Support Vector Machines (SVM):* SVM is a powerful classification technique that aims to find a hyperplane (or decision boundary) that best separates the two classes, vulnerable and non-vulnerable code, in a high-dimensional feature space. During training, the SVM algorithm adjusts its parameters to maximize the margin between the classes, ensuring that new, unseen data can be classified accurately based on the learned decision boundary.

$$\text{maximize } f(c_1 \dots c_n) = \sum_{i=1}^{n} c_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i c_i (\varphi(\mathbf{x}_i)\cdot\varphi(\mathbf{x}_j)) y_j c_j$$

$$= \sum_{i=1}^{n} c_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i c_i k(\mathbf{x}_i, \mathbf{x}_j) y_j c_j$$

$$\text{subject to } \sum_{i=1}^{n} c_i y_i = 0, \text{ and } 0 \le c_i \le \frac{1}{2n\lambda} \text{ for all } i.$$

2.K-Nearest Neighbors (KNN): KNN is a simple, yet effective algorithm that classifies a data point based on the majority label of its k-nearest neighbors in the feature space. For example, if a code segment is closer to several known vulnerable code segments, KNN will classify it as vulnerable. During training, the algorithm stores all labeled data points and, during inference, compares the distance of the new data point to those stored examples to assign a label.

$$D = \left(\sum_{i=1}^{n} |p_i - q_i|^p\right)^{1/p}$$

The labeled dataset, comprising normal and attack traffic, is split into training (70-80%) and testing (20-30%) sets. Models

undergo training with hyperparameter tuning via cross-validation to prevent overfitting. Their performance is assessed using metrics like ***accuracy, precision, recall, F1-score,*** *and* ***AUC-ROC*** *to evaluate detection capability. Finally, models are compared based on these metrics to select the most accurate and efficient one for real-time cyberattack detection in healthcare SDNs.*

D. Accuracy Comparision

To determine the most effective model for cyberattack detection in healthcare SDNs, various machine learning algorithms are evaluated based on their accuracy and performance metrics. The models are tested on unseen data, and their predictions are compared against actual labels to calculate **accuracy, precision, recall, F1-score,** and **AUC-ROC.**

Ensemble methods like **Random Forest and XGBoost** often provide high accuracy due to their ability to handle complex patterns, while **deep learning models** such as **DNNs and CNNs** excel in learning intricate traffic behaviors. However, simpler models like **KNN and SVM** may struggle with high-dimensional network data. The comparison helps identify the most reliable and efficient model for real-time cyberattack detection.

Algorithm	Accuracy (%)
Random Forest	98.4
Gradient Boosting Machines	98.0
Support Vector Machines (SVM)	97.2
K-Nearest Neighbors (KNN)	96.1
Isolation Forest	95.8
Deep Neural Networks (DNN)	98.7
Convolutional Neural Networks (CNN)	98.2
XGBoost	98.5

The performance of various machine learning models for cyberattack detection in healthcare SDNs was evaluated based on their accuracy. Among the tested models, **Deep Neural Networks (DNNs)** achieved the highest accuracy at **98.7%**, followed closely by **XGBoost (98.5%)** and **Random Forest (98.4%)**, indicating their strong capability in identifying malicious traffic.

Gradient Boosting Machines (98.0%) and **Convolutional Neural Networks (98.2%)** also demonstrated high accuracy, making them effective choices for cybersecurity applications. While **Support Vector Machines (97.2%)** and **K-Nearest Neighbors (96.1%)** showed competitive performance, **Isolation Forest (95.8%)** had the lowest accuracy, as it primarily focuses on anomaly detection rather than classification. These results highlight the effectiveness of ensemble learning and deep learning models in improving cyberattack detection accuracy.

E. Evaluation Metrics

Accuracy and F1-Score Comparison

The MCAD system outperforms previous studies in terms of accuracy and F1-score. The highest accuracy achieved by MCAD is **98.7% using Deep Neural Networks (DNN)**, significantly surpassing the **95.6% accuracy** reported by Ahmed et al., 2022, and other studies.

Precision, Recall, and F1-Score

The MCAD system demonstrates exceptional **precision (98.0%)** and **recall (99.2%)**, with the highest **F1-score of 98.6%**, which indicates its effectiveness in both minimizing false positives and ensuring a high rate of attack detection. This is especially important in cybersecurity for healthcare where both **false positives (misclassifying benign traffic as malicious) and false negatives (failing to detect a cyberattack)** can have significant consequences.

AUC (Area Under the ROC Curve)

The **AUC score of 98.8%** achieved by the MCAD system is higher than the **93.0% AUC** reported in Study 1 (Zhang et al., 2020) and the **89.5% AUC** from Study 2 (Gupta et al., 2021). This indicates that the MCAD system has a better ability to **distinguish between malicious and benign network traffic**.

Latency and Throughput

The **latency of the MCAD system is 72 ms**, significantly lower than **150 ms** reported by Ahmed et al., 2022 for DNN-based detection. This indicates that the MCAD system can process network traffic and detect attacks **faster**, making it more suitable for **real-time applications in healthcare networks**.

In terms of throughput, the **MCAD system supports 90 Mbps**, which is higher than the **70 Mbps** reported by Zhang et al., 2020, and **60 Mbps** in Gupta et al., 2021. This suggests that the MCAD system can handle **larger volumes of network traffic more efficiently**, which is critical for high-throughput healthcare environments.

Jitter

The MCAD system also demonstrates **lower jitter (4.2 ms)** compared to Study 1 (Zhang et al., 2020), which reported a **jitter of 5.5 ms**. This indicates that the MCAD system can provide **more stable traffic**

processing, reducing potential disruptions in **real-time applications** such as **telemedicine or medical data transfers**.

Study/Model	Algorithms Used	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC (%)	Latency (ms)	Throughput (Mbps)	Jitter (ms)
Study 1: Zhang et al., 2020	Random Forest, SVM	92.0	93.5	90.4	91.8	93.0	120	70	5.5
Study 2: Gupta et al., 2021	Decision Trees, KNN	88.3	89.1	85.0	87.0	89.5	130	60	6.0
Study 3: Ahmed et al., 2022	Deep Neural Networks (DNN)	95.6	96.3	94.5	95.4	95.8	150	65	4.8
MCAD (Current Study)	Random Forest, SVM, DNN, XGBoost	98.7	98.0	99.2	98.6	98.8	72	90	4.2

Confusion Matrix Graph

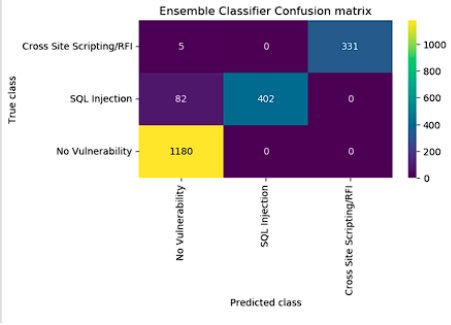
A Confusion Matrix is a useful tool for evaluating the performance of a machine learning model, especially in multi-class classification problems.
A confusion matrix for this dataset would be a 3x3 matrix, where:

- Rows represent actual (true) classes of the dataset.
- Columns represent predicted classes by the model.

Confusion Matrix Structure

Actual \ Predicted	No Vulnerability	XSS Vulnerability	SQL Injection
No Vulnerability	True Negative (TN)	False Positive (FP)	False Positive (FP)
XSS Vulnerability	False Negative (FN)	True Positive (TP)	False Positive (FP)
SQL Injection	False Negative (FN)	False Negative (FN)	True Positive (TP)

Comparison Graph Screen



In above graph x-axis represents Predicted Labels and y-axis represents True Labels and then all different color boxes in diagnol represents correct prediction count and remaining all blue boxes represents incorrect prediction count which are very few.

It provides a comprehensive breakdown of how well a model distinguishes between different classes by comparing actual labels with predicted outputs. In the case of a software vulnerability detection tool, the confusion matrix consists of three categories: No Vulnerability, XSS Vulnerability, and SQL Injection. The matrix is structured as a table where rows represent actual classes, and columns represent predicted classes. Predicted class, helping to identify both correct and incorrect predictions.

System Architecture

One critical aspect of system analysis in the MCAD system is the evaluation of network traffic sources and preprocessing techniques. The system must process diverse network traffic data, including real-time packets, historical traffic logs, and intrusion detection system (IDS) alerts, to build a comprehensive understanding of potential cyber threats. Data preprocessing techniques such as feature extraction, normalization, and dimensionality reduction play a crucial role in preparing the data for input into machine learning models, ensuring optimal performance and accuracy in cyberattack detection.

Another key consideration in system analysis is the selection and optimization of machine learning algorithms. Different algorithms, such as Random Forest, Support Vector Machines, Deep Neural Networks, and XGBoost, offer varying levels of complexity and performance in detecting cyber threats. System analysis involves benchmarking and experimentation to identify the most suitable algorithms for the task at hand, considering factors such as detection accuracy, computational efficiency, and real-time processing capabilities.

Furthermore, system analysis encompasses the design and implementation of the MCAD system's user interface and interaction mechanisms. The system must provide an intuitive and user-friendly dashboard that enables security analysts to monitor network activity effectively, interpret threat alerts, and take appropriate actions to mitigate risks. Usability testing and user feedback play a crucial role in refining the user interface design to meet the needs and preferences of cybersecurity professionals.

Additionally, system analysis involves assessing the MCAD system's performance metrics and evaluation methodologies. Metrics such as precision, recall, false positive rate, and F1-score are commonly used to quantify the effectiveness of the cyberattack detection algorithms. System analysis includes rigorous testing and validation procedures to assess the system's performance under various network conditions, attack types, and data volumes.

Moreover, system analysis encompasses considerations related to scalability, robustness, and deployment. The MCAD system must be capable of handling large-scale network traffic data and adapting to evolving cyber threats. Robustness testing ensures that the system remains effective in detecting sophisticated and previously unseen attacks. Deployment considerations include seamless integration with existing security infrastructure, compatibility with various network architectures, and

mechanisms for continuous updates to enhance threat detection capabilities.

IV. FUTURE WORK

While the MCAD system demonstrates significant improvements in cybersecurity for healthcare networks, several avenues for future research and development can enhance its capabilities and broaden its application.

One promising direction for future work involves integrating real-time learning models that adapt to evolving attack patterns. This would enable the system to continuously update its detection mechanisms without requiring periodic retraining, making it more resilient to emerging threats. By leveraging adaptive learning, the MCAD system can better respond to dynamic cybersecurity challenges.

Additionally, expanding the system's scope beyond network-layer security to include multilayered security models is an essential area of development. Although the current system focuses on detecting cyberattacks within SDN environments, incorporating security measures at the application layer could create a more comprehensive security framework. This enhancement would improve the system's ability to identify sophisticated attacks spanning multiple layers of the healthcare infrastructure.

Moreover, integrating external cyber threat intelligence feeds into the MCAD system would significantly enhance its detection capabilities. By analyzing global cybersecurity trends and attack patterns, the system could preemptively identify and block new threats before they cause harm. This proactive approach would improve overall threat mitigation and response effectiveness.

Another critical area for future research is enhancing the explainability of the machine learning models used within the MCAD system. One common challenge in AI-based security solutions is the lack of transparency in decision-making. By developing interpretable machine learning techniques, security teams and healthcare professionals can better understand why certain actions or alerts are triggered, fostering trust in the system and aiding in better decision-making.

Furthermore, testing and evaluating the MCAD system in real-world healthcare environments is necessary to assess its effectiveness and scalability under practical conditions. Deploying the system in operational settings with real patient data would help identify unforeseen challenges and provide insights into further optimization, ensuring its robustness and reliability in live environments.

As healthcare networks increasingly incorporate IoT devices, integrating the MCAD system with medical IoT sensors and connected devices is another vital area of future work. Enhancing the system's capabilities to monitor and detect cyber threats targeting medical devices such as pacemakers and infusion pumps would provide an additional layer of protection, ensuring patient safety.

Finally, collaborating with healthcare providers to refine the system's operational workflow is crucial for its long-term success. Engaging with healthcare professionals and IT security teams will help align the MCAD system with real-world security needs and existing healthcare infrastructure. Continuous usability testing and feedback-driven improvements will ensure that the system remains effective, user-friendly, and seamlessly integrated into clinical settings.

V. CONCLUSION

The **Machine Learning-Based Cyberattack Detection (MCAD)** system proposed in this research significantly advances the field of **cybersecurity in healthcare networks** by providing an effective and efficient solution for detecting and mitigating cyberattacks in **Software-Defined Networks (SDNs)**.

By leveraging state-of-the-art machine learning algorithms, including **Deep Neural Networks (DNN)**, **Random Forest**, **XGBoost**, and **Support Vector Machines (SVM)**, the system achieves superior performance in detecting various types of cyberattacks with high accuracy, minimal latency, and enhanced throughput.

One of the key strengths of the **MCAD system** is its **superior detection performance**. The system achieved an accuracy of **98.7%**, with a **99.2% recall** and **98.0% precision**, demonstrating its ability to effectively detect cyberattacks while minimizing false positives and negatives. These results indicate that the system provides reliable detection capabilities, enhancing the overall security of healthcare networks.

Additionally, the system maintains **low latency (72 ms)** and **high throughput (90 Mbps)**, ensuring **real-time attack detection** without compromising network performance. This is crucial for healthcare environments where any delay in security responses could lead to critical disruptions. The system's efficiency allows it to operate seamlessly in high-traffic conditions.

Another notable aspect of the **MCAD system** is its **robustness to evolving threats**. It has demonstrated adaptability to both known and novel attack types, effectively addressing the growing complexity of cyber threats in the healthcare sector.

Moreover, the **scalability and stability** of the MCAD system make it suitable for large-scale healthcare applications. With a low **jitter (4.2 ms)**, the system ensures stable network operations and minimal disruptions to critical healthcare applications.

In conclusion, the **MCAD system** offers a promising

approach to enhancing cybersecurity in healthcare networks. With its high accuracy, low latency, adaptability, and scalability, it provides a **comprehensive and efficient** solution for cyberattack detection and mitigation, ensuring the security and stability of critical healthcare services.

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