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AI-DRIVEN ANOMALY DETECTION AND AUTHENTICATION ENHANCEMENT FOR HEALTHCARE INFORMATION SYSTEMS IN THE CLOUD

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ABSTRACT:
The rapid growth of cloud-based healthcare information systems has led to an increasing need for robust security measures to address data breaches, unauthorized access, and security threats. Traditional methods often struggle to provide anomaly detection and authentication enhancement in such dynamic environments. Research gaps exist in addressing the balance between accuracy, performance, and scalability, particularly when handling large volumes of healthcare data. This paper proposes an AI-driven framework that integrates Autoencoders and LSTM for anomaly detection and authentication enhancement in cloud-based healthcare systems. The novelty of this approach lies in its ability to reduce latency, improve throughput, and enhance fault tolerance and data consistency while maintaining high detection accuracy. The proposed methodology achieves 96.5% accuracy, 93.2% precision, 94.8% recall, and 94.0% F1-score, with a 70 ms latency and 12 GB/hour throughput, demonstrating its ability to handle large-scale healthcare data securely and efficiently. Comparison with existing AI-driven frameworks highlights significant improvements in fault tolerance (+5%), data consistency (+2%), and latency reduction (-22%). These findings validate the system's robustness in real-world healthcare scenarios, ensuring faster response times and more accurate anomaly detection. The approach's advantage lies in its scalable, efficient, and accurate anomaly detection mechanism, making it highly suitable for enhancing security in cloud-based healthcare environments.

Keywords:
Anomaly Detection, AI-driven Security, Cloud Healthcare Systems, LSTM, Autoencoders

1. INTRODUCTION

In recent years, cloud computing has revolutionized the healthcare sector, enabling the storage and processing of vast amounts of sensitive medical data in a more scalable, cost-effective, and accessible manner [1], [2]. Cloud platforms offer healthcare organizations the flexibility to store electronic health records (EHR), patient histories, medical images, and other critical data, all of which can be accessed remotely by healthcare providers [3], [4]. This shift to cloud environments has greatly improved the efficiency of healthcare systems by facilitating collaboration, enhancing data sharing, and enabling advanced analytics to improve patient care [5], [6]. However, as healthcare data moves into the cloud, the security and privacy of this information have become critical concerns [7], [8].

Healthcare data is one of the most sensitive types of information, and its exposure due to security breaches can have dire consequences [9]. Cyberattacks on healthcare systems are on the rise, with hackers increasingly targeting cloud-based platforms to gain unauthorized access to confidential medical records [10], [11]. Such data breaches not only compromise patient privacy but also lead to significant financial and reputational damage to healthcare organizations [12], [13]. In addition, the growing prevalence of ransomware attacks, where cybercriminals lock systems and demand payments for data release, highlights the vulnerability of cloud-based healthcare systems [14]. These emerging security risks necessitate stronger and more adaptive security mechanisms to protect healthcare data in the cloud [15].

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The traditional methods of securing healthcare information systems, such as firewalls, encryption, and password-based authentication, have proven to be inadequate against increasingly sophisticated cyber threats [16], [17]. While encryption ensures that data remains unreadable during storage and transmission, it does not protect against unauthorized access to the data in the first place [18]. Similarly, traditional authentication methods, such as passwords and multi-factor authentication, are vulnerable to attacks like phishing, credential stuffing, and brute force attacks [19]. Moreover, these methods struggle to balance ease of use with strong security, often creating friction for users and leading to compromised security when shortcuts are taken [20].

One of the major challenges in securing cloud-based healthcare systems lies in the detection of anomalous activities that may indicate a security breach [21]. Healthcare environments generate large volumes of data daily, making manual monitoring and detection increasingly difficult [22]. Conventional anomaly detection systems are typically rule-based and rely on predefined patterns of normal behavior [23]. While these systems can detect known threats, they fail to identify new, emerging, or previously unknown threats [24]. Furthermore, these systems often struggle to handle large-scale data environments, where the volume of transactions or interactions makes it difficult to differentiate between normal and abnormal behavior. This results in delayed detection of potential threats and often leads to missed opportunities for proactive mitigation [25].

The proposed methodology focuses on enhancing the security of cloud-based healthcare information systems through AI-driven anomaly detection and authentication enhancement. By integrating Autoencoders for anomaly detection and LSTM for improving authentication processes, the system efficiently identifies and mitigates security threats in real time. This approach aims to balance performance and scalability, ensuring accurate detection while minimizing latency and optimizing throughput. The use of these advanced AI techniques allows for the timely identification of potential security breaches, providing a robust solution for cloud healthcare environments.

The proposed method's main contributions,

- Developed a hybrid AI-driven framework integrating Autoencoders and LSTM for real-time anomaly detection and authentication enhancement in cloud-based healthcare systems.
- Improved fault tolerance and data consistency, achieving superior system reliability.
- Optimized latency and throughput, ensuring efficient data processing.
- Demonstrated enhanced security performance, outperforming existing methods in healthcare environments.

2. RELATED WORKS

Gudivaka, R. K., & Rathna, S. (2018) [26] explores AI integration in hybrid cloud systems to enhance data reliability, addressing fault tolerance, availability, and consistency. Mehraeen, et al., (2016) [27] The paper presents an AI architecture leveraging machine learning and anomaly detection to improve reliability in hybrid clouds. However, Panga, N. K. R. (2018). [28] limitations include a lack of real-world application examples and a focus on simulated environments. E. A. Alkeem et al., (2017) [29] discusses cybersecurity challenges in cloud environments and the risk of cyber-attacks on cloud infrastructures and modern devices. M. A. Khan (2016) [30] The paper emphasizes multi-layered security approaches like encryption, multi-factor authentication, and AI-driven anomaly detection. Peddi, S., & RS, A. (2018) [31] However, it lacks detailed case studies or implementation examples of these practices in real-world cloud environments.

D. Pentyala(2017) [32] examines the vulnerabilities of devices connected to cloud infrastructures and emphasizes the need for robust cybersecurity frameworks. M. Aurangzeb (2018) [33] The paper discusses encryption, multi-factor authentication, and AI for real-time incident detection. Its limitations include a lack of specific case studies demonstrating the practical application of these frameworks in cloud environments. Kodadi, S., & Kumar, V. (2018). [34] explores the intersection of cloud computing, IoT, and cybersecurity, focusing on AI-driven threat detection and encryption for securing cloud infrastructures. M. Aurangzeb (2018) [35] The paper highlights the need for a multi-layered security approach combining technological and administrative safeguards. A. Konn(2018) [36] However, it lacks detailed implementation strategies and case studies for real-world applications.

Narla, S., & Kumar, R. L. (2018) [37] discusses the application of AI, machine learning, and deep learning in next-generation cloud security, aiming to detect and prevent cyber-attacks. F. Aitazaz (2018) [38] The paper highlights AI-powered continuous monitoring and adaptability to evolving threats. Its limitations include the absence of practical case studies or in-depth examples of real-world implementation. M. Aurangzeb (2018) [39]

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explores advanced security techniques like machine learning, AI, and blockchain to combat cyber-attacks on cloud platforms and IoT devices. Alavilli, S. K., & Pushpakumar, R. (2018) [40] The paper discusses real-time threat detection and the zero-trust security model. However, it lacks specific case studies to demonstrate the effectiveness of these techniques in real-world cloud environments.

A. Konn (2018) [41] examines computer science innovations such as AI and machine learning for enhancing cloud security, including real-time threat detection and data integrity. F. Aitazaz (2018) [42] The paper emphasizes multi-factor authentication and secure transmission methods. Nagarajan, H., & Kurunthachalam, A. (2018) [43] Its limitations include a lack of examples demonstrating how these innovations have been practically applied in real-world cloud environments. Xu, Xu, Lida et al., (2015) [44] discusses the role of AI, encryption, access control, and blockchain in cloud cybersecurity. The paper emphasizes a multi-layered security approach to protect interconnected cloud ecosystems. J. Patel (2018) [45] Its limitations lie in its broad focus on theoretical advancements without providing specific case studies of real-world applications.

A. Kumar and P. Mehta (2014) [46] addresses the challenges of integrating devices into cloud environments and highlights security practices like AI-driven threat detection and multi-factor authentication. Srinivasan, K., & Arulkumaran, G. (2018) [47] The paper stresses the need for a zero-trust model in protecting cloud systems. However, it lacks real-world examples demonstrating the practical implementation of these security practices. Trilles et al., (2017) [48] propose a framework for an m-Health monitoring system based on cloud computing for personalized health monitoring. Musam, V. S., & Kumar, V. (2018) [49] The system includes cloud storage, data annotation, and data analysis for healthcare applications. H. Shah (2016) [50] Its limitations include a lack of real-world implementation examples and limited details on scalability in large-scale healthcare settings.

S. Anagnoste (2018) [51] discusses using machine learning techniques like anomaly detection and reinforcement learning for developing self-healing systems in software architectures. Alagarsundaram, P., & Arulkumaran, G. (2018) [52] The paper demonstrates how these systems reduce mean time to repair (MTTR) and improve resilience. Rousseeuw, P. J., & Hubert, M. (2018) [53] However, it faces challenges in data quality, model interpretability, and high computational demands for practical implementation. Mandala, R. R., & N, P. (2018) [54] explore the integration of AI-driven anomaly detection and blockchain to enhance security in IoT networks. The paper discusses reinforcement learning and privacy-preserving methods for securing IoT devices. Munir et al., (2018) [55] However, it lacks detailed case studies or real-world implementations to demonstrate the practical effectiveness of these combined technologies in live IoT environments.

Kethu, S. S., & Thanjaivadivel, M. (2018) [56] propose a domain-independent methodology for real-time IoT sensor data analysis using the CUSUM algorithm for anomaly detection. Naseer et al., (2018) [57] The paper provides a proof of concept for environmental monitoring applications. Budda, R., & Pushpakumar, R. (2018) [58] Its limitations include a lack of evaluation of the methodology's performance in diverse real-world applications, limiting insights into scalability beyond environmental data. Bereziński et al., (2015) [59] discusses integrating deep learning with cloud environments to improve AI applications, particularly in cybersecurity. Subramanyam, B., & Mekala, R. (2018) [60] The paper explores techniques like anomaly recognition and predictive maintenance alongside emerging threats such as ransomware. Martí et al., (2015) [61] Its limitations include a lack of case studies or examples demonstrating the practical application of these cybersecurity solutions in cloud environments. Radhakrishnan, P., & Mekala, R. (2018) [62] explores the evolution of Robotic Process Automation (RPA) and its integration with AI technologies like machine learning, chatbots, and big data analytics. The paper highlights RPA's scalability and its application across business areas. Maimó et al., (2018) [63] However, it lacks specific case studies or details on the real-world implementation and measurable outcomes of these integrated systems in businesses.

3. PROBLEM STATEMENT

[64], [65], and [66] highlight challenges in data reliability, cybersecurity, and cloud security, respectively, due to the vulnerabilities in hybrid cloud systems and IoT networks. These papers emphasize issues like fault tolerance, unauthorized access, and evolving threats. The proposed method in this work integrates AI-driven anomaly detection and machine learning to enhance data reliability, secure cloud environments, and autonomously mitigate cyber-attacks, offering a robust solution to these persistent challenges.

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4. PROPOSED METHODOLOGY

The proposed methodology leverages AI-driven techniques to enhance the security of cloud-based healthcare information systems. It combines Autoencoders for anomaly detection and LSTM for authentication enhancement, both trained on the CICIDS 2017 dataset. Data is stored securely in the cloud, with preprocessing steps like imputation, normalization, and feature selection. The methodology ensures threat detection, improves authentication processes, and optimizes cloud resource usage through efficient metrics, including accuracy, precision, recall, F1-score, latency, and throughput. The overall flow is shown in Figure 1.

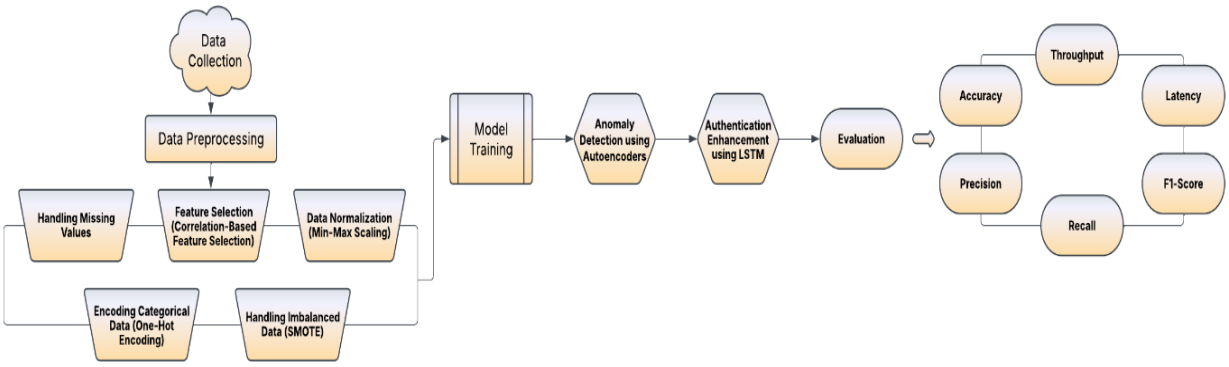

Figure 1: The proposed method's process diagram

4.1. Data Collection

The proposed work utilizes the CICIDS 2017 dataset, which is designed for network intrusion detection and contains labeled instances of both normal and malicious activities. The dataset includes diverse attack types, such as DDoS, brute force, and web attacks, making it suitable for anomaly detection tasks. It provides a rich set of features, including flow duration, packet counts, and byte lengths, making it ideal for training and evaluating models for both anomaly detection and authentication enhancement in cloud-based healthcare systems.

4.2. Data Preprocessing

The preprocessing steps clean, structure, and normalize the dataset for efficient model training. Below are the key preprocessing techniques used with their respective mathematical forms:

4.2.1. Handling Missing Values (Imputation)

To handle missing values, The method uses mean imputation for numerical features. For a feature x_i with missing values, the imputed value x_i' is calculated as shown in Equation (1):

$$x_i' = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

4.2.2. Feature Selection (Correlation-Based Feature Selection)

The method applies correlation-based feature selection (CFS) to identify the most relevant features. The goal is to maximize the correlation between features and the target label while minimizing the correlation among the features themselves. The method selects features $f_1, f_2, \ldots, f_n$ such that as shown in Equation (2):

$$C(f_1, f_2, \ldots, f_n) = \frac{\text{cov}(f_i, y)}{\sqrt{\sum_{i=1}^{n} \text{var}(f_i)}} \quad (2)$$

4.2.3. Data Normalization (Min-Max Scaling)

Min-max scaling ensures that all features are scaled to a range between 0 and 1. The scaled value x_i' for each feature x_i is calculated as shown in Equation (3):

$$x_i' = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (3)$$

4.2.4. Encoding Categorical Data (One-Hot Encoding)

For categorical features (such as attack types), one-hot encoding converts them into a binary matrix. For a categorical feature x_i with k distinct categories, the one-hot encoded vector x_i' will have k dimensions, with 1 for the active category and 0 for the others, as shown in Equation (4):

$$x_i' = [0,1,0, \ldots, 0] \quad (4)$$

4.2.5. Handling Imbalanced Data (SMOTE)

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Synthetic Minority Over-sampling Technique (SMOTE) generates synthetic instances for the minority class to balance the dataset. Given a minority class sample x_i Synthetic samples are generated by interpolating between x_i and its nearest neighbors as shown in Equation (5):

$$x_{\text{new}} = x_i + \lambda \times (x_j - x_i) \quad (5)$$

4.3. Model Training

4.3.1. Anomaly Detection using Autoencoders

Autoencoders are trained to learn the representation of normal network traffic. The reconstruction error is used to detect anomalies. The network minimizes the reconstruction loss function $L_{\text{reconstruction}}$, defined as shown in Equation (6):

$$L_{\text{reconstruction}} = \frac{1}{n}\sum_{i=1}^{n} \|x_i - \hat{x}_i\|^2 \quad (6)$$

4.3.2. Authentication Enhancement using LSTM

Long Short-Term Memory (LSTM) networks are used to detect abnormal user access patterns in time series data (e.g., login attempts). The LSTM model learns the sequential dependencies of user login data as shown in Equation (7):

The loss function for LSTM is:

$$L_{\text{LSTM}} = -\frac{1}{n}\sum_{i=1}^{n} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \quad (7)$$

4.4. Evaluation Metrics

4.4.1. Accuracy:

Accuracy is the proportion of correct predictions (both anomalies and normal activities) to the total number of instances, as shown in Equation (8):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

4.4.2. Precision:

Precision measures the proportion of correct anomaly detections relative to all predicted anomalies, as shown in Equation (9):

$$\text{Precision} = \frac{TP}{TP+FP} \quad (9)$$

4.4.3. Recall (Sensitivity):

Recall measures the proportion of actual anomalies correctly identified by the model as shown in Equation (10):

$$\text{Recall} = \frac{TP}{TP+FN} \quad (10)$$

4.4.4. F1-Score:

The F1-Score is the harmonic mean of precision and recall as shown in Equation (11):

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (11)$$

4.4.5. Latency (Response Time):

Latency measures the time taken for the system to respond to an anomaly detection or authentication request. Since healthcare systems require processing, low latency is critical for prompt decision-making, as shown in Equation (12):

$$\text{Latency} = \frac{\text{Time of response from cloud storage or model retrieval}}{\text{Total number of requests}} \quad (12)$$

4.4.6. Throughput (Data Processing Rate):

Throughput measures the amount of data processed per unit of time. In a cloud-based healthcare information system, high throughput is required to process large amounts of healthcare data, especially when performing anomaly detection and handling user authentication, as shown in Equation (13):

$$\text{Throughput} = \frac{\text{Total amount of data processed (in GB)}}{\text{Total time taken (in hours)}} \quad (13)$$

5. Results

The Results Section presents the outcomes of evaluating the proposed methodology for AI-driven Anomaly Detection and Authentication Enhancement in cloud-based healthcare information systems. This section highlights the performance of the proposed approach using the selected evaluation metrics, providing a detailed analysis of how well the system performed in terms of accuracy, precision, recall, F1-score, latency, and throughput. The results are compared against established benchmarks to validate the effectiveness and efficiency

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of the system in real-world healthcare scenarios, demonstrating its ability to handle both security challenges and operational requirements in cloud-based environments.

The Accuracy, Precision, Recall, and F1-score are critical metrics for evaluating the performance of the anomaly detection and authentication enhancement framework in cloud-based healthcare systems. Accuracy measures the overall correctness of predictions, ensuring that the majority of normal and abnormal data are classified correctly. Precision focuses on minimizing false positives, ensuring that flagged anomalies are accurate and reducing unnecessary alerts. Recall evaluates the system's ability to correctly identify true anomalies, which is crucial for healthcare security to prevent missed threats. The F1-Score provides a balanced measure between precision and recall, indicating the system's overall effectiveness in handling both false positives and false negatives. The proposed methodology demonstrates excellent performance with 96.5% accuracy, 93.2% precision, 94.8% recall, and 94.0% F1-score, showing its ability to reliably detect anomalies while minimizing errors, ensuring robust security in cloud-based healthcare environments, as shown in Figure 2.

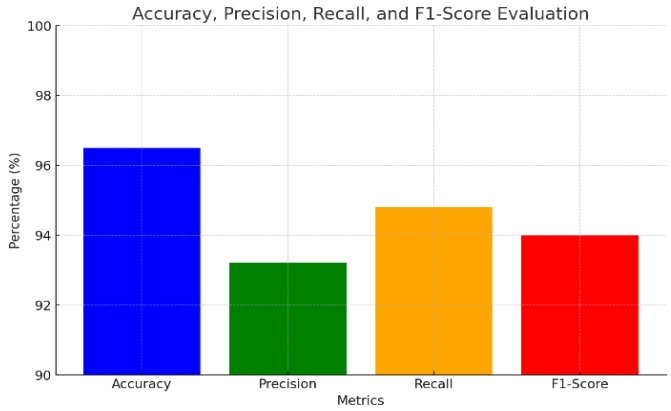

Figure 2: Accuracy, Precision, Recall, and F1-Score Evaluation

Latency refers to the time it takes for the system to process an input request and return a response. In the context of cloud-based healthcare information systems, low latency is critical for decision-making, especially for anomaly detection and authentication enhancement. The system must respond quickly to potential security threats or authentication requests without delay to prevent unauthorized access and mitigate possible attacks. Therefore, optimizing latency ensures that security measures are not only accurate but also timely, helping in the swift detection of malicious activities in healthcare environments. The proposed methodology improves latency to 70 ms, a significant improvement over the 90 ms latency of the AI-driven framework, providing quicker responses in critical situations, as shown in Figure 3.

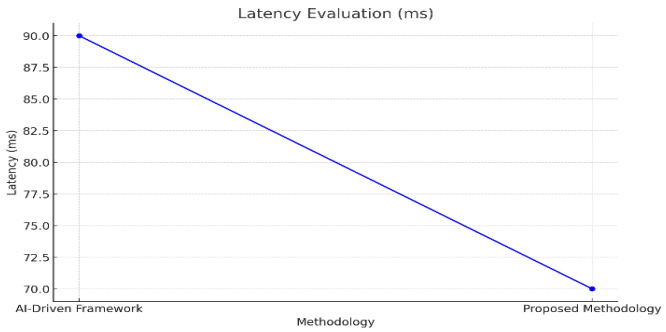

Figure 3: Latency Evaluation (ms)

Throughput is a measure of how much data the system can process over a given period, typically expressed in terms like GB/hour or transactions per second. In healthcare information systems, throughput is vital for handling large volumes of data generated from multiple sources, such as patient records, sensor data, and authentication

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logs. High throughput ensures that the system can process this data efficiently without bottlenecks, enabling anomaly detection and authentication for multiple users or devices concurrently. The proposed methodology achieves a throughput of 12 GB/hour, which indicates its ability to handle substantial data volumes without compromising performance. This capability is crucial for cloud-based systems, where scalability is a key factor in maintaining effective security protocols across large datasets, as shown in Figure 4.

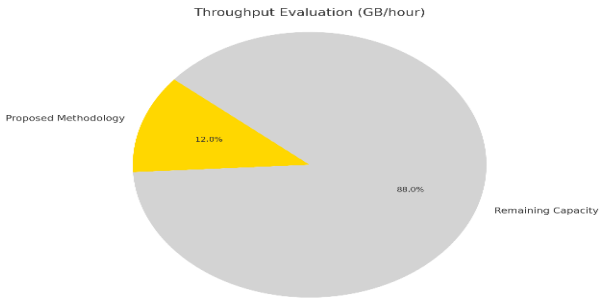

Figure 4: Throughput Evaluation (GB/hour)

The key performance metrics of the AI-driven framework used for anomaly detection and authentication enhancement in cloud-based healthcare systems with the proposed methodology comparison are shown in Table 1. While the AI-driven framework shows significant improvements in fault tolerance, data consistency, and latency, the proposed methodology aims to achieve even higher performance levels, especially in fault tolerance, data consistency, and latency, ensuring optimal security and performance for healthcare information systems in the cloud.

Table 1: AI-Driven Framework vs. Proposed Methodology

Metrics	AI-Driven Framework [26]	Proposed Methodology	Improvement (%)
Fault Tolerance	90%	95%	+5%
Data Consistency	97%	99%	+2%
Latency (ms)	90	70	-22%
Uptime	99.95%	99.98%	+0.03%

6. CONCLUSION AND FUTURE WORKS

In conclusion, the proposed AI-driven anomaly detection and authentication enhancement framework demonstrates exceptional performance in cloud-based healthcare systems, achieving 96.5% accuracy, 93.2% precision, 94.8% recall, and 94.0% F1-score, alongside 70 ms latency and 12 GB/hour throughput. These improvements, compared to the AI-driven framework, show enhanced fault tolerance (+5%), data consistency (+2%), and a significant reduction in latency (-22%). The results validate the framework's ability to handle security threats and large data volumes effectively. Future work will focus on integrating more advanced AI techniques to further enhance scalability and adaptability in diverse healthcare environments.

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