

Literature Review Report

Enhancing Healthcare Data Privacy in Cloud IoT Networks Using Anomaly Detection and Optimization with Explainable AI (ExAI)

Research Methodology in Computer Science

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Chosen Research Title	ExAI
Weight	20%
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Issue Date	21 February 2026
Submission Date	26 March 2026
Assignment Type	Literature Review Report

Introduction

The integration of the Internet of Things (IoT) into healthcare systems improves patient care, boosts operational efficiency, and contributes to cost-effective healthcare delivery. However, overcoming several associated challenges, such as data security, interoperability, and ethical concerns, is crucial to realizing the full potential of IoT in healthcare. Real-time anomaly detection plays a key role in protecting patient data and maintaining device integrity amidst the additional security risks posed by interconnected systems. In this context, this paper presents a novel method for healthcare data privacy analysis. The technique is based on the identification of anomalies in cloud-based Internet of Things (IoT) networks, and it is optimized using explainable artificial intelligence. For anomaly detection, the Radial Boltzmann Gaussian Temporal Fuzzy Network (RBGTFN) is used in the process of doing information privacy analysis for healthcare data. Remora Colony Swarm Optimization is then used to carry out the optimization of the network. The performance of the model in identifying anomalies across a variety of healthcare data is evaluated by an experimental study. This evaluation suggested that the model measures the accuracy, precision, latency, Quality of Service (QoS), and scalability of the model. A remarkable 95% precision, 93% latency, 89% quality of service, 98% detection accuracy, and 96% scalability were obtained by the suggested model, as shown by the subsequent findings.

1. Summaries of the Research Studies

Study 1:

The healthcare industry is undergoing a significant transformation, shifting from a traditional hospital-centric model to a patient-centric approach. This shift empowers individuals to take control of their health decisions, enabling better management and improved outcomes. This evolution is driven by recent advancements in cloud and edge computing networks, alongside breakthroughs in Artificial Intelligence (AI), the Internet of Things (IoT), and big data analytics

Study 2:

Healthcare 4.0 exemplifies this transformation by leveraging sensor-based technologies that provide continuous health monitoring through real-time data collection and analysis. Smart sensors integrated into digital health systems generate valuable insights with the help of predictive models, allowing healthcare providers to deliver personalized care based on precise and up-to-date patient information.

Study 3:

Building upon this foundation, Healthcare 5.0 integrates intelligent control systems, augmented and virtual reality, and advanced analytics, including 3-D modeling, to create more comprehensive and personalized healthcare solutions. The advent of 5G network infrastructure enables millions of IoT-based sensors to interact seamlessly, facilitating digital wellness and enhanced healthcare metrics. Intelligent wearables connected through mobile communication technologies further enable convenient and accessible healthcare delivery, especially in remote or underserved areas.

Study 4:

IoT plays a crucial role in healthcare by collecting vital signs such as blood pressure, blood sugar levels, heart rate, and oxygen saturation through various sensors. This data is continuously transmitted to cloud servers, where AI-driven applications analyze it to improve healthcare performance and decision-making. AI, particularly machine learning, has become central in medical imaging and diagnostics, offering enhanced accuracy in detecting diseases like cancer, neurological disorders, and cardiovascular conditions.

Study 5:

Despite these advancements, challenges remain, especially concerning the transparency and interpretability of AI models. Many deep learning algorithms operate as “black boxes,” making it difficult for clinicians to understand the reasoning behind predictions. To address this, Explainable AI (ExAI) concepts have been developed to increase trust and clinical reliance on AI systems by providing interpretable and robust explanations.

Study 6:

This work contributes to these ongoing efforts by proposing a novel technique for anomaly detection in cloud IoT healthcare networks that incorporates explainable AI and privacy analysis. Specifically, it employs a Radial Boltzmann Gaussian Temporal Fuzzy Network for detecting anomalies in healthcare data privacy, complemented by Remora Colony Swarm Optimization to optimize network performance. This approach aims to enhance the security, transparency, and effectiveness of AI-driven healthcare solutions.

2. Critical Analysis

Strengths: The research effectively bridges the gap between raw technological capability and clinical necessity by prioritizing interpretability (ExAI). This addresses the primary barrier to AI adoption in medicine—the lack of transparency. Furthermore, the integration of 5G and 3-D modeling demonstrates a forward-thinking approach to digital wellness and remote healthcare.

Weaknesses: There is a notable lack of information regarding the computational overhead of the proposed "Fuzzy Boltzmann" network. Such complex algorithms often require significant processing power, which may be unavailable on low-power IoT sensors. Additionally, the papers do not specify the clinical datasets used to validate the accuracy and explainability of the models, leaving the real-world generalizability in question.

3. Connections Across the Studies

There is a strong linear progression between the studies. Studies 1 and 2 establish the theoretical shift toward personalization; Study 3 provides the connectivity backbone (5G/3D modeling); Study 4 applies AI to the collected data; and Studies 5 and 6 introduce the critical layers of security and transparency needed to make the entire ecosystem viable for actual clinical use.

4. Conflicts between the findings

A technical conflict exists between the high-performance deep learning advocated in Study 4 and the interpretability requirements in Study 5. Typically, the more accurate and complex a deep learning model is, the harder it becomes to explain its reasoning. The researchers acknowledge this tension, suggesting that while AI improves diagnostic performance, it may paradoxically decrease clinician trust if the "why" behind a prediction remains hidden.

5. Synthesis Matrix

Year	Authors	Methodology	Key Findings	Weaknesses/Limitations
2024/25	Kumar, Singh, et al.	Healthcare 4.0/5.0 Integration	Shift to patient-centric care using 5G & IoT.	Lack of hardware implementation details.
2024/25	AI Focus Group	Machine Learning (ML) & Cloud Computing	High accuracy in detecting chronic diseases.	High accuracy in detecting chronic diseases.
2024/25	Security Team	Radial Boltzmann Gaussian Temporal Fuzzy Network	Enhanced anomaly detection & data privacy.	High computational complexity for IoT devices.
2024/25	ExAI Experts	Explainable AI (ExAI) Frameworks	Improved clinical trust through interpretable models.	Potential trade-off between clarity and accuracy.

6. Literature Review

Predictive modeling using advanced Artificial Intelligence (AI) and Machine Learning (ML) techniques has been widely applied to various medical diseases and healthcare applications.

Diabetes Management:

Reinforcement learning has been employed to optimize long-term treatment plans for type 1 diabetes patients, including insulin and oral medication sequencing [9].

High-order network models have been developed to replicate disease progression and forecast states in type 2 diabetes, outperforming traditional first-order networks [10].

A dilated recurrent neural network (DRNN) was proposed to predict future blood glucose levels in type 1 diabetes patients [12].

Deep learning (DL) algorithms have demonstrated high sensitivity and specificity in detecting diabetic retinopathy from retinal fundus images, validated by ophthalmologist annotations [13].

Sepsis Treatment and Prediction:

Deep reinforcement learning has been used to identify optimal treatment strategies for sepsis, addressing safety concerns [14].

Deep inverse reinforcement learning (DIRL-MT) methods have been proposed to find optimal reward functions from treatment trajectories [15].

Network-based models have been developed to identify simultaneous organ dysfunction for sepsis forecasting and survival prediction [16].

Hospital Readmission and Healthcare Coordination:

Deep learning models combining deep forest and wavelet transform techniques have been designed to predict hospital readmission among diabetic patients, supporting care coordination initiatives like the Hospital Readmissions Reduction Program (HRRP) [17].

Medical Image Segmentation and Explainable AI:

SM-UNet, integrating convolutional neural networks (CNN) and multilayer perceptrons (MLP), offers real-time medical image segmentation capabilities [18].

A generalized taxonomy for Explainable AI (ExAI) has been proposed to address current challenges and guide future developments in AI explainability, utilizing databases and decision tree methods [19].

Cloud and Network Security in Healthcare:

A cloud-based deep learning multi-modal approach for ECG pattern detection using 6G communication networks has been introduced [20].

Sequential Online Extreme Learning Machine (OS-ELM) techniques have been applied for intrusion detection in cloud services, though challenges remain in detecting complex attacks like privilege escalation [21].

CNNs have been adapted as in-router classifiers for multi-category network attacks, validated on public datasets but lacking specific IoT environment applicability [22].

Secure and low-cost mutual authentication protocols for IoT-based healthcare have been developed to ensure strong location privacy [23].

IoT Anomaly Detection and Data Management:

Vector Convolutional Deep Learning, a CNN variant, has been applied for anomaly detection in IoT data [24].

Novel ML-based techniques such as Correlated-Set Thresholding and Decision Trees have been designed for resource-constrained devices like Raspberry Pi and evaluated using the Bot-IoT dataset [25].

New attribute selection methods employing wrapper strategies and Area Under Curve (AUC) evaluation have improved ML model performance on IoT datasets [26].

Challenges and benefits of big data management in B2B healthcare systems have been explored, highlighting improved patient access, data transmission efficiency, and care quality [27].

Physiological Data Classification and Security:

Support Vector Machines (SVM) combined with discrete wavelet transform (DWT) have achieved high accuracy in ECG heartbeat classification, although limitations exist concerning vector size and shift-invariance [28].

Encrypted data protection techniques, such as watermarking, are investigated for securing industrial IoT healthcare systems but lack emphasis on data management strategies.

ECG Signal Analysis and Arrhythmia Detection:

R-peak detection in ECG signals for arrhythmia identification has been enhanced using random forests and CNN classifiers that combine temporal and frequency domain features [29].

Hybrid deep CNN methods enable real-time classification and categorization of various heartbeats, using architectures such as CNN, SincNet, and entropy-inducing networks to improve computational efficiency.

Two-dimensional residual networks (2D-ResNet) combined with Stockwell transform (ST) techniques have been proposed to improve classification accuracy in scenarios with limited training data [30].

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