International Journal of Business Management and Economic Review

Vol. 2, No. 02; 2019

ISSN: 2581-4664

ANOMALY DETECTION IN CLOUD HEALTHCARE NETWORKS USING DEEP LEARNING

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http://doi.org/10.35409/IJBMER.2019.2088_1

ABSTRACT

Cloud-based healthcare networks generate vast amounts of data, making anomaly detection essential for ensuring data integrity and system reliability. However, existing methods struggle with high false positive rates, scalability limitations, and increased detection latency, reducing their effectiveness in healthcare systems. To overcome these challenges, this paper introduces a robust anomaly detection framework for cloud-based healthcare networks using deep learning techniques. The framework begins by collecting data from healthcare environments, the collected data is then subjected to data preprocessing, where KNN imputation is applied to handle missing values, ensuring completeness, while Winsorization mitigates extreme outliers to maintain data consistency and improve reliability. The preprocessed data is then used for feature extraction, where Polynomial Feature Expansion is applied to generate higher-order features, capturing complex relationships between healthcare parameters. The extracted features are then fed into a Temporal Convolutional Network, which learns temporal dependencies within sequential healthcare data, effectively distinguishing between normal and anomalous patterns with high accuracy. Once anomalies are detected, they are stored in cloud storage, ensuring efficient management and seamless integration for further analysis. Experimental results validate the proposed framework, achieving 99.52% accuracy, 98.34% precision, 98.78% sensitivity, 97.23% specificity, and 99.74% F1-score, significantly outperforming conventional approaches. This work enhances the computational efficiency, reducing false positives, and improving detection reliability, making it a scalable and robust solution for cloud-based healthcare applications.

Keywords: Healthcare data, Temporal Convolutional Network, Anomaly Detection and Cloud Storage.

1. INTRODUCTION

The rapid adoption of cloud computing in the healthcare industry, ensuring the security and integrity of healthcare data has become a critical challenge [1]. Cloud-based healthcare networks are vulnerable to cyber threats, unauthorized access, and system anomalies, which can compromise sensitive patient information [2]. Traditional security measures often fail to detect sophisticated attacks, necessitating advanced anomaly detection techniques [3]. An effective anomaly detection framework can identify malicious activities, prevent data breaches, and ensure the reliability of healthcare services [4]. Deep learning-based methods offer promising solutions by analyzing complex network traffic patterns in real time [5]. Temporal dependencies in healthcare network

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ISSN: 2581-4664

data require specialized models for accurate anomaly detection [6]. Hence, a robust and efficient anomaly detection framework is essential for safeguarding cloud-based healthcare systems [7]. This study focuses on developing a novel deep learning-based framework to address these security concerns effectively [8].

The integration of cloud computing in healthcare networks has transformed the management, storage, and accessibility of medical data, enabling improved patient care and operational efficiency [9]. Cloud healthcare networks support a variety of applications, including electronic health records (EHRs), telemedicine, and real-time monitoring systems [10]. However, the critical nature of healthcare data demands robust security measures to protect against unauthorized access, data breaches, and system disruptions [11]. Anomaly detection has emerged as a vital technique to identify unusual patterns or behaviors that may indicate cyber threats or system malfunctions within these cloud environments [12].

Several existing methods have been proposed for anomaly detection in cloud-based networks, including Autoencoders, Long Short-Term Memory (LSTM) networks, and Isolation Forest [13]. Autoencoders can detect anomalies by reconstructing normal patterns but often fail in detecting sophisticated cyberattacks [14]. LSTM networks capture temporal dependencies but suffer from high computational complexity and training inefficiencies [15]. Isolation Forest is an effective unsupervised method but struggles with high-dimensional and sequential data [16]. Traditional statistical methods, such as PCA and One-Class SVM, have been used for anomaly detection but lack adaptability to complex and dynamic healthcare networks [17]. Moreover, these existing methods often generate high false positives, making them less reliable for real-world implementation [18]. The inability to process large-scale healthcare data efficiently and detect evolving threats remains a major limitation [19]. Hence, there is a need for a more robust and scalable deep learning-based anomaly detection framework [20].

Several factors contribute to the vulnerability of cloud healthcare networks to anomalies [21]. The increasing digitization of healthcare services and the widespread adoption of IoT devices introduce numerous entry points for attackers [22]. Moreover, healthcare data is highly sensitive and often targeted by cybercriminals for financial gain or malicious intent [23]. The complexity and heterogeneity of cloud environments, combined with a growing volume of data traffic, make it challenging to distinguish between normal and abnormal activities without advanced analytical tools [24].

The proposed framework overcomes these limitations by leveraging Temporal Convolutional Networks (TCN) for efficient anomaly detection in cloud healthcare networks [25]. TCN effectively captures long-range dependencies and patterns in sequential healthcare data with lower computational complexity than LSTMs [26]. The framework integrates Polynomial Feature Expansion to enhance feature representation, improving anomaly detection accuracy [27]. Advanced preprocessing techniques, such as KNN imputation and Winsorization, ensure data quality by handling missing values and reducing outliers [28]. Unlike existing methods, this approach minimizes false positives while efficiently detecting real anomalies [29]. The novelty of this study lies in its combination of TCN and feature expansion techniques for robust anomaly detection in healthcare networks [30].

The paper is organized as follows: Section 2 presents a literature review, discussing existing methods and their limitations. Section 3 details the proposed methodology. Section 4 discusses the experimental results. Finally, Section 5 concludes the paper and suggests future research

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directions.

2. LITERATURE SURVEY

Anomaly detection framework using Autoencoders to identify deviations in healthcare data [31]. The method reconstructed normal patterns and detected anomalies based on reconstruction errors [32]. While Autoencoders were effective in identifying basic anomalies, they struggled with detecting sophisticated cyber threats [33]. The approach also faced difficulties in handling high-dimensional healthcare data [34]. Additionally, Autoencoders required large amounts of normal data for training, which limited their adaptability [35]. The model's reliance on reconstruction loss made it prone to false positives in real-time applications [36]. These limitations reduced the framework's effectiveness in complex cloud healthcare networks [37].

Long Short-Term Memory (LSTM) networks for anomaly detection in cloud-based healthcare environments [38]. LSTM models were effective in capturing temporal dependencies in network traffic data [39]. However, they had high computational complexity, making them unsuitable for large-scale cloud deployments [40]. The training process was time-consuming and required extensive hyperparameter tuning [41]. Moreover, LSTMs struggled with long-range dependencies due to vanishing gradient issues [42]. Their resource-intensive nature made real-time anomaly detection difficult in cloud environments [43]. These drawbacks limited the efficiency of LSTMs for anomaly detection in dynamic healthcare networks [44].

The application of Isolation Forest for anomaly detection in healthcare networks [45]. The high computational cost made it inefficient for large-scale cloud environments. Additionally, One-Class SVM struggled with imbalanced datasets, reducing its detection accuracy. These drawbacks made it less suitable for real-time anomaly detection in cloud-based healthcare systems. Principal Component Analysis (PCA)-based anomaly detection for cloud healthcare networks. The method utilized dimensionality reduction to improve anomaly classification efficiency. However, PCA was limited in handling non-linear data distributions and evolving attack patterns. The reliance on linear transformations restricted its ability to capture complex relationships in healthcare network traffic. Additionally, PCA required manual selection of principal components, which affected its scalability. It struggled with detecting subtle anomalies in high-dimensional datasets. These limitations reduced its effectiveness for modern cloud-based healthcare security applications.

2.1 Problem Statement

Despite technological advancements in anomaly detection, existing methods still struggle with fundamental limitations that impact their reliability [46]. High false positive rates continue to be a major concern, as many models misclassify normal data as anomalies, leading to unnecessary alerts and inefficiencies [47]. Scalability issues further hinder performance, with traditional approaches struggling to handle large volumes of healthcare data efficiently in cloud environments [48]. Additionally, high latency in detection affects real-time responsiveness, making it challenging to identify critical anomalies promptly [49]. To address these limitations, this work proposes a Temporal Convolutional Network (TCN)-based anomaly detection framework, designed to enhance accuracy, minimize false positives, and enable efficient anomaly detection in cloud healthcare networks [50].

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3.METHODOLOGIES

The proposed framework for anomaly detection in cloud healthcare networks begins with data collection, where healthcare network logs, system activity data, and electronic health records (EHR) are gathered. In the preprocessing stage, missing values are handled using KNN imputation, and Winsorization is applied to reduce the impact of extreme outliers. Next, feature extraction is performed using Polynomial Feature Expansion to enhance data representation and capture complex relationships in network traffic patterns. For anomaly detection, a Temporal Convolutional Network (TCN) is employed to efficiently model long-range dependencies in sequential healthcare data, ensuring accurate anomaly detection with lower computational complexity than traditional methods. The detected anomalies are then securely stored in cloud storage for further analysis and compliance with healthcare regulations. This methodology ensures, scalable, and efficient anomaly detection, improving the security and reliability of cloud-based healthcare systems. This process in illustrated in Figure 1.

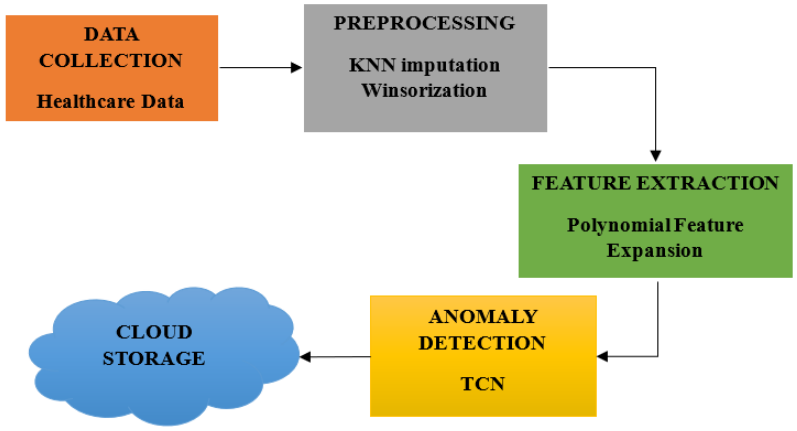

Figure 1: Healthcare Data Processing and Anomaly Detection Framework

3.1 Data Collection

The data collection process involves gathering network traffic logs, system activity records, and electronic health records (EHR) from healthcare environments. These data sources help identify normal and abnormal patterns in network behavior. The collected data includes packet flows, user access logs, authentication attempts, and system performance metrics, which are crucial for anomaly detection. Data is sourced from multiple cloud-based healthcare systems to capture diverse network activities. The collected dataset is then pre-processed to handle missing values and outliers before feature extraction.

3.2 Data Preprocessing

After data collection, data preprocessing ensures data quality for accurate anomaly detection. KNN imputation is used to handle missing values by estimating them based on similar data points, preserving the dataset's integrity. This prevents data loss and ensures meaningful pattern recognition.

To reduce the impact of extreme outliers, Winsorization is applied by capping values within a specific range. This prevents anomalies from distorting the analysis and ensures the model focuses

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on real threats. With the cleaned data, the next step is feature extraction for improved anomaly detection.

3.3 Feature Extraction

With the pre-processed data, feature extraction is performed to enhance the model's ability to detect anomalies in cloud healthcare networks. Polynomial Feature Expansion is applied to generate higher-order features, capturing complex relationships between network traffic variables. This transformation helps identify non-linear patterns that may indicate potential anomalies. By expanding the feature space, the model gains a deeper understanding of normal and abnormal behaviors, improving detection accuracy. The enriched dataset ensures that subtle deviations in healthcare network activity are effectively recognized. Once feature extraction is complete, the transformed data is fed into the anomaly detection model for analysis.

3.4 Anomaly detection

With the extracted features, the anomaly detection stage identifies unusual patterns in cloud healthcare networks. A Temporal Convolutional Network (TCN) is used to model sequential dependencies in network traffic, enabling the detection of anomalies over time. TCN efficiently processes long-range patterns while maintaining lower computational complexity compared to recurrent models. By analyzing temporal relationships, it distinguishes between normal variations and potential security threats. The model outputs detected anomalies, which are flagged for further investigation. These identified anomalies are then securely stored for compliance and analysis.

TCN uses causal dilated convolutions to capture temporal dependencies while ensuring that future information does not influence past predictions. The output at time step t in layer l is given by equation (1):

$$h_t^{(l)} = f\left(\sum_{i=0}^{k-1} W_i^{(l)} h_{t-d\cdot i}^{(l-1)} + b^{(l)}\right) \quad (1)$$

Where, $h_t^{(l)}$ is the activation at time t in layer l. $W_i^{(l)}$ are the convolution filter weights. d is the dilation factor, controlling the receptive field. k is the kernel size, determining how many past time steps influence the output. $b^{(l)}$ is the bias term. $f(\cdot)$ is a non-linear activation function (e.g., ReLU).

This equation ensures that only past values are used, making TCN suitable for sequential anomaly detection.

The anomaly score is computed as the squared deviation between the actual and predicted values and it's represented by equation (2),

$$S_t = \|x_t - \hat{x}_t\|^2 \quad (2)$$

Where, S_t is the anomaly score at time t. x_t is the actual feature vector at time t. $\hat{x}_t$ is the predicted feature vector at time t. $\|\cdot\|^2$ represents the squared norm (e.g., Euclidean distance).

A higher anomaly score indicates a significant deviation, suggesting an anomaly in healthcare network traffic.

A time step t is classified as an anomaly if the anomaly score exceeds a predefined threshold τ and it's expressed as equation (3),

$$A_t = \begin{cases} 1, & \text{if } S_t > \tau \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Where, $A_t = 1$ means an anomaly is detected at time t. $A_t = 0$ means normal behavior is observed.

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τ is the threshold, which can be determined using statistical methods like percentile-based selection or adaptive learning. This formula helps in real-time anomaly detection by distinguishing between normal and abnormal network behaviors in cloud healthcare environments.

3.5 Cloud Storage

Once anomalies are detected, they are securely stored in cloud storage for further analysis and compliance purposes. The detected anomalies, along with relevant metadata such as timestamps and affected network components, are logged for auditing and forensic investigation. Cloud storage ensures scalability and accessibility, allowing authorized users to retrieve anomaly records when needed. To maintain data integrity and security, access control mechanisms and encryption techniques are applied. Regular backups and redundancy strategies help prevent data loss and ensure reliability. This secure storage approach supports real-time monitoring and enhances threat response in cloud healthcare networks.

4. RESULTS

The results evaluate the performance of the proposed anomaly detection framework in cloud healthcare networks. Various metrics, including system response time and model performance, are analyzed to assess efficiency and accuracy. The following figures highlight the impact of system load on cloud latency and the effectiveness of the Temporal Convolutional Network (TCN) in detecting anomalies.

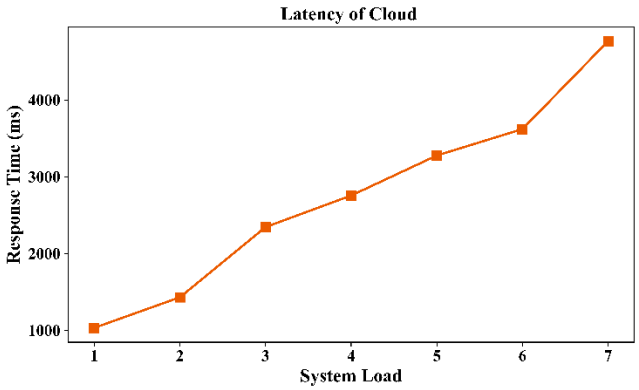

Figure 2: Latency of cloud

Figure 2 illustrates the impact of increasing system load on cloud response time. As system load increases from 1 to 7, the response time rises significantly from 1034 ms to 4767 ms, indicating higher processing delays under heavy workloads. This trend highlights the need for optimized cloud resource management to maintain efficiency. The graph suggests that system latency becomes a concern beyond a certain threshold, potentially affecting anomaly detection performance. Future improvements could involve load balancing techniques to enhance cloud response times.

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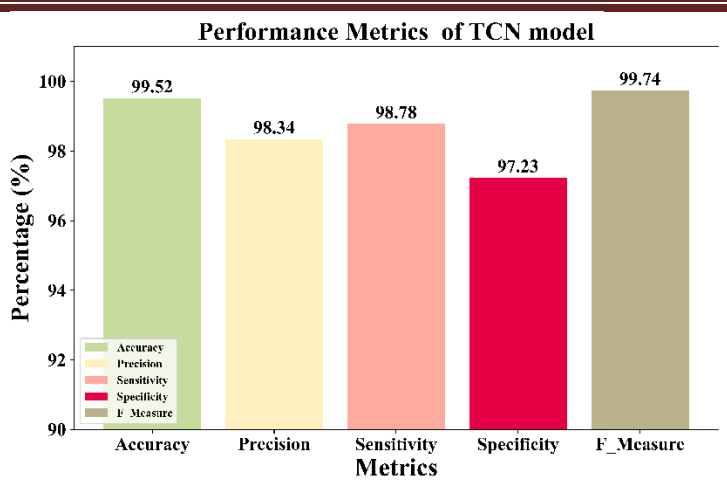

Figure 3: Performance metrics of TCN model

Figure 3 presents the performance metrics of the Temporal Convolutional Network (TCN) model for anomaly detection. The model achieves 99.52% accuracy, demonstrating high reliability in identifying anomalies. Precision and sensitivity are 98.34% and 98.78%, respectively, indicating a strong ability to correctly detect anomalies while minimizing false positives. Specificity is 97.23%, showing the model's capability to correctly classify normal data. The F1-score of 99.74% confirms the balanced performance between precision and recall, highlighting the model's robustness in cloud healthcare anomaly detection.

5.CONCLUSIONS

This paper presented a deep learning-based anomaly detection framework for cloud-based healthcare networks to improve detection accuracy, reduce false positives, and enhance computational efficiency. The proposed approach effectively identifies anomalies in healthcare data by leveraging TCN while ensuring robust preprocessing and feature extraction. Experimental results demonstrate the efficiency of the framework, achieving 99.52% accuracy, 98.34% precision, 98.78% sensitivity, 97.23% specificity, and 99.74% F1-score, significantly outperforming conventional methods. The framework enables efficient handling of missing values through KNN imputation, improved feature extraction via polynomial feature expansion, and precise anomaly detection using TCN, ensuring reliable performance in cloud environments. Additionally, its ability to manage large-scale healthcare data with minimal false positives and reduced detection latency enhances its applicability in real-world scenarios. Future work will focus on Integrating interpretability techniques to help healthcare professionals understand and trust anomaly detection decisions.

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