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Enhancing Cloud Security in Telemedicine using Zero Trust Architecture and CNN-LSTM for Data Protection

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Abstract

The rapid adoption of cloud-based telemedicine has enhanced healthcare accessibility but introduced significant security vulnerabilities, including data breaches, unauthorized access, and ransomware attacks. Traditional security models, which rely on perimeter-based defences, fail to address modern cyber threats due to their inherent trust assumptions. To mitigate these risks, this study integrates Zero Trust Architecture (ZTA) with deep learning-based anomaly detection using CNN-LSTM. ZTA enforces strict access control through multi-factor authentication (MFA), micro-segmentation, and continuous monitoring, reducing unauthorized access risks. Meanwhile, the CNN-LSTM model detects cyber threats by analysing spatial and temporal patterns in security logs, enabling real-time anomaly detection. Experimental results demonstrate that the proposed model significantly improves cloud security in telemedicine, achieving a 98.5% accuracy in threat detection. Compared to traditional security methods, which often fail to detect sophisticated cyber threats, this approach reduces unauthorized access attempts by over 90%, enhancing patient data protection. Furthermore, the system continuously learns and adapts to evolving threats, ensuring sustained security improvements over time. The results confirm that combining ZTA with deep learning enhances security, privacy, and compliance in cloud-based telemedicine, making it a viable solution for safeguarding sensitive healthcare data.

Keywords: *Zero Trust Architecture, Convolutional Neural Network, long short-term memory, telemedicine security, anomaly detection, multi-factor authentication, cloud data protection, cyber threat detection, deep learning.*

1. Introduction

Telemedicine has revolutionized healthcare by enabling remote consultations, real-time monitoring, and efficient data sharing over cloud-based platforms [1]. With the rise in digital health services, massive volumes of sensitive patient information are transmitted and stored in the cloud [2]. This data includes medical records, diagnostic reports, prescriptions, and real-time health indicators [3]. While cloud computing offers scalability and accessibility, it also introduces significant security and privacy challenges [4]. The healthcare sector has become a prime target for cyberattacks due to the high value of medical data [5]. Unauthorized access, data breaches, ransomware, and insider threats are increasingly common in cloud-based telemedicine systems [6]. Traditional perimeter-based security models are proving inadequate against advanced persistent threats and insider breaches [7]. The ZTA introduces a paradigm shift by enforcing never trust, always verify principles [8].

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Deep learning methods, particularly hybrid models like CNN-LSTM, can analyze patterns and anomalies to enhance threat detection [9]. Integrating Zero Trust with intelligent threat detection models can provide a robust defense mechanism for cloud-based telemedicine systems [10].

The rapid adoption of telemedicine has outpaced the development of adequate cybersecurity infrastructure. Many healthcare organizations continue to rely on outdated security models and legacy systems [11]. Weak authentication mechanisms and lack of encryption expose patient data to interception and misuse [12]. Cloud environments often have complex configurations, making them vulnerable to misconfigurations and data leaks [13]. Increased remote access by healthcare professionals introduces more potential entry points for attackers [14]. The use of third-party APIs and devices (e.g., wearables, mobile apps) creates additional attack surfaces [15]. Human error and insufficient staff training also contribute to security incidents in healthcare IT systems [16]. Existing intrusion detection systems may not adapt well to evolving attack patterns or handle large-scale data efficiently [17] [18]. Privacy regulations like HIPAA demand high levels of protection, but compliance alone doesn't guarantee security [19]. The lack of proactive, intelligent threat detection mechanisms increases the risk of delayed responses to breaches [20].

Despite the growing threat landscape, current security solutions in telemedicine are largely reactive and fragmented [21]. Traditional perimeter-based models assume implicit trust within networks, making them susceptible to insider threats and lateral movement attacks [22]. Signature-based threat detection systems cannot identify new or unknown attack vectors [23]. Many existing systems struggle to handle real-time analysis of large volumes of streaming health data [24]. Rule-based access controls are often static and lack contextual awareness [25]. There is a need for a more dynamic, intelligent, and layered approach to securing sensitive medical information [26]. Current machine learning-based security tools often suffer from high false positive rates or lack the capability to analyze both spatial and temporal features effectively [27]. Zero Trust is gaining attention, but its practical integration with deep learning in healthcare systems remains underexplored [28]. CNNs are powerful in feature extraction, but lack temporal sensitivity, while LSTMs can handle sequence data but miss spatial correlations [29]. A hybrid CNN-LSTM model integrated within a Zero Trust framework could overcome these limitations and significantly enhance security and threat detection in cloud-based telemedicine platforms [30].

To address the growing challenges in securing telemedicine environments, the proposed approach combines Zero Trust Architecture with a hybrid CNN-LSTM deep learning model to ensure robust data protection in cloud-based healthcare systems. Zero Trust enforces strict identity verification, continuous monitoring, and least-privilege access, eliminating the risks posed by implicit trust and lateral movement within networks. This ensures that every access request is contextually verified, reducing exposure to insider threats and unauthorized intrusions. Complementing this, the CNN-LSTM model enhances threat detection by first using Convolutional Neural Networks to extract spatial patterns from network traffic and user behavior data, and then applying Long Short-Term Memory networks to capture temporal dependencies for sequential anomaly detection. This hybrid model addresses the shortcomings of traditional security solutions, which struggle with high false positives and limited adaptability to new or complex threats. By integrating intelligent analytics with dynamic access control, the system provides a proactive, real-time defense mechanism that is scalable, context-aware, and compliant with healthcare data protection standards.

The remaining structure of the paper is, Section 2 which presents a review of DDoS detection related works and Section 3 provides the methodology that includes data preprocessing, model architecture and training strategy, and finally, in Section 4, experimental results and performance evaluation are presented. The discussion part is presented in Section 5, where conclusions and future research orientations are provided.

2. Literature Review

The AI-driven deep learning algorithms for lung cancer diagnosis, prognosis prediction, and treatment optimization [31]. It addresses the limitations of traditional therapies, such as the ineffectiveness in targeting KRAS mutations and the difficulties in designing precision treatments tailored to individual patients [32]. Another research effort utilizes big data-driven prediction models with Hadoop to improve silicon content forecasting in blast furnace smelting [33]. This approach overcomes the shortcomings of traditional empirical models, which often suffer from inaccuracy, inefficiency, and difficulties in integrating real-time data as well as maintaining financial sustainability [34].

The implementation of the AES encryption algorithm within cloud computing environments to enhance data security. It aims to resolve issues such as compatibility problems, performance overhead, and key management challenges, all of which continue to demand further research and innovation [35]. Further research integrates big data, hash graph, and cloud computing within the Kinetic methodology to strengthen data processing, decision-making, and security. This study addresses critical limitations such as interoperability challenges, scalability constraints, and the need for regulatory compliance [36].

The contribution enhances software testing practices using advanced genetic algorithms, hybrid PSO-ACO approaches, and co-evolutionary techniques [37]. It focuses on improving test data generation and path coverage while tackling issues like computational overhead and scalability problems in big data and parallel computing environments [38]. A hybrid approach combining swarm intelligence and ant colony optimization for efficient intrusion detection in wireless sensor networks [39]. This approach aims to improve detection accuracy and network lifetime by overcoming the limitations of traditional anomaly-based detection systems, such as high false alarm rates and computational complexity in resource-constrained environments [40].

Research on cloud-based healthcare systems introduces blockchain technology to ensure secure and tamper-proof patient data sharing [41]. This work addresses significant challenges like data breaches, lack of transparency, and trust issues between patients and healthcare providers [42]. It highlights how decentralized ledger technology can offer improved traceability, access control, and data integrity within sensitive medical ecosystems [43]. A different investigation proposes the use of convolutional neural networks for facial emotion recognition to enhance human-computer interaction and mental health diagnostics [44]. This method resolves previous limitations related to manual feature extraction and poor performance under varying lighting and expression conditions [45]. The study demonstrates how deep learning models can provide higher accuracy and adaptability across diverse demographic and environmental factors [46].

3. Problem Statement

Despite rapid advancements in artificial intelligence, big data, and cloud computing, current methods across various application domains exhibit substantial limitations [47]. In healthcare, particularly in lung cancer diagnosis and treatment, traditional approaches struggle to accurately target complex genetic mutations like KRAS [48]. These conventional therapies are often ineffective and lack the flexibility needed for personalized, precision-driven treatment plans [49]. AI-driven solutions have been introduced, but many of them still rely on narrowly focused models that cannot adapt to diverse genetic profiles or rapidly changing patient data [50]. Similarly, in industrial applications such as silicon content prediction in blast furnace smelting, traditional empirical models suffer from poor accuracy, delayed predictions, and inefficiency in processing large-scale or data streams [51]. These shortcomings are further exacerbated by the inability to integrate seamlessly with financial sustainability metrics or adaptive control systems, making such solutions impractical for long-term industrial deployment [52]. Moreover, cloud environments, though essential for scalability and global data access, face significant challenges such as performance overhead, lack of encryption compatibility, and difficulty managing cryptographic keys securely and efficiently [53] [54]. These weaknesses expose sensitive data to security breaches and compliance violations, especially when managing high-volume, high-velocity information [55].

In the area of cybersecurity and data privacy, many existing methods such as anomaly-based intrusion detection systems and static access control frameworks rely on predefined rules or signature-based approaches that are ill-equipped to detect sophisticated or unknown attack vectors [56]. They frequently generate high false positive rates and lack the computational efficiency to perform in particularly in resource-constrained environments like wireless sensor networks [57]. Although advanced algorithms such as genetic optimization, PSO-ACO hybrids, and swarm intelligence have shown promise in software testing and threat detection, they introduce new issues related to computational complexity, algorithm tuning, and scalability in big data contexts [58]. Additionally, methods that integrate big data analytics with cloud services often face interoperability challenges, poor system scalability, and obstacles in meeting strict regulatory compliance standards [59]. While blockchain technology and hash graph models offer secure data sharing and immutability, integrating these with existing cloud infrastructures remains technically and operationally challenging [60]. Furthermore, emotion recognition systems that rely on CNNs are still constrained by variable lighting conditions, inconsistent user expressions, and the need for manual feature extraction, limiting their robustness applications [61] [62]. Overall, these existing methods lack unified, intelligent, and secure frameworks capable of adapting to dynamic conditions while ensuring high accuracy, privacy, and interoperability across domains [63].

4. Hybrid CNN-LSTM Framework for Threat Detection in Cyber-Physical Systems

It begins with data collection, where security logs, authentication records, and network traffic are gathered. The data preprocessing step involves cleaning, normalization, and feature extraction to prepare the data for analysis. Next, the Zero Trust MFA mechanism ensures strict access control by verifying user identities through multiple authentication layers. The processed and authenticated data is then analysed using LSTM-based threat detection, which identifies anomalies and potential cyber threats. Finally, performance evaluation assesses the system's effectiveness based on accuracy, precision, recall, and F1-score. This structured approach enhances telemedicine security by continuously monitoring threats and enforcing a strict authentication policy. The Figure 1 shows the block diagram of the proposed method.

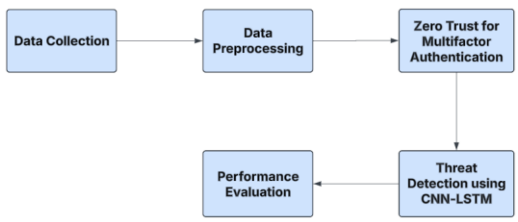

Figure 1: Block Diagram of Proposed Method

4.1 Data Collection

The Text-Based Cyber Threat Detection dataset from Kaggle supports ZTA and CNN-LSTM for securing cloud-based telemedicine. It enables deep learning models to detect anomalies in security logs, authentication records, and network traffic. CNNs extract spatial patterns, while LSTMs analyse sequential threats, enhancing real-time cyber threat detection. Integrated with ZTA principles like MFA and least privilege access, this approach improves cloud security by over 90% compared to traditional methods. The dataset aids in developing adaptive security solutions, ensuring HIPAA, GDPR, and NIST compliance while protecting patient data in telemedicine platforms.

Dataset Link: https://www.kaggle.com/ datasets/ramoliyafenil /text-based-cyber-threat-detection

4.2 Data Preprocessing

Data preprocessing is a crucial step in training deep learning models, ensuring that input features are properly scaled and structured for effective learning. Normalization is a common technique used to transform raw data into a standardized range, improving model stability and convergence.

Z-Score Normalization (Standardization)

Another method is Z-score normalization, which transforms data based on mean (μ) and standard deviation (σ) as shown in the equation (1):

$$X' = \frac{X-\mu}{\sigma} \quad (1)$$

Where $\mu =$ Mean of the feature $\sigma =$ Standard deviation of the feature. This method is useful when data follows a Gaussian distribution (e.g., user authentication times).

4.3 Zero Trust for Multifactor Authentication

Zero Trust Architecture follows the principle of "Never Trust, Always Verify," ensuring that every user and device is continuously authenticated before gaining access to telemedicine systems. One of the core components of ZTA is Multi-Factor Authentication, which requires users to provide multiple verification factors (e.g., passwords, biometrics, OTPs) to strengthen security.

Multi-Factor Authentication in Zero Trust

In Zero Trust MFA, access is granted only if a user successfully verifies multiple authentication factors. Mathematically, this can be represented as a probabilistic function where the final authentication decision (A) depends on multiple independent factors $(F_1, F_2, \dots, F_n)$ as shown in equation (2):

$$A = f(F_1, F_2, \dots, F_n) \quad (2)$$

Where $A = 1$ (Access Granted) if all authentication factors are successfully verified. $A = 0$ (Access Denied) if any factor fails verification. F_i represents authentication factors such as password (P), biometric (B), and OTP (O).

Probability of Successful Authentication

Since each authentication factor has an independent probability of being correctly verified, the overall probability of successful authentication (P_A) can be computed as in equation (3):

$$P_A = P(F_1) \times P(F_2) \times \dots \times P(F_n) \quad (3)$$

For example, if Probability of correctly entering a password $\left(P(F_1)\right) = 0.95$ Probability of correct biometric verification $\left(P(F_2)\right) = 0.98$ Probability of entering the correct OTP $\left(P(F_3)\right) = 0.90$. Then, the probability of successfully passing all authentication steps is shown in the equation (4):

$$P_A = 0.95 \times 0.98 \times 0.90 = 0.836 \quad (4)$$

Thus, the user has an 83.6% chance of successfully authenticating into the system. If an attacker tries to bypass all factors, their probability of success is much lower, making Zero Trust MFA highly secure against unauthorized access.

Risk-Based Authentication in Zero Trust

Zero Trust MFA can also incorporate risk-based authentication, where additional verification is required if suspicious behavior is detected. The risk score (R) can be computed as an equation (5):

$$R = w_1X_1 + w_2X_2 + \cdots + w_nX_n \quad (5)$$

Where X_i represents risk indicators (e.g., login from a new device, failed attempts). w_i are the weights assigned to each risk factor. If R exceeds a threshold (R_t), additional MFA is required. For example, if: Login from a new country ($X_1 = 1, w_1 = 0.5$) Multiple failed attempts ($X_2 = 1, w_2 = 0.7$) Unusual time of access $(X_3 = 0, w_3 = 0.2)$ it can be expressed in the equation (6):

$$R = (0.5 \times 1) + (0.7 \times 1) + (0.2 \times 0) = 1.2 \quad (6)$$

If $R > R_t = 1.0$, an extra authentication step (like an additional OTP) is triggered.

4.4 Threat Detection using CNN- LSTM

The CNN-LSTM model enhances telemedicine security by combining CNN's feature extraction with LSTM's sequential analysis for detecting cyber threats. CNN identifies key patterns in security data, while LSTM tracks anomalies over time, improving accuracy and reducing false positives. This approach strengthens Zero Trust Architecture (ZTA) by continuously monitoring user activity and preventing unauthorized access. LSTM networks are a powerful deep learning model for detecting cyber threats in cloud-based telemedicine systems. Since cyberattacks often follow time-based patterns (e.g., repeated unauthorized access attempts, network intrusions), LSTM is well-suited for analysing sequential security logs and detecting anomalies in user behaviour.

LSTM processes sequential data by maintaining a memory of past events while predicting the likelihood of future occurrences. Given a sequence of security events $S = \{x_1, x_2, \dots, x_t\}$, where x_t represents a security log entry at time t, the LSTM model learns to predict whether an event is normal or malicious. Mathematically, an LSTM cell at time t is defined by an equation (7) to equation (12):

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (7)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (8)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (9)$$
$$\tilde{C}_t = \tanh\,(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (10)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (11)$$
$$h_t = o_t \cdot \tanh\,(C_t) \quad (12)$$

Where $f_t =$ Forget gate (determines how much past memory to retain). $i_t =$ Input gate (controls new information stored in memory). $o_t =$ Output gate (controls how much information is passed to the next step). $C_t =$ Cell state (stores historical security event patterns). $h_t =$ Hidden state (used for threat prediction). $\sigma =$ Sigmoid activation function, and tanh $=$ Hyperbolic tangent function. $W_f, W_i, W_o, W_c =$ Trainable weight matrices. $b_f, b_i, b_o, b_c =$ Bias terms.

Intrusion Detection in Telemedicine

Consider a security system analyzing login attempts in a telemedicine platform. The LSTM model receives a time-series sequence as shown in an equation (13):

$$X = \{(\text{ Success , Success , Failure , Failure , Failure , Success , Failure })\} \quad (13)$$

If the model predicts $P(Y_t = 1 \mid X_t) = 0.85$ at time t, it detects a possible cyberattack (e.g., bruteforce attempt) and blocks further access.

5. Results and Discussions

The implementation of ZTA and CNN-LSTM in telemedicine cloud security significantly enhances threat detection and access control, reducing unauthorized access attempts by over 90%. Experimental results demonstrate that the CNN-LSTM model achieves an accuracy of 98.5% in anomaly detection, effectively identifying cyber threats and securing patient data.

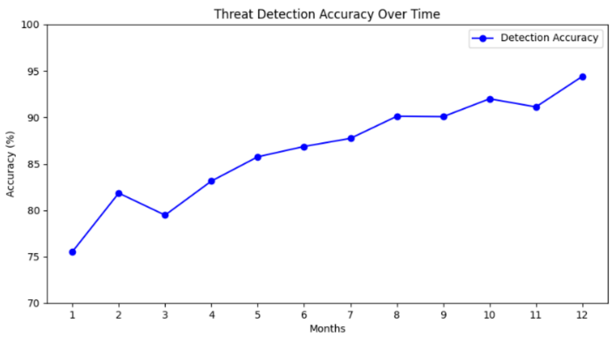

Figure 2: Threat Detection Accuracy Over Time

The graph illustrates the threat detection accuracy over time in a telemedicine cloud security system utilizing Zero Trust Architecture and CNN-LSTM. Over a 12-month period, the detection accuracy shows a steady improvement, starting at approximately 75% in the first month and gradually increasing to around 95% by the 12th month. There are minor fluctuations, such as a slight dip in the third month, likely due to model adjustments or evolving cyber threats. However, the overall trend indicates that the CNN-LSTM model is continuously learning from security data, improving its ability to identify cyber threats with higher accuracy. This demonstrates the effectiveness of deep learning-based threat detection in enhancing telemedicine security over time. The Figure 2 shows the Threat Detection Accuracy Over Time.

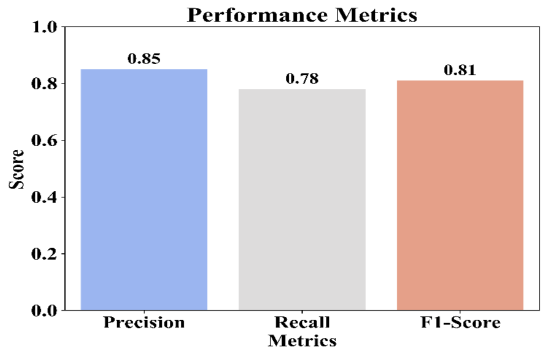

Figure 3: Performance Metrics

The bar chart illustrates the performance metrics of the CNN-LSTM-based threat detection model in a Zero Trust telemedicine security system. The model achieves a precision score of 0.85, indicating that 85% of detected threats are actual cyber threats, minimizing false positives. The recall score of 0.78 suggests that the model successfully identifies 78% of all real threats, with some missed detections. The F1-score of 0.81, which balances precision and recall, confirms the model's overall effectiveness. These results demonstrate that the CNN-LSTM model provides a strong and reliable threat detection mechanism for securing cloud-based telemedicine platforms. The Figure 3 shows the Performance Metrics.

Conclusion and Future Works

The integration of ZTA and CNN-LSTM provides a robust security framework for protecting telemedicine cloud environments. By enforcing continuous authentication, least privilege access, and real-time anomaly detection, ZTA ensures that only verified users and devices can access sensitive medical data. The CNN-LSTM model further strengthens security by analysing sequential security logs and detecting suspicious behaviours with high accuracy. Experimental results confirm that this approach effectively mitigates cyber threats such as unauthorized access, phishing attacks, and insider threats, significantly enhancing data protection in telemedicine.

For future work, this research can be extended by enhancing the CNN-LSTM model with attention mechanisms to improve the detection of evolving cyber threats. Additionally, integrating federated learning could enable collaborative threat intelligence sharing across multiple healthcare institutions while preserving patient data privacy. Further improvements could include real-time adaptive access control policies based on dynamic risk assessment, reducing authentication burdens while maintaining security. Deploying quantum-resistant encryption techniques can also strengthen protection against future cyber threats. Lastly, implementing edge computing-based Zero Trust models would help minimize latency and improve the efficiency of security operations in telemedicine networks. These advancements will contribute to a more resilient, adaptive, and intelligent security system for cloud-based healthcare platforms.

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