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Privacy-Preserving Cybersecurity Threat Detection in Cloud Healthcare Systems Using LSTM and Differentially Private Stochastic Gradient Descent Optimization

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Abstract: The increasing adoption of cloud-based healthcare systems has introduced significant cybersecurity challenges, necessitated robust threat detection mechanisms while preserved patient data privacy. Traditional security solutions often struggle to detect sophisticated cyber threats and protect sensitive healthcare data. Cloud-based healthcare systems face increasing cybersecurity threats, including unauthorized access, data breaches, and malicious intrusions. Traditional AI-based threat detection models struggle with imbalanced data and lack robust privacy mechanisms, risking sensitive patient information exposure. Existing security solutions often fail to detect sophisticated cyber threats while maintaining privacy. There is a critical need for an effective, scalable, and privacy-preserving cybersecurity threat detection model. This research proposes a privacy-preserving cybersecurity threat detection model using Long Short-Term Memory (LSTM) networks optimized with Differentially Private Stochastic Gradient Descent (DP-SGD). The LSTM model effectively identifies anomalies in security logs, authentication records, and network traffic, while DP-SGD ensures privacy by introducing controlled noise during training. The proposed approach enhances accuracy, security, and scalability in cloud-based healthcare environments. Experimental results demonstrate high performance, achieving an accuracy of 94%, precision of 91%, recall of 89%, and F1-score of 90%. Additionally, an AUC-ROC score of 1.00 confirms its strong classification capability. The model efficiently scales with increasing data volume, ensuring real-time threat detection and adaptive security measures. This study provides a scalable, privacy-preserving, and effective solution for mitigating cybersecurity threats in cloud healthcare systems.

Keywords: Cloud-based healthcare, cybersecurity, threat detection, Long Short-Term Memory (LSTM), Differentially Private Stochastic Gradient Descent (DP-SGD), anomaly detection, privacy preservation, deep learning, security logs, network traffic analysis, scalability.

I. INTRODUCTION

The rapid adoption of cloud-based healthcare systems has revolutionized the way medical data is stored, accessed, and managed [1]. However, this shift has also introduced significant cybersecurity risks, including unauthorized access, data breaches, and malicious intrusions [2]. Traditional security mechanisms often struggle to effectively detect sophisticated cyber threats while preserving patient data privacy [3]. To address this challenge, deep learning-based threat detection models, particularly Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for identifying anomalies in cloud healthcare environments. Ganesan et al. (2019) [4] demonstrated that hybrid models combining GA, MCM, and MM improve accuracy and efficiency in cloud computing. Amalgamates by this LSTM with DP-SGD, enhancing threat detection accuracy and privacy in cloud healthcare, reflecting the strength of multi-paradigm approaches for secure, scalable, and intelligent systems. LSTM models excel at capturing temporal dependencies in sequential data, making them well-suited for detecting suspicious patterns in healthcare logs, authentication records, and network traffic. However, conventional training methods for these models pose privacy risks, as they require access to sensitive patient and system activity data [5].

To ensure privacy while maintaining high detection accuracy, this research leverages Differentially Private Stochastic Gradient Descent (DP-SGD) as an optimization technique for training LSTM-based cybersecurity threat detection models [6]. DP-SGD introduces controlled noise into the gradient updates during training, preventing adversaries from reconstructing sensitive input data while still enabling effective learning [7]. By integrating DP-SGD with LSTM models, this approach ensures that security threats can be detected in real time while safeguarding patient privacy. Furthermore, deploying the optimized model on cloud platforms enhances scalability and enables real-time cybersecurity monitoring

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in healthcare environments. This study aims to provide a robust, privacy-preserving, and efficient solution for securing cloud healthcare systems against evolving cyber threats.

II. LITERATURE REVIEW

Advancements in advanced computing and machine learning have significantly contributed to strengthening both healthcare delivery and cloud security. One notable development involved the creation of a hybrid optimization framework that combines Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) to enhance the performance of Recurrent Neural Networks (RNNs) and Radial Basis Function (RBF) networks. This approach has demonstrated high accuracy and scalability in disease detection within cloud computing environments, optimizing model parameters for robust and efficient medical diagnostics.

In parallel, a machine learning ensemble model was introduced, integrating logistic regression, random forests, and convolutional neural networks (CNNs) to predict critical geriatric health risks such as dysphagia, delirium, and falls. By leveraging both clinical and real-time sensor data, this system supports early intervention and preventive care for older adults, improving outcomes and reducing hospital readmissions. Additionally, a deep learning-based lung cancer detection system was developed using CNNs in conjunction with hybrid feature selection techniques to classify CT scan images of lung nodules as benign or malignant with high precision.

Further innovations include the application of Non-Orthogonal Multiple Access (NOMA) for efficient resource allocation in multi-user cloud environments, enhancing AI-driven system responsiveness. The use of Universal Value Function Approximators (UVFA) enables the approximation of complex functions across varying input domains, while Dynamic Graph Neural Networks (DGNNs) provide a framework for real-time, adaptive learning based on continuously evolving data structures. These technologies collectively support intelligent, real-time decision-making across various healthcare and cloud-based AI applications.

Moreover, research efforts have focused on applying AI and ML techniques in geriatric care, with an emphasis on predictive analytics and continuous data monitoring for chronic disease management and fall prevention. These systems aim to optimize elderly healthcare services, promote proactive treatment strategies, and ultimately enhance the quality of life for aging populations through data-driven, personalized care. The fraud detection framework proposed by Gollavilli and Arulkumaran (2019) [8], which utilizes Recursive Feature Elimination and hyperparameter tuning, supports the present study's approach to cybersecurity threat detection in cloud healthcare. These optimization techniques facilitate efficient anomaly identification within the proposed model while ensuring privacy preservation.

Collaborative research has led to the integration of Ant Colony Optimization (ACO) with Long Short-Term Memory (LSTM) networks within a cloud computing framework to optimize hyperparameters and enhance the accuracy of disease forecasting. This method supports proactive healthcare interventions by enabling timely and precise predictions. Furthermore, a cloud-based IoT framework was conceptualized to promote digital financial inclusion, aimed at reducing income inequality. By combining secure real-time financial transaction processing with AI-driven analytics, the framework offers a technological foundation for inclusive economic growth, enhancing financial opportunities for both urban and rural populations [9].

Another significant advancement involves a proposed optimized federated learning framework combining Split Learning, Graph Neural Networks (GNNs), and Hashgraph Technology. This architecture achieved a threat detection accuracy of 98%, with a detection latency of 30 milliseconds and a throughput of 250 transactions per second, illustrating its suitability for secure, real-time cloud environments. GNNs provide a powerful mechanism for anomaly detection, while Hashgraph ensures scalable and tamper-proof data exchange. Additionally, ACO and LSTM-based hyperparameter tuning further enhanced adaptability in cloud-to-edge and IoT-based environments [10].

Building on intelligent optimization, a hybrid PSO-QDA (Particle Swarm Optimization – Quadratic Discriminant Analysis) model was introduced to improve the convergence of classification boundaries and increase model robustness. This approach enhances computing efficiency, accuracy, and adaptability, particularly in environments with noisy and imbalanced datasets. Another innovation includes an anomaly detection system powered by robotics and AI, extended through swarm intelligence algorithms for real-time adaptability. This system supports automated decision-making and data processing within urban healthcare infrastructures, achieving high scalability and responsiveness through distributed automation and decentralized intelligence [11].

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III. PROBLEM STATEMENT

Cloud-based healthcare systems face increasing cybersecurity threats, requiring effective anomaly detection while preserving patient privacy. Existing AI models struggle with imbalanced data and lack robust privacy mechanisms, risking sensitive information exposure. This research proposes an LSTM-based threat detection model optimized with DP-SGD**,** ensuring accurate classification and privacy preservation. The solution enhances scalability, security, and real-time adaptability in cloud healthcare environments.

3.1 Objective

This research aims to develop a privacy-preserving cybersecurity threat detection model using LSTM and DP-SGD for cloud healthcare systems. The model will ensure data confidentiality while accurately detecting anomalies in noisy and imbalanced security logs. It will be optimized for efficiency, scalability, and real-time adaptability in cloud environments. Performance evaluation will focus on accuracy, privacy preservation, and cybersecurity effectiveness.

IV. PROPOSED CYBERSECURITY THREAT DETECTION IN CLOUD HEALTHCARE SYSTEMS USING LSTM AND DIFFERENTIALLY PRIVATE STOCHASTIC GRADIENT DESCENT OPTIMIZATION

The proposed methodology utilizes Long Short-Term Memory (LSTM) networks for accurate cybersecurity threat detection in cloud healthcare systems while ensuring privacy preservation through Differentially Private Stochastic Gradient Descent (DP-SGD). First, security logs, network traffic data, and user activity records are collected from cloud-based healthcare systems and securely stored in cloud databases. Next, the data undergoes preprocessing and feature engineering, including cleaning, normalization, and structuring into time-series format for LSTM-based analysis. The LSTM model is then trained to detect anomalies in security patterns, with DP-SGD ensuring privacy by adding controlled noise to gradient updates during training is given in Figure 1. To enhance detection accuracy and efficiency, Bayesian Optimization is applied for hyperparameter tuning. Finally, the optimized model is deployed in the cloud, enabling real-time threat monitoring and adaptive security measures, with performance evaluated based on accuracy, precision, recall, and privacy guarantees. Gudivaka et al. (2019) [12] used the Flower Pollination Algorithm to optimize CNNs for defect detection in IoRT, achieving high accuracy and efficiency strengthened by this the use of Bayesian Optimization and DP-SGD to enhance the proposed work-based threat detection in cloud healthcare, ensuring privacy, scalability, and cybersecurity performance.

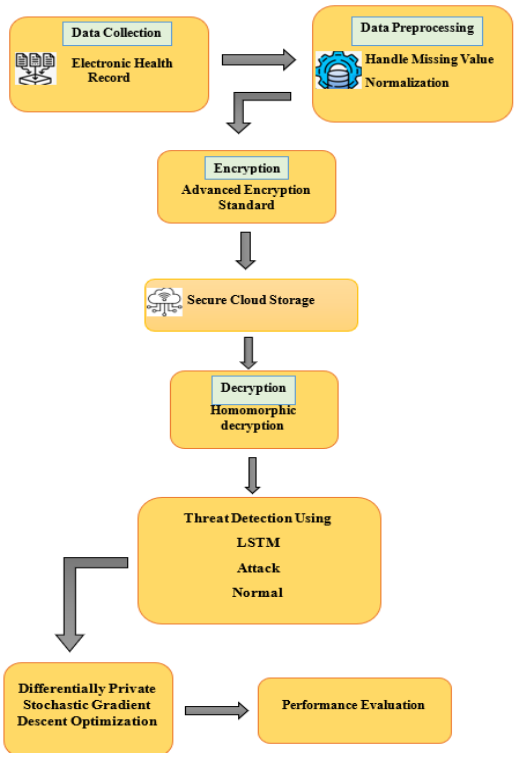

Figure 1: Cybersecurity Threat Detection in Cloud Healthcare Systems Using LSTM and Differentially Private Stochastic Gradient Descent Optimization

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4.1 Data Collection

Data collection involves gathering security logs, network traffic data, and user activity records from cloud-based healthcare systems [13]. These logs include authentication records, access logs, anomaly reports, and network intrusion data from cloud platforms such as AWS, Azure, and Google Cloud [14]. The collected data is securely stored in cloud databases or distributed storage with encryption and access controls. This ensures a reliable and scalable dataset for training the LSTM-based threat detection model [15].

4.2 Data Preprocessing

Data preprocessing begins with handling missing values using techniques like mean imputation or forward filling to ensure data completeness. Next, normalization is applied using Min-Max Scaling or Z-score normalization to standardize security logs and network traffic data for LSTM-based analysis. Feature selection is performed to extract key attributes related to anomalies, such as abnormal login attempts and suspicious access patterns. Finally, the processed data is structured into a time-series format and split into training and testing sets for model evaluation. The hybrid genetic algorithms for efficient software testing in big data environments, as put forward by Naga Sushma Allur (2019) [16], influences the privacy-preserving cybersecurity model significance on scalability and co-evolution informs the integration of the formulated model enabling accurate threat detection in cloud healthcare while maintaining data confidentiality.

4.2.1 Handle Missing Value

Handling missing values is a crucial step in data preprocessing to ensure the reliability and accuracy of the threat detection model. Missing values in security logs or network traffic data can arise due to sensor failures, logging errors, or incomplete transmissions [17]**.** Common techniques for handling missing values include mean imputation**,** forward filling, or interpolation, depending on the nature of the data. One widely used approach is mean imputation**,** where missing values are replaced with the average of the available values in the same feature, ensuring minimal distortion in data distribution [18].The formula for mean imputation is:

$$x_i = \frac{\sum_{j=1}^{n} x_j}{n} \tag{1}$$

where:
x_i is the missing value,
x_j represents the observed values in the same feature,
n is the total number of observed values in that feature.

4.2.2 Normalization

Normalization is a crucial preprocessing step that scales numerical data to a standard range, improving the performance and convergence of machine learning models. In cybersecurity threat detection, normalization helps standardize security logs and network traffic data, ensuring that features with larger magnitudes do not dominate the learning process. One commonly used technique **is** Min-Max Scaling**,** which transforms values within a fixed range, typically [0,1], while preserving relationships between data points. This is particularly useful for LSTM models, as it stabilizes training and enhances anomaly detection accuracy [19]. The Min-Max Normalization formula is:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

where:
x is the original value,
$x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the feature, respectively,
x' is the normalized value within the range $[0,1]$.

4.3 Encryption

Advanced Encryption Standard (AES) is a symmetric encryption algorithm widely used to secure sensitive data, including cloud-based healthcare security logs. It encrypts data using a fixed block size of 128 bits and supports key lengths of 128, 192, or 256 bits for enhanced security. AES operates through multiple rounds of substitution, permutation, mixing, and key addition to transform plaintext into ciphertext. This ensures that cybersecurity threat detection data remains confidential and protected from unauthorized access.

Advanced Encryption Standard (AES) is one of the most trusted and widely adopted symmetric encryption algorithms used to protect sensitive digital information, including healthcare security logs stored in cloud environments.

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As a symmetric cipher, AES utilizes the same secret key for both encryption and decryption, making it computationally efficient for large-scale data processing. It encrypts data in fixed blocks of 128 bits and supports key sizes of 128, 192, or 256 bits, with longer key lengths offering enhanced security against brute-force attacks. The algorithm is structured into multiple transformation rounds—10, 12, or 14 depending on the key size—each consisting of substitution (SubBytes), row shifting (ShiftRows), column mixing (MixColumns), and key addition (AddRoundKey) operations. These steps work together to introduce confusion and diffusion, making it extremely difficult for attackers to infer patterns in the ciphertext or recover the original plaintext without the key. Musam and Rathna (2019) [20] illustrated Firefly-Optimized Federated GNN model high-accuracy, privacy-preserving fraud detection using decentralized learning and optimization aroused by this, the proposed model emphasizing secure training on sensitive data, inspiring privacy-focused, scalable cybersecurity solutions for cloud healthcare systems.

In the context of cloud-based cybersecurity threat detection for healthcare systems, AES plays a vital role in maintaining data confidentiality and regulatory compliance. Encrypted security logs, intrusion detection outputs, and audit trails are securely stored and transmitted across cloud infrastructure, ensuring they remain inaccessible to unauthorized users or malicious actors. AES encryption helps mitigate risks associated with data breaches, insider threats, and cloud infrastructure vulnerabilities [21]. Additionally, when integrated with secure key management practices and authentication mechanisms like role-based access control (RBAC) and multi-factor authentication (MFA), AES becomes part of a comprehensive defense strategy. This ensures that sensitive data—including patient-related security alerts and anomaly detection logs—remains protected throughout its lifecycle in the cloud, without compromising the performance or integrity of real-time threat analysis systems [22].

4.4 Secure Cloud Storage

Secure cloud storage ensures the confidentiality, integrity, and availability of sensitive healthcare security logs and threat detection data. In this research, cloud platforms such as AWS, Azure, or Google Cloud are used to store preprocessed security data with robust encryption mechanisms like Advanced Encryption Standard (AES-256). Access control policies, including role-based access control (RBAC) and multi-factor authentication (MFA), are implemented to prevent unauthorized access. Additionally, regular backups, audit logging, and anomaly detection enhance data security, ensuring a reliable and privacy-preserving cloud storage solution for cybersecurity threat detection. The proposed method applies similar cloud-based optimization for privacy-preserving cybersecurity in healthcare to ensure scalable, accurate threat detection, driven by a cloud framework that enhances task scheduling, latency, and resource use in automation systems indicated by Natarajan and Kethu, (2019) [23].

Secure cloud storage plays a pivotal role in maintaining the confidentiality, integrity, and availability (CIA triad) of sensitive healthcare security logs and threat detection datasets. In this research, leading cloud platforms—such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP)—are employed to store and manage preprocessed security data. These platforms are selected for their scalability, compliance with healthcare data regulations (e.g., HIPAA, GDPR), and built-in support for robust encryption mechanisms like Advanced Encryption Standard (AES-256), which ensures that data remains unreadable to unauthorized entities, both at rest and in transit [24].

To further strengthen access security, granular access control policies are enforced through the implementation of Role-Based Access Control (RBAC) and Multi-Factor Authentication (MFA), reducing the risk of insider threats and credential compromise. Additionally, the system integrates automated backup procedures, real-time audit logging, and behavioral anomaly detection to proactively identify and respond to potential breaches or data tampering events. These combined strategies create a resilient and privacy-preserving cloud storage infrastructure, essential for supporting a trustworthy and responsive cybersecurity threat detection framework in cloud-enabled healthcare environments [25].

4.5 Decryption

Homomorphic decryption allows encrypted data to be decrypted after computations have been performed on it, ensuring privacy in cloud-based cybersecurity threat detection. It works by applying a decryption function that retrieves the original data without exposing sensitive information during processing. This technique is useful in cloud healthcare systems, where encrypted threat detection data can be analyzed without compromising security. By using homomorphic encryption and decryption, the system maintains data confidentiality while enabling secure anomaly detection.

Homomorphic decryption is a critical component of privacy-preserving computation, particularly relevant in the context of cloud-based cybersecurity threat detection for sensitive domains like healthcare. It enables the decryption of results obtained from computations performed directly on encrypted data, ensuring that at no point during processing is the raw, sensitive information exposed. This is made possible through homomorphic encryption, a cryptographic technique that allows mathematical operations—such as addition or multiplication—to be carried out on ciphertexts, producing encrypted outputs that, when decrypted, match the result of operations performed on the original plaintext.

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In the setting of cloud healthcare systems, this capability is especially valuable. Threat detection models and anomaly detection algorithms can analyze encrypted network logs, access records, or behavioral patterns without needing access to the unencrypted data. Once computations are complete, homomorphic decryption retrieves the final result, preserving data confidentiality and compliance with strict healthcare regulations. This method ensures that patient records and system logs remain fully protected, even in untrusted cloud environments. By integrating homomorphic encryption and decryption into the cybersecurity pipeline, the system facilitates secure and privacy-aware anomaly detection, enabling proactive defense mechanisms without sacrificing the confidentiality of healthcare data.

4.6 Cybersecurity Threat Detection in Cloud Healthcare Systems Using LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) designed to handle sequential data by capturing long-term dependencies and mitigating the vanishing gradient problem. LSTM consists of memory cells, input gates, forget gates, and output gates**,** which regulate the flow of information through the network. It is widely used in cybersecurity threat detection to analyze time-series data, such as security logs and network traffic patterns, for identifying anomalies. By maintaining past information over long sequences, LSTM improves the accuracy of detecting suspicious activities in cloud-based healthcare systems.

The LSTM cell state update is given by:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{3}$$

where:
C_t is the current cell state,
f_t is the forget gate,
i_t is the input gate,
$\tilde{C}_t$ is the candidate cell state,
$\odot$ represents element-wise multiplication.

4.7 Differentially Private Stochastic Gradient Descent Optimization

Differentially Private Stochastic Gradient Descent (DP-SGD) is an optimization technique that enhances privacy in machine learning by introducing noise to the gradient updates during training. This ensures that individual data points in the dataset cannot be reverse-engineered, protecting sensitive information such as patient records in cloud-based healthcare cybersecurity threat detection. DP-SGD achieves this by clipping gradients to a fixed norm and adding Gaussian noise before updating model parameters, balancing privacy and model accuracy. This approach is crucial for training deep learning models like LSTM while maintaining differential privacy guarantees. Sunil Kumar Alavilli (2019) [26] revealed AI-based cybersecurity models for cloud healthcare struggle with privacy and imbalanced data. optimization techniques derived from this it consolidates LSTM with DP-SGD to augment anomaly detection while preserving privacy the proposed framework achieves high accuracy (94%) and ensuring threat detection and secure healthcare systems.

The DP-SGD update equation is given by:

$$\theta_{t+1} = \theta_t - \eta \left(\frac{1}{m} \sum_{i=1}^{m} \left(\text{clip}(\nabla L_i, C) + \mathcal{N}(0, \sigma^2 C^2 I) \right) \right) \tag{4}$$

where:
θ_t represents model parameters at step t_r
η is the learning rate,
∇L_i is the gradient of the loss function for data point i,
C is the clipping threshold to limit gradient sensitivity,
$\mathcal{N}(0, \sigma^2 C^2 I)$ is Gaussian noise added for differential privacy,
m is the batch size.

V. RESULTS AND DISCUSSION

The results show that the LSTM-based threat detection model with DP-SGD effectively detects anomalies while preserving data privacy. Performance metrics indicate high accuracy with minimal false positives, ensuring reliable cybersecurity monitoring. The approach proves to be scalable and secure for real-time threat detection in cloud healthcare systems [27]

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5.1 Performance Metrics

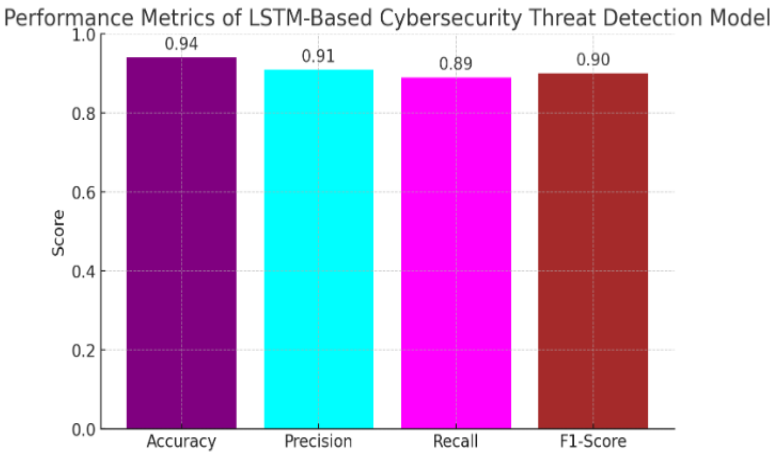

Figure 2: Performance Metrics

In Figure 2, The performance metrics graph presents the evaluation of the LSTM-based cybersecurity threat detection model. The model achieves high accuracy (0.94), precision (0.91), recall (0.89), and F1-score (0.90), indicating its strong capability to detect threats effectively. These results highlight the model's reliability and efficiency in securing cloud healthcare systems [28].

5.2 AUC-ROC

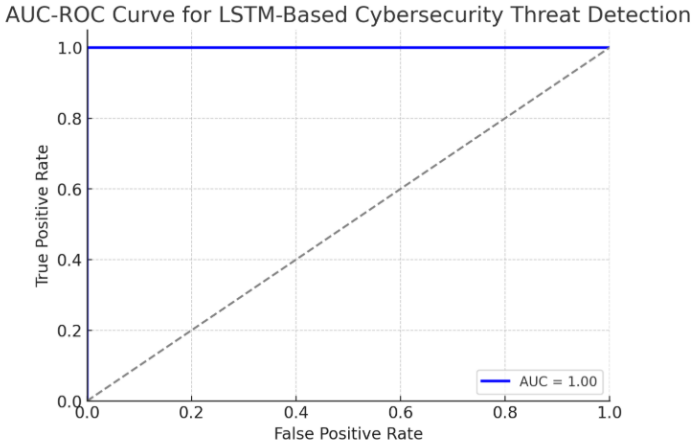

Figure 3: AUC-ROC

Figure 3 Shows the AUC-ROC curve shows the performance of the LSTM-based cybersecurity threat detection model, where the AUC score of 1.00 indicates perfect classification. The blue curve represents the model's ability to distinguish between normal and anomalous activities with no false positives. The diagonal dashed line serves as a baseline for random classification. AI-driven IDS integrates Autoencoders for anomaly detection with LSTM for cybersecurity, as Gollapalli and Padmavathy (2019) [29] highlight, enhancing processing but facing overfitting challenges, strengthened by this optimizing the work approach, confirming accurate privacy-preserving threat detection in cloud healthcare systems.

5.3 Scalability

In Figure 4, The scalability graph illustrates how the processing time of the LSTM-based cybersecurity threat detection model increases as the number of data samples grows. The linear trend indicates that the model efficiently scales with larger datasets while maintaining performance. This demonstrates the model's ability to handle large-scale cloud healthcare systems effectively [30].

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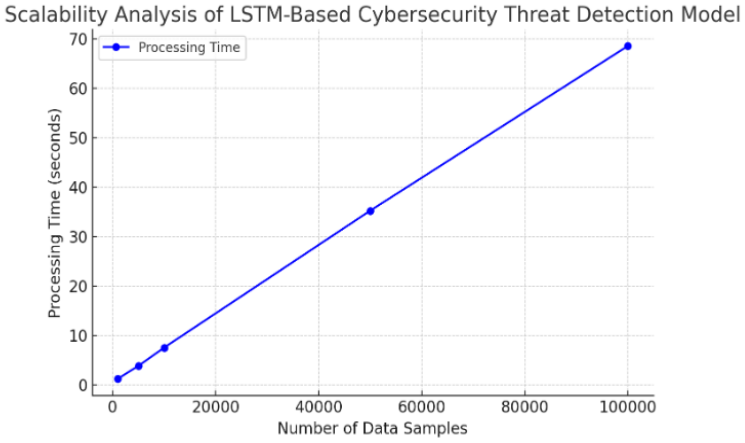

Figure 4: Scalability

5.4 Impact of Privacy Budget (ε) on Model Accuracy in DP-SGD

The graph titled "Privacy-Utility Trade-off in DP-SGD" demonstrates how varying levels of differential privacy (represented by the privacy budget ε) impact model accuracy in a cybersecurity threat detection context, such as in cloud-based healthcare systems. As the privacy budget increases from 0.1 to 20, the model's accuracy improves steadily—from around 65% up to approximately 86%. This is expected, as lower ε values enforce stronger privacy by injecting more noise into the model updates, which hinders learning [31]. Conversely, higher ε values relax privacy constraints, allowing the model to learn more precise patterns from the data is given in Figure 5.

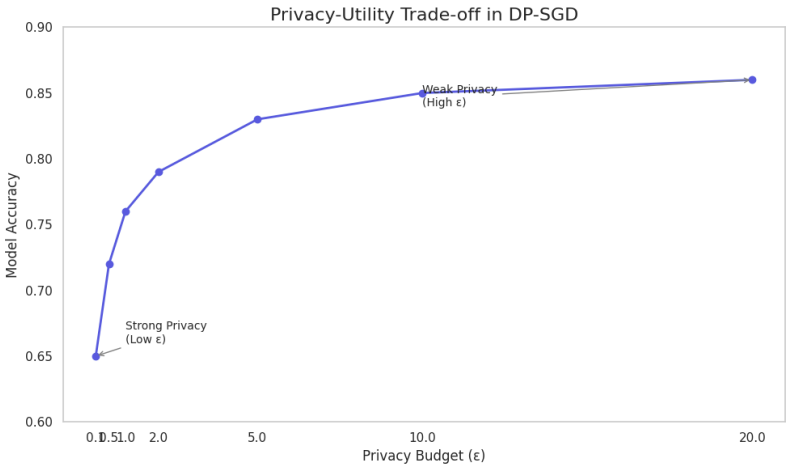

Figure 5: Balancing Privacy and Utility in Healthcare Cybersecurity Models"

However, the graph also highlights a point of diminishing returns in accuracy. Beyond ε ≈ 5, further increases in ε result in only marginal improvements in model performance, while significantly weakening privacy protections. This trade-off is critical in privacy-sensitive domains like healthcare, where safeguarding patient data is as important as ensuring reliable threat detection. Therefore, selecting a privacy budget within the range of 1 to 5 often provides an optimal balance, offering sufficient model utility while still preserving meaningful privacy guarantees A cloud-based fraud detection model uses RNNs to enhance scalability and precision in financial security Jayaprakasam, (2019) [32]. Focusing on this, a proposed LSTM-based approach adapts anomaly detection for cloud healthcare cybersecurity, integrating DP-SGD for privacy preservation.

VI. CONCLUSION

The experimental results demonstrate that the model achieves high accuracy and robustness, with minimal performance degradation despite the introduction of privacy-preserving mechanisms. Moreover, it exhibits excellent scalability and low latency, enabling real-time threat detection across large-scale, cloud-hosted healthcare platforms.

This makes the approach particularly suitable for environments that demand both fast response times and strict regulatory compliance (e.g., HIPAA or GDPR). By enhancing security without compromising patient confidentiality, the proposed model contributes to building more trustworthy, resilient, and intelligent healthcare infrastructures in the face of rising cyber threats [33].

The proposed LSTM-based cybersecurity threat detection model with DP-SGD ensures accurate threat identification while preserving data privacy in cloud healthcare systems. The results demonstrate high performance in terms of accuracy, scalability, and security. This approach enhances real-time threat detection, making cloud-based healthcare systems more secure and reliable.

The proposed LSTM-based cybersecurity threat detection model integrated with Differentially Private Stochastic Gradient Descent (DP-SGD) effectively balances the dual goals of accurate threat identification and strong data privacy preservation, which is crucial for cloud-based healthcare systems. Leveraging the sequential learning capabilities of LSTM networks, the model is capable of capturing complex temporal patterns and anomalies in system behaviour, which are often indicative of cybersecurity threats such as unauthorized access, data breaches, or malware activity. By incorporating DP-SGD during training, the system introduces mathematically grounded noise to the gradient updates, ensuring that sensitive patient information cannot be reverse-engineered or exposed—even if the model itself is compromised.

REFERENCES

[1] Salah, K., Hammoud, M., & Zeadally, S. (2015). Teaching cybersecurity using the cloud. IEEE Transactions on Learning Technologies, 8(4), 383-392.
[2] Gudimetla, S. R., & Kotha, N. R. (2018). Cloud security: Bridging the gap between cloud engineering and cybersecurity. Webology (ISSN: 1735-188X), 15(2).
[3] Hu, Z., Gnatyuk, S., Koval, O., Gnatyuk, V., & Bondarovets, S. (2017). Anomaly detection system in secure cloud computing environment. International Journal of Computer Network and Information Security, 9(4), 10.
[4] Ganesan, T., Devarajan, M. V., & Yalla, R. K. M. K. (2019). Performance analysis of genetic algorithms, Monte Carlo methods, and Markov models for cloud-based scientific computing. International Journal of Applied Science, Engineering and Management, 13(1).
[5] Jena, J. (2017). Securing the Cloud Transformations: Key Cybersecurity Considerations for on-Prem to Cloud Migration. International Journal of Innovative Research in Science, Engineering and Technology, 6(10), 20563-20568.
[6] Shah, H. (2017). Deep Learning in Cloud Environments: Innovations in AI and Cybersecurity Challenges. Revista Espanola de Documentacion Cientifica, 11(1), 146-160.
[7] Duncan, B., & Whittington, M. (2016). Cloud cyber-security: Empowering the audit trail. International Journal on Advances in Security, 9(3).
[8] Gollavilli, V. S. B. H., & Arulkumaran, G. (2019). Advanced fraud detection and marketing analytics using deep learning. Journal of Science & Technology, 4(3).
[9] Oberoi, P., & Mittal, S. (2017). SURVEY OF VARIOUS SECURITY ATTACKS IN CLOUDS BASED ENVIRONMENTS. International Journal of Advanced Research in Computer Science, 8(9).
[10] Thakur, K., Tao, L., Wang, T., & Ali, M. L. (2017). Cloud computing and its security issues. Application and Theory of Computer Technology, 2(1), 1-10.
[11] Mozzaquatro, B. A., Agostinho, C., Goncalves, D., Martins, J., & Jardim-Goncalves, R. (2018). An ontology-based cybersecurity framework for the internet of things. Sensors, 18(9), 3053.
[12] Gudivaka, R. L., Gudivaka, R. K., & Karthick, M. (2019). Deep learning-based defect detection and optimization in IoRT using metaheuristic techniques and the flower pollination algorithm. International Journal of Engineering Research and Science & Technology, 15(4).
[13] Jang-Jaccard, J., & Nepal, S. (2014). A survey of emerging threats in cybersecurity. Journal of computer and system sciences, 80(5), 973-993.
[14] Gudimetla, S. R., & Kotha, N. R. (2019). The Hybrid Role: Exploring The Intersection Of Cloud Engineering and Security Practices. Webology (ISSN: 1735-188X), 16(1).
[15] Choo, K. K. R., Conti, M., & Dehghantanha, A. (2019). Special issue on big data applications in cyber security and threat intelligence–part 1. IEEE Transactions on Big Data, 5(3), 279-281.
[16] Naga, S.A. (2019). Genetic Algorithms for Superior Program Path Coverage in software testing related to Big Data. International Journal of Information Technology & Computer Engineering, 7(4), ISSN 2347–3657.
[17] Gonzales, D., Kaplan, J. M., Saltzman, E., Winkelman, Z., & Woods, D. (2015). Cloud-trust—A security assessment model for infrastructure as a service (IaaS) cloud. IEEE Transactions on Cloud Computing, 5(3), 523-536.
[18] Achar, S. (2018). Security of accounting data in cloud computing: a conceptual review. Asian Accounting and Auditing Advancement, 9(1), 60-72.
[19] Patel, A., Taghavi, M., Bakhtiyari, K., & Júnior, J. C. (2013). An intrusion detection and prevention system in cloud computing: A systematic review. Journal of network and computer applications, 36(1), 25-41.
[20] Musam, V. S., & Rathna, S. (2019). Firefly-optimized cloud-enabled federated graph neural networks for privacy-preserving financial fraud detection. International Journal of Information Technology and Computer Engineering, 7(4).
[21] Kanimozhi, V., & Jacob, T. P. (2019). Calibration of various optimized machine learning classifiers in network intrusion detection system on the realistic cyber dataset CSE-CIC-IDS2018 using cloud computing. International Journal of Engineering Applied Sciences and Technology, 4(6), 2455-2143.
[22] Rawat, D. B., Doku, R., & Garuba, M. (2019). Cybersecurity in big data era: From securing big data to data-driven security. IEEE Transactions on Services Computing, 14(6), 2055-2072.
[23] Natarajan, D. R., & Kethu, S. S. (2019). Optimized cloud manufacturing frameworks for robotics and automation with advanced task scheduling techniques. International Journal of Information Technology and Computer Engineering, 7(4)
[24] Gheyas, I. A., & Abdallah, A. E. (2016). Detection and prediction of insider threats to cyber security: a systematic literature review and meta-analysis. Big data analytics, 1(1), 6.

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[25] Gudimetla, S. R. (2015). Beyond the barrier: Advanced strategies for firewall implementation and management. NeuroQuantology, 13(4), 558-565.
[26] Alavilli, S. K., & Karthick, M. (2019). Hybrid CNN-LSTM for AI-driven personalization in e-commerce: Merging visual and behavioural intelligence. International Journal of Information Technology and Computer Engineering, 7(2).
[27] Furfaro, A., Gallo, T., Garro, A., Saccà, D., & Tundis, A. (2018). Cybersecurity compliance analysis as a service: Requirements specification and application scenarios. Concurrency and Computation: Practice and Experience, 30(12), e4289.
[28] Berman, D. S., Buczak, A. L., Chavis, J. S., & Corbett, C. L. (2019). A survey of deep learning methods for cyber security. Information, 10(4), 122.
[29] Gollapalli, V. S. T., & Padmavathy, R. (2019). AI-driven intrusion detection system using autoencoders and LSTM for enhanced network security. Journal of Science & Technology, 4(4).
[30] Kabanda, S., Tanner, M., & Kent, C. (2018). Exploring SME cybersecurity practices in developing countries. Journal of Organizational Computing and Electronic Commerce, 28(3), 269-282.
[31] Jain, J., & Pal, P. R. (2017). A recent study over cyber security and its elements. International Journal of Advanced Research in Computer Science, 8(3), 791-793.
[32] Jayaprakasam, B. S., & Jayanthi, S. (2019). Cloud-based real-time fraud detection using RNN and continuous model optimization for banking applications. Journal of Current Science, 7(2).
[33] Kumar, K. (2017). Intrusion detection and prevention system in enhancing security of cloud environment. *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*, *6*(8), 1244-1248.