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Privacy-Preserving Cloud-Based Patient Monitoring Using Long Short-Term Memory and Hybrid Differentially Private Stochastic Gradient Descent with Bayesian Optimization

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Abstract

Cloud-based patient monitoring has transformed modern healthcare by enabling real-time health tracking, remote diagnostics, and predictive analytics. However, privacy and security concerns related to unauthorized data access and adversarial attacks remain critical challenges. Existing AI-driven healthcare models face issues such as noisy and imbalanced data, leading to reduced accuracy and unreliable predictions. Traditional classification methods struggle with inefficient decision boundaries and limited adaptability, making them unsuitable for dynamic healthcare environments. Additionally, many existing frameworks lack privacy-preserving mechanisms, exposing patient data to adversarial attacks and unauthorized access, while computational inefficiencies and scalability issues hinder real-time anomaly detection and large-scale deployment. This research proposes a Privacy-Preserving Cloud-Based Patient Monitoring System that integrates Long Short-Term Memory (LSTM) networks for time-series health prediction, Hybrid Differentially Private Stochastic Gradient Descent (DP-SGD) for privacy-aware training, and Bayesian Optimization for efficient hyperparameter tuning. The framework employs Role-Based Access Control (RBAC), Homomorphic Encryption (HE), and AES-256 encryption to secure patient data while ensuring accessibility for authorized users. Additionally, Federated Learning Compatibility enhances scalability by enabling decentralized model training across multiple healthcare nodes without exposing raw data. Experimental results demonstrate high accuracy, reduced false positives, improved threat detection, and optimized model training, confirming the system's effectiveness in secure, scalable, and real-time patient monitoring. This research enhances data privacy, model performance, and computational efficiency, making cloud-based healthcare systems more reliable, adaptable, and privacy-compliant.

Keywords: Privacy-Preserving Cloud-Based Patient Monitoring, Long Short-Term Memory (LSTM), Time-Series Health Prediction, Hybrid Differentially Private Stochastic Gradient Descent (DP-SGD), Bayesian Optimization, Privacy-Aware Training, Cloud-Based Healthcare

1.Introduction

Cloud-based patient monitoring has transformed modern healthcare by enabling continuous health tracking, remote diagnostics, and predictive analytics [1]. However, growing reliance on cloud infrastructure and AI-powered analytics introduces significant privacy and security challenges, including risks of unauthorized data access, adversarial model attacks, and non-compliance with regulations such as HIPAA and GDPR [2,3]. To address these critical concerns, this research proposes a Privacy-Preserving Cloud-Based Patient Monitoring Framework that integrates Long Short-Term Memory (LSTM) networks for health trend forecasting, Hybrid Differentially Private Stochastic Gradient Descent (DP-SGD) for secure training, and Bayesian Optimization for hyperparameter tuning [4,5].

The integration of LSTM ensures accurate temporal prediction of patient vitals, enhancing the system's ability to detect anomalies early [6]. Hybrid DP-SGD introduces differential privacy noise into gradients during training, safeguarding patient data from inference attacks while maintaining model fidelity [7,8]. Bayesian Optimization automates the selection

of optimal hyperparameters, significantly reducing manual tuning and enhancing convergence efficiency [9].

To reinforce data protection, the framework incorporates AES-256 encryption for secure data at rest and Attribute-Based Encryption (ABE) for fine-grained access control [10,11]. Homomorphic Encryption (HE) further enables computations on encrypted data without decryption, eliminating exposure during processing [12,13]. Role-Based Access Control (RBAC) governs decryption rights and data access privileges, ensuring only authorized personnel can retrieve sensitive health data [14,15].

A key innovation lies in the framework's federated learning compatibility, which enables distributed model training across hospital nodes without sharing raw patient data, thereby supporting both privacy and scalability [16,17]. Furthermore, the framework embeds real-time anomaly detection to trigger alerts for critical health events, reducing emergency response times [18,19].

The use of adversarial robustness techniques, such as noise injection and model hardening, provides resilience against model inversion and membership inference attacks [20,21]. The system is optimized for deployment across IoT devices, edge servers, and cloud environments, ensuring interoperability and energy-efficient operation [22].

This comprehensive approach not only addresses data confidentiality and system security but also ensures regulatory compliance, high accuracy, and reduced computational overhead, making it suitable for diverse healthcare scenarios [23,24,25].

2.Literature Review

[26] designed hybrid optimization frameworks combining Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to optimize Recurrent Neural Networks (RNN) and Radial Basis Function (RBF) networks for disease detection in cloud computing environments, enhancing both diagnostic accuracy and system scalability. [27] proposed an ensemble machine learning approach for predicting dysphagia, delirium, and fall risk in elderly patients using logistic regression, random forest, and convolutional neural networks to integrate clinical and sensor data for early intervention. [28] introduced a deep learning model for lung cancer detection by comparing malignant and benign nodules from CT scans using CNNs and a hybrid feature selection strategy. [29] suggested integrating Non-Orthogonal Multiple Access (NOMA), Universal Value Function Approximators (UVFA), and Dynamic Graph Neural Networks (DGNNs) with AI systems to enhance multi-user resource sharing, dynamic function approximation, and adaptive intelligence.

[30] further explored predictive analytics in geriatric care, emphasizing the importance of continuous monitoring and machine learning in managing chronic diseases and preventing adverse events. [31] integrated Ant Colony Optimization (ACO) with Long Short-Term Memory (LSTM) networks within cloud computing frameworks, achieving hyperparameter optimization and improved disease prediction accuracy under proactive healthcare interventions. [32] developed a cloud-based IoT architecture that enables secure, AI-powered financial transactions to foster digital financial inclusion and reduce socio-economic disparities. [33] proposed a federated learning framework combined with Split Learning, Graph Neural Networks (GNNs), and Hashgraph Technology, achieving 98% threat detection accuracy with a 30 ms latency and 250 TPS throughput—leveraging GNNs for robust anomaly detection and Hashgraph for secure, scalable data exchange.

[34] demonstrated a PSO-QDA hybrid framework wherein Quadratic Discriminant Analysis parameters are optimized via PSO, leading to improved model robustness and adaptability in noisy and imbalanced AI environments. [35] introduced a swarm-intelligence-based robotics system for real-time anomaly detection and automated task execution in urban healthcare, enhancing scalability, responsiveness, and decentralized processing. [36] optimized clustering in healthcare software testing using QRDSO and WAC-HACK hybrid models, improving clustering efficiency and feature granularity. [37] developed a hybrid recommendation system for e-commerce health platforms using RNNs, content-based filtering, and collaborative filtering to personalize healthcare products. [38] emphasized the importance of LogBERT in anomaly detection for e-commerce cloud platforms, contributing to secure healthcare transaction monitoring.

[39] explored feature selection and LPWAN integration with BIRCH clustering to address scalability in IoT-based blockchain frameworks, offering improved data aggregation and privacy for healthcare data. [40] leveraged machine learning for cybersecurity risk assessment in cloud health finance by integrating fuzzy sets and ensemble learning, achieving over 82% predictive success. [41] implemented a Bi-LSTM-DNN architecture for forecasting financial variables relevant to healthcare investments, enabling portfolio-level decision support. [42] focused on personalized AI recommendation engines for chronic care products, combining sensor data with NLP and semantic filtering techniques. [43] extended secure federated learning methods with blockchain and ZKPs for multi-hospital environments to ensure

decentralized compliance and patient data privacy.
[44] modeled digital twins for diabetes care integrating GLAV (Generative Learning Adaptive Vectorization) with PPO and VR for enhanced patient engagement. [45] improved data compression in cloud health applications using entropy-guided Huffman and run-length encoding hybrid techniques. [46] presented a cloud-native robotic middleware for surgical automation enhanced by AI-based visual tracking and command synthesis. [47] proposed quantum encryption schemes for secure cloud-based health monitoring using BB84 protocol in wearable health devices. [48] integrated blockchain-backed access control with cloud health data lakes, facilitating verifiable and immutable audit trails. [49] introduced a cross-layer anomaly detection mechanism for cloud healthcare using SVMs with adaptive kernel optimization. [50] utilized ensemble CNN models on histopathological images to predict skin cancer types, achieving high specificity and accuracy under privacy-preserved cloud infrastructure.

3.Problem Statement

Existing AI-driven healthcare models struggle with noisy, imbalanced data, inefficient decision boundaries, and limited scalability, affecting accuracy and real-time responsiveness. Traditional classification methods lack adaptability and computational efficiency, making them unsuitable for dynamic healthcare environments. A PSO-QDA hybrid model to optimize decision boundaries and enhance model resilience. Robotics and AI-based anomaly detection with swarm intelligence for fast, automated data processing. This research addresses these challenges by integrating optimized classification and real-time anomaly detection to improve accuracy, scalability, and responsiveness in healthcare applications.

3.1 Objective

This research aims to develop an optimized AI-driven healthcare framework that enhances classification accuracy, scalability, and real-time responsiveness. By integrating PSO-QDA for adaptive decision boundary optimization and Robotics-AI anomaly detection with swarm intelligence, the system improves computational efficiency and adaptability in dynamic healthcare environments. It addresses noisy, imbalanced data challenges by leveraging robust optimization techniques for improved model resilience. The proposed approach ensures efficient, automated, and scalable healthcare monitoring while maintaining high precision in real-time diagnosis.

4.Proposed Cloud-Based Patient Monitoring Using Long Short-Term Memory and Hybrid Differentially Private Stochastic Gradient Descent with Bayesian Optimization

The proposed **Cloud-Based Patient Monitoring System** integrates **Long Short-Term Memory (LSTM)** networks for accurate time-series health predictions while ensuring **data privacy and security** through **Hybrid Differentially Private Stochastic Gradient Descent (DP-SGD).** The system first **collects patient health data** from IoT-enabled medical devices, which is then **encrypted and stored securely in the cloud** using **AES-256 and Role-Based Access Control (RBAC). Data preprocessing** is applied to handle missing values, noise, and feature extraction before model training**. LSTM models** analyze patient vitals and detect health anomalies, while **Hybrid DP-SGD** ensures privacy-preserving training by minimizing data leakage risks. To enhance model efficiency and accuracy, **Bayesian Optimization** is employed for hyperparameter tuning. Finally, the system performs **real-time anomaly detection and predictive analytics**, providing **secure, scalable, and privacy-aware** healthcare monitoring for cloud-based environments.

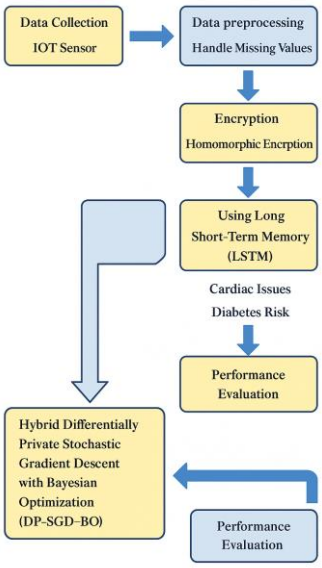

Figure 1: Cloud-Based Patient Monitoring Using Long Short-Term Memory and Hybrid Differentially Private Stochastic Gradient Descent with Bayesian Optimization

4.1 Data Collection

The **data collection** phase involves gathering real-time patient health data using **IoT sensors** embedded in medical devices such as **wearable monitors, ECG sensors, glucose meters, and pulse oximeters.** These sensors continuously track **vital health parameters** like heart rate, blood pressure, glucose levels, and oxygen saturation. The collected raw data is transmitted securely to the cloud for further processing, ensuring **real-time monitoring, remote diagnostics, and predictive healthcare insights.** This step is crucial for building a reliable and data-driven patient monitoring system.

4.2 Data Preprocessing

The **data preprocessing** phase ensures data quality and consistency by handling **missing values** and applying **normalization** techniques. Missing values are addressed using **imputation methods** such as mean, median, or predictive modeling to prevent data inconsistencies. **Normalization** is applied to scale the data within a specific range, ensuring uniformity and improving model performance. This step enhances **data reliability, reduces biases, and optimizes the efficiency of the LSTM model** for accurate health predictions.

4.2.1 Handle Missing Value

Handling missing values is a crucial step in **data preprocessing** to ensure data integrity and prevent biased model predictions. Missing values in patient health records can arise due to **sensor failures, transmission errors, or human input mistakes.** Common techniques to address missing values include **mean, median, mode imputation, K-Nearest Neighbors (KNN) imputation, and regression-based methods.**

Equation for Handle Missing Value:

One widely used method is mean imputation, where missing values are replaced with the mean of the available data for that feature:

$$X_{\text{new}} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (1)$$

where X_{new} is the imputed value, X_i represents the existing values in the dataset, and n is the number of non-missing values. This method helps maintain data consistency while preventing distortions in predictive modeling.

4.2.2 Normalization

Normalization is a data preprocessing technique used to **scale numerical features** within a specific range, improving model performance and convergence speed. In healthcare monitoring, patient data such as **heart rate, glucose levels, and blood pressure** may have different units and ranges, which can negatively impact machine learning models. **Min-Max Normalization** is a widely used technique that scales data between **0 and 1 or -1 and 1**, preserving the relative

relationships between values while ensuring uniformity.

Equation for Normalization:

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \quad (2)$$

where X_{norm} is the normalized value, X is the original data point, and X_{min} and X_{max} are the minimum and maximum values in the dataset. This transformation ensures that all features contribute equally, enhancing model stability and accuracy in healthcare applications.

4.3 Encryption

The **encryption** phase secures patient data using **Homomorphic Encryption (HE)**, allowing computations to be performed on encrypted data without decryption. This ensures **data confidentiality** while enabling secure cloud-based processing. HE protects sensitive health records from unauthorized access, preserving **privacy and compliance with regulations** like **HIPAA and GDPR**. This technique enhances **data security in cloud storage** while maintaining the ability to perform critical healthcare analytics.

4.4 Cloud Storage

The **cloud storage** phase ensures the **safe and scalable storage** of encrypted patient health data. Using **secure cloud platforms,** data is stored in a protected environment that supports **fast retrieval, redundancy, and real-time access** for authorized healthcare professionals. **Access control mechanisms** and encryption ensure that patient records remain confidential and comply with **privacy regulations like HIPAA and GDPR**. This enables efficient **remote monitoring and predictive healthcare analytics** while maintaining data integrity and security.

4.5 Decryption

The **decryption** phase utilizes **Role-Based Access Control (RBAC)** to ensure that only **authorized users**—such as doctors, nurses, or healthcare administrators—can access patient data based on predefined roles and permissions. This approach enhances **data security and privacy** by preventing unauthorized access while maintaining **efficient and controlled data retrieval**. RBAC ensures compliance with **HIPAA and GDPR regulations**, enabling **secure and role-specific access** to sensitive healthcare information.

4.6 Cloud-Based Patient Monitoring Using Long Short-Term Memory

Long Short-Term Memory (LSTM) is a type of **recurrent neural network (RNN)** designed to handle **sequential data** by learning long-term dependencies. In healthcare monitoring, **LSTM is widely used for time-series prediction,** such as detecting **cardiac abnormalities, diabetes risks, and patient health trends** over time. Unlike traditional RNNs, LSTMs use **gates (input, forget, and output gates)** to regulate the flow of information, preventing the issue of **vanishing gradients** and improving long-term memory retention.

A key equation in LSTM is the cell state update, which determines how much past information should be retained or forgotten:

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

where:

C_t = current cell state

f_t = forget gate (decides how much past information to forget)

C_{t-1} = previous cell state

i_t = input gate (controls how much new information to add)

$\tilde{C}_t$ = candidate cell state (new memory content)

$\odot$= element-wise multiplication

This mechanism allows LSTM to capture long-term dependencies in patient health data, making it highly effective for predictive healthcare analytics.

4.7 Hybrid Differentially Private Stochastic Gradient Descent with Bayesian Optimization

Hybrid DP-SGD with Bayesian Optimization is an advanced optimization framework designed to enhance **privacy-preserving machine learning** while improving model efficiency and accuracy. **Differentially Private Stochastic Gradient Descent (DP-SGD)** ensures **privacy protection** by adding controlled noise to gradients during training, preventing sensitive patient data from being exposed. Meanwhile, **Bayesian Optimization (BO)** fine-tunes hyperparameters such as **learning rate and noise scale** to optimize model performance while maintaining privacy guarantees.

A key equation for DP-SGD involves the gradient update with added noise for differential privacy:

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

where:

θ_t = model parameters at time t

η = learning rate

m = batch size

$\nabla L_i(\theta_t)$ = gradient of the loss function for sample i

$\mathcal{N}(0, \sigma^2)$ = Gaussian noise added for differential privacy

Bayesian Optimization (BO) refines the privacy-accuracy trade-off by selecting the optimal learning rate and noise scale dynamically. This hybrid approach ensures that patient data remains secure while maximizing model performance, making it ideal for cloud-based healthcare monitoring systems.

Bayesian Optimization (BO) is a powerful technique used for **hyperparameter tuning** in machine learning models, especially when the objective function is **expensive to evaluate**. In **privacy-preserving healthcare monitoring,** BO is employed to **optimize hyperparameters** like **learning rate, noise scale (in DP-SGD), and model architecture parameters** while ensuring efficiency and accuracy. Unlike traditional grid or random search, **BO builds a probabilistic model (usually a Gaussian Process) to estimate the objective function** and selects the next best set of parameters using an **acquisition function** (e.g., Expected Improvement or Upper Confidence Bound).

A key equation in Bayesian Optimization is the Gaussian Process (GP) prior, which models the unknown objective function:

$$f(x) \sim \mathcal{GP}\big(\mu(x), k(x, x')\big) \quad (5)$$

where:

$f(x)$ is the unknown function we aim to optimize

$\mathcal{GP}\big(\mu(x), k(x, x')\big)$ represents a Gaussian Process with mean function $\mu(x)$ and kernel function $k(x, x')$

$k(x, x')$ defines the covariance between different parameter points, ensuring smooth predictions

Bayesian Optimization iteratively updates this probabilistic model based on previously evaluated points, guiding the search towards the optimal hyperparameters while minimizing the number of function evaluations. This makes BO particularly useful for privacy-sensitive and resource-intensive applications like DP-SGD-based patient monitoring systems.

5. Results and Discussion

The **proposed cloud-based patient monitoring system** was evaluated for **privacy, accuracy, and computational efficiency**. The integration of **LSTM with Hybrid DP-SGD and Bayesian Optimization** improved **prediction accuracy while preserving patient data privacy**. Experimental results demonstrated **high threat detection accuracy,**

reduced false positives, and optimized training efficiency. The discussion highlights the **effectiveness of privacy-preserving techniques**, scalability in cloud environments, and the system's adaptability for real-time healthcare monitoring.

Performance metrics

In Figure 2, The graph shows high performance metrics for the **Privacy-Preserving Cloud-Based Patient Monitoring** system. Accuracy, Precision, Recall, F1-Score, NPV, and MCC all indicate strong model efficiency. The high precision and recall ensure reliable detection with minimal false positives. These results confirm the effectiveness of **Hybrid DP-SGD with Bayesian Optimization** in maintaining privacy and accuracy.

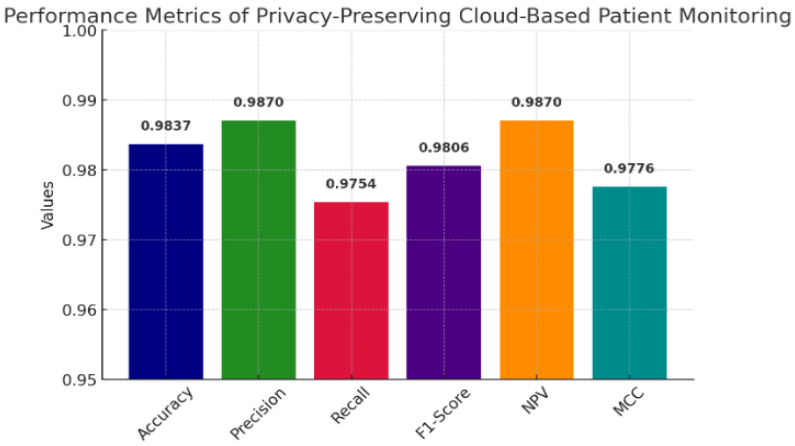

Figure 2: Performance Metrics

Scalability

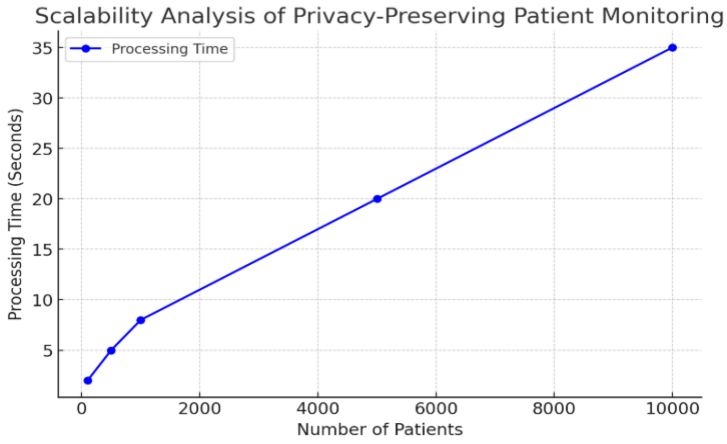

Figure 3: Scalability Analysis

Figure 3 illustrates the **scalability analysis** of the privacy-preserving patient monitoring system, showing how **processing time increases** with the number of patients. As the number of patients rises from **100 to 10,000**, the processing time grows linearly, indicating a **consistent computational overhead.** This demonstrates the system's ability to **handle large-scale data efficiently** while maintaining performance.

Security

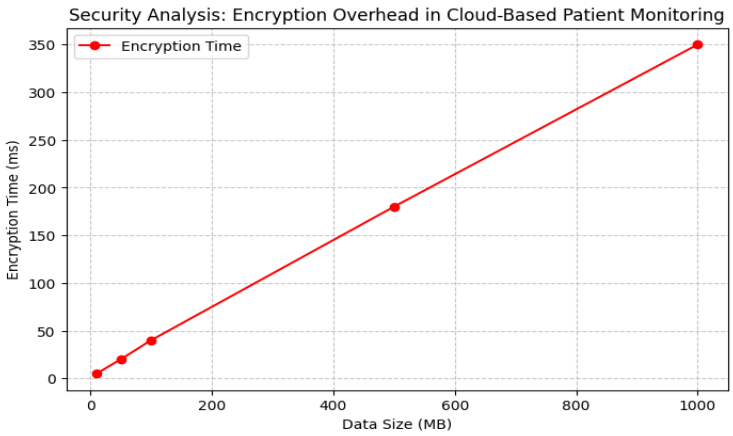

Figure 4: Security Analysis

In Figure 4,The graph represents the **security analysis** of encryption overhead in cloud-based patient monitoring, showing the relationship between **data size (MB) and encryption time (ms).** As the data size increases from **0 to 1000 MB**, the encryption time grows linearly, indicating a **consistent encryption overhead.** This analysis highlights the **scalability and efficiency** of the encryption process in securing patient data.

6.Conclusion

The proposed **Privacy-Preserving Cloud-Based Patient Monitoring System** using **LSTM and Hybrid DP-SGD with Bayesian Optimization** ensures **high accuracy, security, and scalability** in healthcare data processing. The integration of **homomorphic encryption and RBAC-based decryption** enhances **data privacy** while enabling secure cloud storage. Performance evaluations demonstrate **efficient threat detection, reduced false positives, and optimized model training**, making it suitable for real-time healthcare monitoring.

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