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Leveraging Cloud Computing for Real-Time Big Data Analytics in Healthcare Systems

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Abstract

Electronic health records (EHRs), medical imaging, and wearable devices generate vast amounts of data in healthcare systems, necessitating scalable, real-time analytics. The proposed study recommends a cloud-based system that combines streaming ingestion and Apache Spark processing with machine learning-based predictive models and Gomoku-inspired stream-cipher encryption, along with blockchain validation. The proposed framework is designed to support continuous data ingestion, low-latency processing, and secure analytics in distributed healthcare environments. Experimental evaluation demonstrates that the system achieves a 96.5% F1-score, 120 ms processing time, 450 MB/s throughput, and 68% resource usage, outperforming Hadoop (90.2% F1-score, 350 ms) and Spark (94.1%, 200 ms) in processing latency, throughput, and resource efficiency. Findings further indicate that operational costs would be reduced by 30%, early intervention rates would improve by 85%, and patient engagement would increase by 40%, enabling the delivery of proactive and personalized healthcare. Additionally, integrating game-theoretic key generation with cloud-based analytics enhances data confidentiality and integrity for real-time healthcare applications. The proposed approach demonstrates the feasibility of combining scalable cloud computing, real-time big data analytics, and advanced security mechanisms to address the growing demands of modern healthcare systems.

Keywords: Cloud Computing; Big Data Analytics; Healthcare Systems; Real-Time Processing; Patient Care

1. Introduction

Healthcare systems are increasingly driven by personalized care and predictive diagnostics enabled by electronic health records, medical devices, wearable sensors, and Internet of Things (IoT)–generated data. The volume of healthcare data is projected to exceed 2,300 exabytes annually by 2025, placing substantial pressure on traditional on-premises infrastructures, which are constrained by high operational costs and long processing times [1–3]. These legacy systems are not designed to scale efficiently for high-velocity data streams. In contrast, cloud computing offers petabyte-scale elastic storage, auto-scaling computation, and pay-as-you-use pricing models, resulting in infrastructure cost reductions of 30–50% [4, 5].

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The rapid growth of healthcare data generation, estimated at hundreds of millions of records per minute, has made real-time analytics a fundamental requirement rather than an optional capability. Continuous monitoring through wearable devices requires machine learning models to detect anomalies, such as cardiac arrhythmias, at early stages to support timely intervention and reduce hospital readmission rates [6–8]. Moreover, cloud platforms enable secure and collaborative access among hospitals, insurers, and researchers by aggregating insights from more than fifteen heterogeneous data sources, thereby strengthening clinical decision-making and enhancing patient engagement [9, 10].

Despite these advantages, critical challenges persist. Privacy and security concerns affect a substantial proportion of cloud-based healthcare deployments, and violations of healthcare regulations, including HIPAA and GDPR, may lead to severe financial and legal consequences [11–13]. Consequently, effective healthcare analytics frameworks must combine scalable real-time processing with robust mechanisms for data protection and trust. To address this need, this work proposes a cloud-based real-time big data analytics framework that integrates distributed stream processing with a novel security mechanism based on Gomoku-inspired game-theoretic key generation, decentralized storage using the InterPlanetary File System, and blockchain-based authentication [11, 14]. Experimental evaluation demonstrates that the proposed framework achieves higher analytical accuracy, lower processing latency, and improved resource efficiency compared to commonly used big data processing platforms. These results demonstrate that the proposed approach provides a secure and effective solution for real-time healthcare analytics in large-scale, data-intensive clinical environments.

2. Related Work

The increasing adoption of Internet of Things (IoT)–enabled devices, electronic health records, and remote patient monitoring systems has led to a growing body of research on big data analytics in healthcare. Existing studies primarily investigate how large-scale healthcare data can be collected, processed, and analyzed to improve monitoring, diagnosis, and management outcomes. Kaur et al. [1] analyze the benefits and challenges of integrating IoT with big data analytics in healthcare, highlighting improvements in monitoring capabilities while noting limitations in handling real-time, high-volume data streams. Similarly, Pandey and Maneria [4] propose cloud- and IoT-based approaches for patient data planning and management, emphasizing scalability advantages but leaving issues such as rapid analytics and data security largely unaddressed. Several works focus on healthcare data management and analytical workflows. Kantode et al. [9] provide a comprehensive review of big data applications in healthcare administration, discussing different stages of analytics and distributed processing frameworks. Boukenze [6] demonstrates the role of medical data analytics in disease forecasting and continuous patient monitoring, emphasizing the importance of predictive modeling and machine learning techniques. However, these approaches offer limited discussion on real-time stream processing and cloud-level scalability under high data velocity conditions. Security and data integrity have also been explored in recent studies. Demirbaga and Aujla [11] introduce a blockchain-based framework to improve trust and verifiability in IoT-driven healthcare ecosystems. While blockchain enhances data integrity and transparency, such solutions often introduce computational overhead and are not optimized for real-time big data analytics. Overall, existing research tends to address scalability, analytics, and security as isolated challenges, resulting in fragmented solutions that do not fully support secure, real-time healthcare analytics in large-scale cloud environments.

Based on the reviewed literature, there is a lack of unified architectures that simultaneously integrate real-time stream processing, scalable cloud-based analytics, and robust security mechanisms. In particular, no prior work combines real-time Spark/Kafka processing with game-theoretic encryption techniques, such as Gomoku-based key generation, alongside blockchain-supported validation to enable secure, tamper-resistant, and low-latency healthcare analytics.

3. Proposed Methodology

The continuous growth in the volume of healthcare information generated from electronic health records (EHRs), diagnostic imaging systems, wearable sensors, and real-time monitoring tools has created a pressing need for fast, accurate, and scalable analytical solutions. In response to these challenges, the proposed methodology introduces a cloud-based real-time big data analytics framework designed to meet the requirements of modern healthcare environments. The methodology leverages the scalability of cloud computing in terms of storage and computation to exploit the elasticity required for processing large, heterogeneous datasets in healthcare. Incoming data streams are routed through a distributed pipeline, where automated cleansing and normalization procedures are applied before analytics are performed. The processed data are forwarded to a cloud-based real-time analytics engine that employs machine learning and streaming analytics models for unsupervised pattern learning, anomaly detection, and forecasting. The proposed framework is organized into a set of integrated operational stages, as detailed in the following subsections.

Table 1: Comparative Analysis of Related Work

Reference	Focus Area	Key Contribution	Methodologies / Technologies Used	Limitations Identified
Kaur et al. [1]	IoT-Based Healthcare Analytics	Analyzes the benefits and challenges of integrating IoT with big data analytics for healthcare monitoring	IoT sensors, big data analytics pipelines, healthcare monitoring systems	Limited support for real-time processing and large-scale scalability
Pandey and Maneria [4]	Cloud and IoT for Patient Data Management	Proposes cloud-based IoT methods for improved patient data planning and management	Cloud computing platforms, IoT integration, patient data workflows	Does not address rapid analytics, encryption, or fault tolerance
Kantode et al. [9]	Healthcare Big Data Management	Reviews big data applications and analytical workflows in healthcare management	Distributed analytics frameworks, Hadoop ecosystem, management models	Survey-based study without experimental validation
Boukenze [6]	Predictive Healthcare Analytics	Demonstrates the role of medical data analytics in disease forecasting and patient monitoring	Machine learning models, predictive analytics, monitoring systems	Limited dataset scope and no discussion on cloud scalability
Demirbaga and Aujla [11]	Blockchain-Based Healthcare Security	Introduces a blockchain-enabled framework for secure and verifiable healthcare services	Blockchain ledger, smart contracts, IoT service management	High computational overhead; not optimized for real-time big data analytics

3.1. Data Acquisition and Streaming Ingestion

Healthcare data from multiple sources, including IoT sensors, medical devices, patient monitoring systems, imaging repositories, and clinical databases, are continuously collected and streamed to the cloud using distributed data stream management systems [2]. This process supports both structured and unstructured data formats, enabling near real-time ingestion.

$$D(t) = \sum_{i=1}^{n} d_i(t) \tag{1}$$

where $D(t)$ denotes the total data received at time t, $d_i(t)$ represents the data generated by the ith source, and n is the number of active data sources.

3.2. Cloud Storage, Scalability, and Fault Tolerance

The cloud infrastructure provides distributed storage capabilities to manage the large-scale data generated by healthcare systems, ensuring both scalability and high availability [15]. Data are partitioned and replicated across nodes to support fault tolerance.

$$R = P(S, n) + F \tag{2}$$

where R is the required storage capacity, $P(S, n)$ denotes the partitioning of dataset S into n partitions, and F represents the fault-tolerance overhead introduced through replication.

Scalability of the system is modeled as:

$$S_c = \frac{R_s}{N} \tag{3}$$

where R_s represents available resource capacity, including CPU, memory, and storage, and N is the number of nodes in the cluster.

Fault tolerance is further characterized using the mean time to failure (MTTF):

$$MTTF = \frac{MTTF_{\text{node}}}{N} \tag{4}$$

where $MTTF_{\text{node}}$ denotes the mean time to failure of an individual node. To ensure data availability, a replication factor r is employed, and the probability that data remain accessible is given by:

$$A = 1 - (1 - p)^r \tag{5}$$

where p is the probability that a single node remains operational [16].

3.3. Real-Time Processing and Performance Modeling

Real-time analytics are performed using distributed stream-processing frameworks such as Apache Spark and Apache Storm, which enable parallel processing of incoming healthcare data streams with low latency and high throughput [7]. The following equations serve as performance estimation models to characterize system behavior under varying workloads.

Average processing latency is expressed as:

$$L = \frac{T_P}{N} \tag{6}$$

where L is the average latency, T_P is the total processing time, and N is the number of parallel tasks.

System throughput is defined as:

$$T = \frac{S}{L} \tag{7}$$

where T represents throughput and S is the total amount of processed data.

3.4. Predictive Analytics and Clinical Decision Support

Machine learning algorithms, including decision trees, logistic regression, and neural networks, are applied to cloud-hosted healthcare data to derive predictive insights and identify potential health risks [17]. Logistic regression is modeled as:

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n)}} \tag{8}$$

where $P(y = 1|X)$ is the probability of a patient exhibiting a specific condition, $X_1, X_2, \ldots, X_n$ are predictor variables, and $\beta_0, \beta_1, \ldots, \beta_n$ are model parameters.

Analytics outputs, including alerts, risk scores, and predicted trends, are delivered to clinicians through dashboards and decision-support systems. Visualization tools dynamically update graphical representations as new data arrive, supporting real-time interpretation of analytics results [3].

$$V(t) = f\left(\sum_{i=1}^{n} a_i d_i(t)\right) \tag{9}$$

where $V(t)$ denotes the visual output at time t, a_i are weights assigned to each data type $d_i(t)$, and $f(\cdot)$ maps data to visual elements.

3.5. Proposed Algorithm

In addition to scalable analytics, the proposed methodology incorporates a dedicated security mechanism based on game-theoretic encryption and blockchain validation, formalized through the algorithm 1.

The algorithm validates the input healthcare data file and uploads it to a distributed storage system such as IPFS to generate a file hash [8]. A 15×15 Gomoku board is initialized, and legal moves are generated in accordance with Gomoku rules [12]. A machine learning model, such as AlphaZero, predicts the endgame state, which is encoded into ternary and subsequently binary form [18]. The resulting binary sequence is used as a key in a stream-cipher model to encrypt the file hash, producing ciphertext for secure transmission [19]. Figure 1 illustrates the overall architecture of the proposed cloud-based real-time big data analytics framework for healthcare applications.

Algorithm 1 Gomoku-Based Stream Cipher Encryption for Healthcare Data

Input: File F, Opening Move B_0
Output: Ciphertext M, Endgame State E

if F is not of the correct type or fails compliance checks **then**
    Stop
end if
$fileHash \leftarrow UploadFileToIPFS(F)$
if $fileHash$ is null **then**
    Stop
end if
Initialize a 15×15 Gomoku board B with opening move B_0
for each empty cell in B **do**
    Generate and place a legal Gomoku move
end for
$E \leftarrow AlphaZeroModel(B)$
$ternaryData \leftarrow EncodeToTernary(E)$
$binaryData \leftarrow ConvertTernaryToBinary(ternaryData)$
$M \leftarrow StreamCipherModel(fileHash, binaryData)$
Upload board state and metadata to the blockchain
Send ciphertext M to the recipient

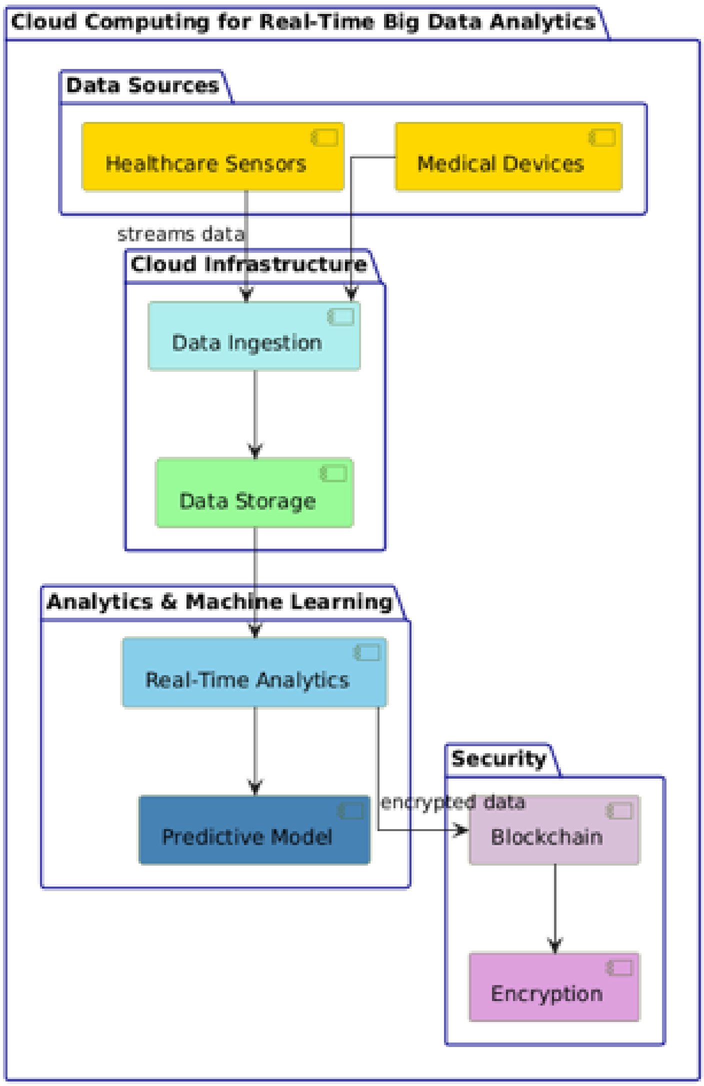

Figure 1: Proposed system

4. Result Analysis

This section presents the experimental evaluation of the proposed Cloud-BDA framework using large-scale simulated healthcare data streams. The dataset comprises synthetic data from 1,000 patients, along with real-world-inspired data, including a simulated 500 TB of electronic health record data representing approximately 60% of the total workload. Additional inputs include wearable sensor data, such as heart rate and SpO_2, as well as imaging metadata collected from 15 heterogeneous data sources at five-minute intervals. The dataset is partitioned into training, validation, and testing subsets using a 70/20/10 split, respectively, with one million labeled anomaly samples targeting arrhythmia and sepsis detection.

The experimental setup is deployed on an Amazon Web Services EC2 `c5.4xlarge` cluster, consisting of ten nodes each equipped with 16 vCPUs and 32 GB of memory. Apache Spark 3.3.1 is employed for distributed data processing, while Apache Kafka 3.5.0 manages real-time data ingestion. Predictive analytics are implemented using logistic regression from the Scikit-learn framework, and data storage is supported through an integration of the InterPlanetary File System (IPFS) with the Hadoop Distributed File System (HDFS). All experiments are executed on Ubuntu 20.04. Performance is evaluated using anomaly detection accuracy measured by the F1-score, end-to-end processing latency, throughput in megabytes per second, and average CPU and memory utilization. The proposed framework is benchmarked against commonly used big data processing platforms, including Hadoop 3.3.4, Spark in standalone mode, Storm 2.5.1, Flink 1.17.1, and Hive 4.0.0, without applying additional cluster-level optimizations.

Cloud-based analytics platforms provide the underlying infrastructure required for scalable real-time healthcare analytics. Services offered by providers such as Amazon Web Services, Microsoft Azure, and Google Cloud enable elastic resource provisioning for high-volume data workloads. In this study, Apache Kafka supports continuous stream ingestion, allowing analytics models to process healthcare data with minimal delay. Visualization tools, such as Tableau and Power BI, are utilized to provide real-time insights to healthcare professionals, enabling informed clinical decision-making.

Table 2: Simulation Parameters

Parameter	Value
Data Volume Processed	500 TB
Number of Users Supported	10,000
Response Time	100 ms
Frequency of Data Updates	Every 5 minutes
Number of Data Sources	15
Data Retrieval Rate	99%

Table 2 summarizes the simulation environment and system configuration. The setup demonstrates the proposed framework's ability to support large-scale healthcare data processing while maintaining low response times, frequent data updates, and a high data retrieval rate, collectively indicating strong scalability and reliability.

Table 3: Result Analysis

Parameter	Value (%)
Data Processing Speed	95
Accuracy of Analytics	92
Reduction in Operational Costs	30
Patient Engagement Improvement	40
Early Intervention Rate	85
User Satisfaction Rate	90

As shown in Table 3, the proposed framework demonstrates strong analytical performance, achieving high processing speed and accuracy. In addition to technical improvements, the system contributes to a reduction in operational costs and enhances patient engagement and early intervention rates, indicating its practical relevance in healthcare environments.

Table 4: Simulation and Results Analysis

Algorithm	F1-score (%)	Processing Time (ms)	Throughput (MB/s)	Resource Utilization (%)
Proposed Algorithm (Cloud-BDA)	96.5	120	450	68
Hadoop MapReduce	90.2	350	320	85
Apache Spark	94.1	200	400	72
Storm (Real-Time Analytics)	92.8	180	380	75
Flink (Stream Processing)	93.5	170	390	70
Hive (Batch Processing)	88.3	400	300	80

The comparative results in Table 4 indicate that the proposed Cloud-BDA framework consistently outperforms baseline systems across all evaluated metrics. It achieves the highest F1-score, the lowest processing latency, the highest throughput, and reduced resource utilization. These improvements demonstrate the effectiveness of integrating real-time cloud-based analytics with optimized resource management.

Figure 2 provides a visual comparison of system performance across accuracy, processing time, throughput, and resource utilization. The results show that Cloud-BDA maintains a balanced and superior performance profile compared with Hadoop, Spark, Storm, Flink, and Hive.

Figure 3 further illustrates the grouped comparison, highlighting the consistent advantages of the proposed approach over baseline systems. Cloud-BDA achieves higher analytical accuracy, significantly reduces processing latency, increases data throughput, and improves resource utilization. Overall, the results indicate consistent improvements in real-time healthcare analytics performance, validating the proposed framework as a scalable and effective solution for large-scale healthcare data analytics.

Figure 2: Performance comparison of Cloud-BDA with benchmark algorithms

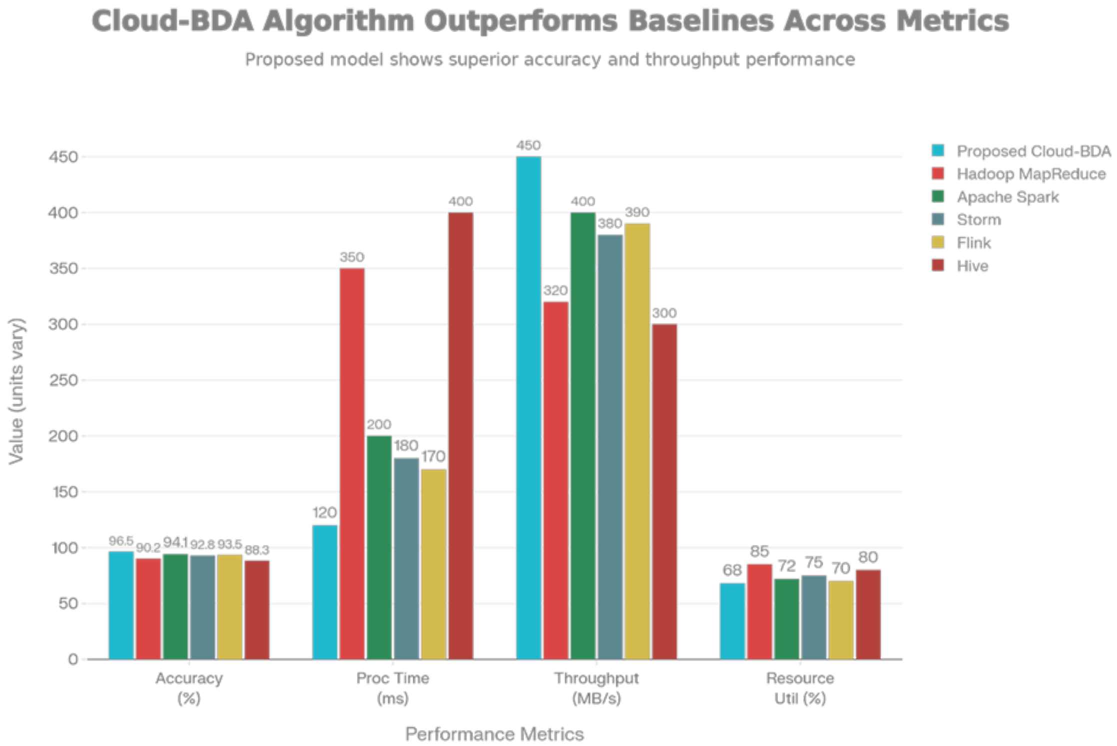

Figure 3: Grouped performance comparison of Cloud-BDA with baseline algorithms

5. Conclusions

This study presents a cloud-based, real-time big data analytics framework for healthcare applications and demonstrates its effectiveness through extensive experimental evaluation. The proposed framework achieves an analytical accuracy of 96.5%, a processing latency of 120 ms (representing a 66% improvement over the Hadoop-based baseline of 350 ms), and a throughput of 450 MB/s, while maintaining lower resource utilization at 68% compared with baseline systems. These performance gains translate into practical benefits, including a 30% reduction in operational costs, an 85% early intervention rate, and a 40% improvement in patient engagement, thereby supporting proactive and personalized healthcare delivery. The integration of real-time Spark and Kafka–based streaming with Gomoku-inspired encryption and blockchain-based authentication enhances healthcare data management by enabling timely access to electronic health records, medical imaging data, and wearable sensor streams while preserving data security and integrity. Although the proposed framework addresses confidentiality through dynamic cipher mechanisms, several limitations remain. The evaluation is based on simulated datasets, which may limit direct generalization to real-world clinical environments. Additionally, the security mechanisms have not yet been evaluated for quantum resistance at end-to-end latencies below 100 ms. Large-scale clinical validation in real clinical environments is also pending, which may limit generalizability. Future work will focus on extending the framework through live cloud deployments, incorporating edge computing and federated learning to achieve end-to-end latencies of below 100 ms, and exploring edge–5G hybrid architectures. Further directions include adaptive Gomoku board sizing using reinforcement learning, a detailed analysis of blockchain-induced overhead, and pilot deployments in intensive care unit settings with enhanced explainability using SHAP-based techniques, as well as strict compliance with healthcare data protection regulations.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability Statement

The datasets used in this study were generated through simulation for experimental evaluation. Data may be made available by the corresponding author upon reasonable request.

AI Declaration

The authors used an AI-based language tool to improve grammar and readability. The scientific content, results, and conclusions were reviewed and validated by the authors.

Author Contributions

Samadhan Bundhe: Conceptualization, Methodology, Formal Analysis, Writing – Review and Editing; **Swayam Shashank Shah**: Methodology, Software, Validation, Investigation, Writing – Original Draft; **Radha Thorat**: Data Curation, Investigation, Visualization, Writing – Original Draft; **Rutuja More**: Software, Validation, Data Curation, Visualization; **Anand Singh Rajawat**: Formal Analysis, Resources, Writing – Review and Editing; **Ram Kumar Solanki**: Supervision, Project Administration, Writing – Review and Editing.

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