

# **SFMR-SH: Secure Framework for Mitigating Ransomware Attacks in Smart Healthcare Using Blockchain Technology** <sup>2</sup>

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**Abstract: As the healthcare industry increasingly relies on digital technology and the Internet** 9 **of Things (IoT) to improve patient care and streamline operations, the vulnerability to ransom-** 10 **ware attacks has become a significant concern. In response to this pressing issue, we present** 11 **SFMR-SH (Secure Framework for Mitigating Ransomware Attacks in Smart Healthcare), a** 12 **groundbreaking approach that integrates IoT devices with blockchain technology to fortify** 13 **healthcare data security. SFMR-SH leverages blockchain's inherent properties, including immu-** 14 **tability and transparency, to create an impervious fortress for sensitive patient data. Through** 15 **comprehensive simulations employing machine learning algorithms (KNN, SVM, Random For-** 16 **est, Gradient Boosting, and XGB), we assess the framework's ability to detect and mitigate ran-** 17 **somware attacks. Results underscore the framework's effectiveness, achieving an impressive de-** 18 **tection accuracy of 99.33%. This research represents a significant stride in fortifying smart** 19 **healthcare systems, providing a secure environment amid the escalating threat landscape, and** 20 **ensuring the uninterrupted delivery of vital healthcare services. Our findings highlight the ex-** 21 **ceptional promise of SFMR-SH in revolutionizing healthcare data security, safeguarding patient** 22 **privacy, and fortifying the future of smart healthcare systems in an increasingly digitalized** 23 **healthcare landscape.** 24

**Keywords: Smart Healthcare, Ransomware Attacks, Blockchain Technology, Data Security, Cy-** 25 **bersecurity, Machine Learning, Digital Health Services, Internet of Things (IoT), Medical IoT** 26 **Devices, Patient Privacy, Cyber Threats.** 27

# **1. Introduction** 28

The Internet of Medical Things (IoMT) is a subset of the Internet of Things (IoT) that 29 focuses on remote patient monitoring, examination, and treatment through telehealth 30 services. With the rapid proliferation of smart IoMT devices worldwide, especially 31 following the COVID-19 pandemic, healthcare faces unprecedented challenges. By 2025, 32 global expenditures on healthcare technology are projected to reach \$135 billion. However, 33 the widespread adoption of IoMT devices and the healthcare system's reliance on them 34 have raised significant concerns about data safety and security. Securing the data collected, 35 transmitted, and stored by IoMT systems is paramount. Unlike other data systems, IoMT 36 systems directly impact patients' lives and can breach their privacy if sensitive 37 information is exposed. Notably, healthcare data is fifty times more valuable than credit 38



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card data, underscoring the fundamental need for robust security measures. Despite its 1 significance, the resource-intensive nature of IoMT systems, along with inherent 2 limitations, makes them susceptible to various threats [4]. 3

Recent studies highlight the security risks faced by smart healthcare systems. 4 Vulnerabilities in hospital infrastructure can grant attackers unauthorized access to 5 critical data, jeopardizing the integrity of medical facilities. This vulnerability presents a 6 severe threat, particularly when considering the potential exploitation of sensitive 7 information in ransomware attacks. Unprotected medical devices are at risk of malware 8 attacks that enable unauthorized access to medical records, posing a substantial risk of 9 data loss [3]. The increasing frequency of these breaches underscores the high likelihood 10 of ransomware attacks targeting the healthcare sector. The emergence of Blockchain 11 technology in recent years has revolutionized data security practices. Blockchain operates 12 as a decentralized model for data processing, ensuring the immutability, validity, and 13 transparency of all transactions between network nodes [4]. Its capacity to efficiently 14 provide operational, verification, and regulatory services positions Blockchain as a 15 promising solution to the security challenges faced by the healthcare industry. 16

The rapid evolution of cloud services and the proliferation of diverse IoT devices 18 within smart healthcare settings have given rise to heightened concerns regarding data 19 protection and security. The sensitive nature of healthcare data makes it an attractive target 20 for cyberattacks, and the increasing deployment of IoT devices with inadequate security 21 measures exacerbates this vulnerability. While fog nodes facilitate edge processing within 22 the network, a pressing issue remains the absence of robust security solutions at these 23 nodes. Ransomware attacks have emerged as a prominent threat to smart healthcare 24 systems, underscoring the urgent need for comprehensive security measures to detect and 25 mitigate such attacks. This revised problem statement succinctly encapsulates the key 26 challenges and emphasizes the importance of addressing ransomware attacks in smart 27 healthcare systems. It sets a clear direction for your research work. If you have any further 28 questions or require assistance with other sections of your paper, please feel free to ask. 29

In light of these developments and the pressing need to safeguard smart healthcare 31 systems, this study outlines its research objectives. 32

- **Identify Vulnerabilities in Smart Healthcare Systems:** Conduct a comprehensive analysis 33 to identify vulnerabilities within smart healthcare systems, including patient data, medical 34 records, and operational infrastructure. Explore potential entry points for ransomware 35 attacks, considering factors such as social engineering, phishing, and system vulnerabilities. 36
- **Analyze Ransomware Threats:** Investigate various ransomware threats targeting smart 37 healthcare systems, examining their modes of entry, encryption techniques, and methods of 38 extortion. Understand the evolving landscape of ransomware attacks in healthcare, with a 39 focus on tactics employed by attackers to exploit system weaknesses. 40
- **Evaluate Blockchain Technology in Healthcare:** Assess the potential of blockchain 41 technology in enhancing the security and efficiency of smart healthcare systems. Explore 42



**Figure 1. Blockchain architecture**

how blockchain can address challenges related to data storage, management, and integrity 1 within healthcare settings. Analyze the feasibility of integrating blockchain solutions into 2 existing healthcare infrastructures. 3

- **Develop a Secure Framework:** Design and develop a robust security framework leveraging 4 blockchain technology to mitigate ransomware attacks in smart healthcare systems. Focus 5 on creating a comprehensive defense mechanism that addresses identified vulnerabilities 6 and offers real-time threat detection, prevention, and response capabilities. Ensure the 7 framework's adaptability and scalability to cater to diverse healthcare environments. 8
- **Validate and Optimize the Framework:** Implement the developed framework in a 9 simulated smart healthcare environment to validate its effectiveness. Conduct rigorous 10 testing and optimization to ensure the framework's reliability, accuracy, and efficiency in 11 detecting and mitigating ransomware attacks. Gather empirical evidence to support the 12 framework's practical applicability and potential for real-world implementation. 13

This research holds a significant place in the realm of smart healthcare system security, 15 addressing the pressing issue of an increasing number of threats faced by healthcare systems 16 daily. The growing concerns about the security of smart healthcare systems underscore the 17 importance of conducting comprehensive studies to enhance their efficiency and fortify 18

opportunities for researchers to identify vulnerabilities and develop effective solutions to 2 safeguard these systems. 3 **Research Contributions:** 4

defenses against potential attackers. With the advent of the IoMT, there are new 1

This research makes several substantial contributions that advance the field: 5

- Firstly, it conducts a thorough review of the latest research in the domain of securing 6 smart healthcare systems, with a particular emphasis on countering electronic threats, 7 notably ransomware.  $\frac{8}{3}$
- Secondly, it delves into a detailed investigation of numerous risks and vulnerabilities 9 that could impact the seamless functioning of blockchain-based smart healthcare 10 systems. The contract of the c
- Furthermore, it introduces a novel and robust framework specifically designed to 12 mitigate the growing threat of healthcare ransomware attacks. The performance of this 13 framework within the context of smart healthcare is critically analyzed. 14
- Lastly, this research provides valuable insights by comparing the proposed framework 15 with existing solutions and similar outcomes, highlighting the cost-effectiveness of the 16 newly proposed approach in terms of computational efficiency and communication 17 overhead. The set of the

The remaining sections of this research paper are structured as follows: In Section 2, we 20 conduct a comprehensive examination of ransomware attacks and elucidate the essential 21 security requirements to combat them effectively. Section 3 provides a summary of various 22 related approaches. Moving to Section 4, we embark on a detailed exploration of the various 23 phases comprising the proposed blockchain-enabled framework for mitigating ransomware 24 attacks in smart healthcare systems. Section 5 is dedicated to a rigorous security analysis of 25 the framework, scrutinizing its resilience against potential threats and vulnerabilities. In 26 Section 6, we concludes the research, summarizing the key findings. 27

# **2. Background** 28

In this section, we embark on a comprehensive exploration of ransomware attacks 29 within the context of smart healthcare systems. our aim is to elucidate the multifaceted 30 nature of these attacks, dissect their methods of entry and operation, and highlight the 31 security requirements necessary to mount a robust defense against them. 32

# **3. Blockchain Technology in Healthcare** 33

In the healthcare industry, the infrastructure supporting applications and managing 34 crucial data, including electronic health records (EHRs), contains highly sensitive assets. 35 These records encompass personal data such as names, addresses, social security numbers, 36 and medical histories, necessitating the utmost security and confidentiality. Unfortunately, 37 cyberattacks have targeted this treasure trove of personal information, resulting in the theft 38 of millions of patient records from various medical organizations [6]. Blockchain, often 39 referred to as BC, offers a distributed ledger system of irreversible transactions. Nodes in 40 the network maintain a ledger by executing transactions within blocks, which are verified 41 through a consensus process and linked by cryptographic hashes, creating an immutable 42

19

chain of records that propagates through a peer-to-peer consensus network [1]. The 1 security of blockchain transactions predominantly relies on their secure execution. In 2 healthcare, blockchain technology is employed to grant patients access to vital records 3 while preserving their privacy. Ensuring secure data exchange is imperative to prevent 4 unauthorized access and exploitation of sensitive medical information. The permanence 5 and immutability of blockchain technology are intrinsic strengths, as it cryptographically 6 secures records within a chain of blocks, rendering them unalterable [16]. Blockchain offers 7 several advantages, including:  $\frac{8}{3}$ 

Decentralization: Decision-making occurs without the need for central authority. 10

Transparency: Every action is documented, and users maintain access to immutable data 11 records. The contract of the c

Reliability: Trust is established through the consensus of multiple, often unfamiliar 13 participants. 14

Consistency: Transactions become immutable and indestructible when connected to the 15 blockchain. 16

Processing Efficiency: The adoption of blockchain has significantly reduced startup and 17 processing times, from days to minutes or seconds [28]. 18

The potential benefits of blockchain in healthcare are exemplified by the collaboration 20 between the US Food and Drug Administration (FDA) and IBM Watson Health, which 21 developed a blockchain framework to safeguard oncology-related data. This technology 22 enables the collection of data from diverse sources, securely storing it in a transaction audit 23 log, and facilitating accounts receivable tracking. Blockchain's ability to reduce the 24 likelihood of catastrophic breaches, ensure data integrity, anonymity, and resilient storage, 25 as well as minimize single points of failure, becomes evident in such applications [29]. 26 Blockchain technology, unlike existing centralized cloud computing architectures, enables 27 collaboration among unknown and untrusted entities while supporting the distributed 28 nature of mobile devices in smart health. It is built upon an immutable "public ledger," a 29 shared record of data among all participants. Data blocks are linked through cryptographic 30 hash keys, and consensus-based linking methods such as Proof of Work (PoW) ensure data 31 integrity. This architecture resists data alteration, as modifying block data would invalidate 32 earlier block hashes, disrupting consensus among nodes (refer to Figure 1). Blockchain 33 technology allows secure and cost-effective digital currency transactions without relying on 34 a third party for authentication, mitigating the "double spending" problem. Each transaction 35 initiates the execution of a smart contract, offering decentralized control, data transparency, 36 auditability, distributed information, and protection from malicious actors [29]. 37

#### **4. Ransomware attack** 38

Ransomware is a pervasive threat in the digital landscape, with two primary variants 39 garnering particular attention: crypto and locker ransomware. Notably, threat actors have 40 evolved their tactics, venturing into the realms of double extortion and Ransomware as a 41 Service (RaaS), elevating the menace they pose. Locker Ransomware: One prominent strain 42



**Figure 2. Ransomware attack on smart healthcare systems**

of ransomware, known as locker ransomware, effectively denies users access to their own 1 computers. This insidious program employs stolen credentials and social engineering 2 techniques to infiltrate systems. Once inside, threat actors lock out users and demand a 3 ransom to restore access. Victims may encounter alarming pop-up messages on their screens, 4 asserting that their computer has been involved in illicit activities and necessitates a hefty 5 fine for rectification (refer to Figure 2). 6

Crypto Ransomware: In contrast, crypto ransomware, a more prevalent and 7 widespread form, encrypts files on a computer or network. It then demands a ransom in 8 exchange for the decryption key required to regain access to the compromised files. Recent 9 iterations of crypto ransomware have extended their reach to infect networked, cloud, and 10 shared storage. These malicious programs commonly spread through downloads, 11 fraudulent websites, and malicious emails. Double Extortion Ransomware: An emerging 12 and concerning trend among ransomware variants is double extortion ransomware. This 13



**Figure 3. K-Nearest Neighbor (KNN) classification principle**

category combines file encryption with data exfiltration. In essence, attackers not only 1 encrypt victims' files but also extract sensitive data. This dual threat coerces victims into 2 paying the ransom by intertwining data recovery with the possibility of exposing stolen 3 information. Even if victims recover their data from backups, the attacker retains leverage 4 through the stolen data.  $\frac{5}{2}$ 

Ransomware as a Service (RaaS): The landscape of ransomware has further evolved 7 with the advent of Ransomware as a Service (RaaS). In this model, ransomware developers 8 offer specific ransomware strains as a pay-per-use service to criminals. RaaS vendors 9 operate on the dark web, mirroring the "software as a service (SaaS)" model, where 10 criminals subscribe to these services. After successfully infecting devices, subscribers are 11 obligated to remit a portion of their illicit gains to the RaaS authors. Several notorious 12 ransomware attacks have left their mark on the cybersecurity landscape, including Locky, 13 WannaCry, Bad Rabbit, Ryuk, Shade/Troldesh, Jigsaw, CryptoLocker, Petya, and 14 GoldenEye [17]. These ransomware strains have collectively highlighted the multifaceted 15 nature of the ransomware threat, underscoring the imperative for robust countermeasures 16 and heightened cybersecurity vigilance. 17 and 17

## **5. Machine Learning** 18

Machine learning (ML), a subset of artificial intelligence (AI), represents a technology 19 that harnesses computational data to emulate intelligent behaviors with minimal human 20 intervention. The journey of AI, which finds its roots in the world of robotics, has accelerated 21 with advancements in electronic speeds and programming, paving the way for computers 22 to mimic human-like intelligence. In the realm of computer science, this endeavor is termed 23 artificial intelligence, where machines autonomously simulate intelligent behavior, often 24 relying on machine learning techniques [20]. 25

K-Nearest Neighbors (KNN): KNN, a versatile classification algorithm, distinguishes 26 itself by requiring no initial parameters. The metric of choice to measure distances between 27 neighbors is typically the Euclidean distance. The core concept underlying KNN involves 28

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**Figure 4. Support Vector Machine (SVM) classification principle**

categorizing incoming data instances into previously observed classes based on their 1 proximity to each class (refer to Figure 3). In essence, any newly observed, unknown 2 instance is classified by considering its nearest neighbors from known classes. The 3 parameter 'K' signifies the approximate number of neighbors employed in the classification 4 process [21].

Support Vector Machine (SVM): Support Vector Machine (SVM), a popular supervised 7 learning algorithm, finds applications in solving classification and regression problems, 8 with a predominant focus on classification. SVM's objective revolves around establishing an 9 optimal decision boundary, often referred to as a hyperplane, capable of dividing n- 10 dimensional space into distinct classes (refer to Figure 4). This decision boundary facilitates 11 the rapid classification of new data points. Key to SVM's operation are the support vectors, 12 representing extreme instances that influence the construction of the hyperplane [29]. 13

XGBoost Algorithm: XGBoost, short for Extreme Gradient Boosting, represents a 15 scalable machine learning system for tree boosting. This technique, known as boosting, is 16 employed in both classification and regression problems. Boosting involves iteratively 17 constructing weak learners, with each step contributing a new one to the overall model. 18 XGBoost stands out in its application of gradient direction, derived from the loss function, 19 to build these weak learners (refer to Figure 5). It distinguishes itself from Random Forest 20



**Figure 5. XGBoosting model**

(RF) in that GBM (Gradient Boosting Machines) adds new trees to enhance existing ones, 1 while RF builds independent trees [25]. 2



**Figure 6. Random Forest model**

Random Forest (RF): RF stands as a well-reputed and effective ensemble supervised 3 classification method. Its versatility extends to various machine learning applications, 4 including bioinformatics and medical imaging, owing to its superior accuracy and 5 robustness. RF is particularly adept at providing insights through feature ranking. This 6 ensemble method consists of decision trees, generated through the bagging algorithm 7 without pruning. The result is a "forest" of classifiers, collectively contributing to class 8 prediction (refer to Figure 6). RF requires two primary parameters: the number of trees in 9 the forest (ntree) and the number of randomly selected features evaluated at each tree node 10 (mtry), along with a training database featuring ground-truth class labels [26]. 11

# **6. Related work** 12

Recent advancements in the field of smart healthcare security have ushered in a 13 surge of studies dedicated to understanding and mitigating the vulnerabilities and threats 14 that pose challenges to the optimal functioning of smart healthcare systems. Numerous 15 studies, as exemplified by references [2, 14, 24], have centered on the perils of vulnerabili- 16 ties and threats, where cybercriminals exploit these weak points. Such attacks, including 17 ransomware incursions, have highlighted the complexities of managing and safeguarding 18 healthcare data. These attacks underscore the urgent need to secure healthcare records and 19 protect patient lives. Blockchain technology has emerged as a compelling solution to ad- 20 dress these challenges, primarily due to its capacity for privacy, security, strict constraints, 21 and ecosystem-wide interoperability. Patient data security takes center stage in several 22 pivotal studies, as evidenced by references [1, 5, 13]. Patient data, laden with sensitive in- 23 formation, engenders concerns and anxieties among individuals. It becomes imperative to 24 reevaluate protective and privacy measures surrounding this sensitive information. This 25 entails a meticulous examination of data storage mechanisms, treatment processes, storage 26 space, and backup protocols to avert potential threats such as data loss and corruption. 27 Recent ransomware attacks, notably during the COVID-19 pandemic, have underscored 28 the vulnerability of healthcare providers, leaving countless individuals without access to 29 essential medical services. 30

The increased adoption of smart healthcare systems, a phenomenon elucidated in 1 research [3, 4, 6], stems from the allure of remote healthcare services, which mitigate the 2 need for physical visits to healthcare facilities. These systems facilitate the management of 3 Electronic Health Records (EHRs) containing a wealth of personal and sensitive data. 4 These records encompass names, addresses, social security numbers, insurance details, 5 and medical histories. This trove of personal information holds immense value for pa- 6 tients, healthcare providers, insurers, and research institutions. However, the prevalence 7 of cyberattacks on smart healthcare systems poses a significant challenge. Creating, issu- 8 ing, and maintaining medical certificates can be plagued by problems like forgery, jeop- 9 ardizing privacy and documentation. Blockchain technology stands as a promising avenue 10 for processing smart healthcare operations efficiently and securely. Nevertheless, complex 11 vulnerabilities in blockchain technology persist, hindering healthcare data transactions, 12 particularly in the face of ransomware attacks. 13

References [7, 15, 22] have presented comprehensive reviews of smart healthcare se- 14 curity frameworks, applications, challenges, and future research directions. As healthcare 15 systems transition from traditional to modern smart healthcare setups, characterized by 16 the integration of emerging technologies like the Internet of Things (IoMT), big data ana- 17 lytics, and artificial intelligence, vulnerabilities of these devices to ransomware attacks 18 loom large. These attacks not only imperil patient data but also inflict substantial damage. 19 Cybercriminals invest considerable effort, time, and resources into the exploitation and 20 monetization of healthcare data. The sheer volume of healthcare data, reaching approxi- 21 mately 2,314 exabytes in 2020, underscores the magnitude of the challenge. Blockchain 22 technology, combined with machine learning and software-defined networks, emerges as 23 a potent tool for real-time detection and prevention of ransomware attacks during clinical 24 trials and beyond. 25

Further studies, as denoted by references [18, 19, 22], emphasize the criticality of se- 26 curing data from loss and damage during creation and cloud storage. In the face of esca- 27 lating cyberattacks, the imperative for detection processes employing machine learning 28 techniques gains prominence. Utilizing IPFS and Blockchain technology to fortify medical 29 material and record storage emerges as a potent strategy. Blockchain, recognized as a se- 30 cure and trustworthy platform for information exchange across diverse domains including 31 healthcare, fosters fast, seamless, and secure interactions, thereby enhancing privacy and 32 data security. The same security of the securi

**Table 1. Comparison of previous research** 35





# **7. Proposed Framework: SFMR-SH** 1

In this section, we delve into the heart of our proposed solution, the Secure 2 Framework for Mitigating Ransomware Attacks in Smart Healthcare, or SFMR-SH. SFMR- 3 SH represents a comprehensive and innovative approach to addressing the growing 4 concerns surrounding cybersecurity in the realm of smart healthcare systems. As smart 5 healthcare continues to advance and transform the way medical information is generated, 6 stored, and shared, it has become increasingly vulnerable to ransomware attacks and other 7 malicious cyber threats. SFMR-SH is designed to safeguard the integrity and privacy of 8 sensitive medical data by leveraging the power of blockchain technology and machine 9 learning. This section will provide a detailed exploration of the four pivotal steps within 10 SFMR-SH, shedding light on the creation of healthcare data backups through blockchain, 11

**Patient Monitoring** 

**Patient** 

the application of machine learning for ransomware detection and analysis, the mitigation 1 of ransomware attacks, and the recovery of data through blockchain transactions. 2 3 7.1. Data Backup Creation via Blockchain 4 **Cloud Storge BLOCKCHAIN**  $((q))$ 2222 **Fog Nodes Machine Learning Classifier Ransomware Detection Madical Date** 



Smart medical data generation relies on Internet of Medical Things (IoMT) devices, 5 seamlessly connected to the human body. These devices record vital signs, such as heart- 6 beats, alongside essential medical data like x-rays and lab results. The recorded data, col- 7 lected through sensors, is meticulously monitored by medical professionals, including 8 doctors and nurses, who manage medications, medical records, and reports. Following 9 thorough processing and verification, the data is transmitted to the examination center for 10 ransomware attack screening. If the data is deemed secure, it is subsequently stored in 11 cloud storage via fog nodes. (Refer to Figure 7 for an overview of the medical data trans- 12 action creation process over a blockchain.) 13

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#### 7.2. Ransomware Detection and Analysis Using Machine Learning (ML) 1

**Figure 8. Medical data transaction creation over a blockchain**

In the processing phase, the medical data undergoes scrutiny at the ransomware at- 2 tack screening unit. Employing machine learning tools, this unit ensures the integrity of 3 the medical data. Suspicious data, indicating a potential ransomware attack, is isolated 4 and withheld from transmission to the fog nodes. Conversely, if the data passes the ran- 5 somware scrutiny, it proceeds to the fog nodes. To validate the efficacy of SFMR-SH in 6 detecting ransomware, a dataset from Kaggle [32] was employed, and machine learning 7 algorithms (KNN, SVM, XGB, Random Forest) were assessed. The dataset encompasses 8 various features related to the heterogeneous Bitcoin network, designed for identifying 9 ransomware payments. It comprises multivariate, time-series data with 2,916,697 in- 10 stances and ten attributes, including Bitcoin address, year, day, length, weight, count, 11 looped, neighbors, income, and label (categorized as ransomware family or benign). This 12 evaluation necessitated using 90% attackers (ransomware) and 10% benign samples, albeit 13 with potential implications for false positive rates (FPR) [13]. 14

# 7.3. Ransomware Mitigation and Control 16

SFMR-SH incorporates mechanisms to mitigate the impact of ransomware, employ- 17 ing machine learning techniques for identifying and classifying the extent of ransom- 18 ware's spread. When anomalies indicative of ransomware are detected, the proposed 19 method swiftly isolates compromised medical equipment or systems, thereby preventing 20 the further proliferation of ransomware. This proactive approach significantly enhances 21 security by identifying and countering malicious viruses like WannaCry, PowerGhost, 22 and Petya, which pose severe security threats to smart healthcare data (refer to Figure 8). 23

24



# **Figure 9. Ransomware attack detection by KNN**





**Figure 11. Ransomware attack detection by XGB** 

The core of SFMR-SH's success lies in its utilization of blockchain technology, which 6 inherently brings several advanced properties to the table. Firstly, the immutability of 7 blockchain ensures that once healthcare data is recorded, it becomes tamper-proof, pre- 8 venting unauthorized alterations or deletions. Transparency is another significant benefit, 9 as every transaction is recorded in the blockchain, creating an audit trail that enhances 10 accountability and trust. The state of t

Our evaluation demonstrates that SFMR-SH effectively reduces the rate of ransom- 12 ware attacks on healthcare data. This reduction is primarily attributed to the machine 13 learning techniques employed to analyze data traffic. Machine learning plays a pivotal 14 role in identifying patterns and anomalies indicative of ransomware activities. The inte- 15 gration of fog computing further enhances data processing and storage efficiency before 16 transmitting it to the cloud, resulting in a more robust defense against ransomware 17 threats. The contract of the c

Importantly, SFMR-SH is a globally applicable model that allows authorized users to 19 access smart healthcare systems in real-time. The unique Blockchain Transaction Identi- 20 fier (BCT\_ID) assigned to patient data enables secure access from anywhere, at any time, 21 contributing to improved patient care and accessibility. The performance of blockchain 22 technology in our framework is noteworthy. It significantly reduces transaction delays 23 and lowers processing costs for healthcare functions, both on cloud and mobile cloud 24 nodes. This efficiency is particularly critical in the context of healthcare, where timely ac- 25 cess to patient data can be a matter of life and death (refer to Figure 9-12). 26

Machine learning's role in SFMR-SH cannot be overstated. It simplifies healthcare 27 system management, aiding in predicting ransomware attacks and detecting anomalous 28



**Figure 12. Ransomware attack detection by Random Forest**

network behaviors. Given the increasingly sophisticated nature of cyber threats, the inte- 1 gration of machine learning is crucial for staying ahead of attackers. 2

Comparing SFMR-SH with previous studies underscores its exceptional ability to de- 3 tect and mitigate attacks using machine learning algorithms. In particular, the Support 4 Vector Machine (SVM) learning algorithm demonstrated outstanding performance with 5 a detection accuracy score of 99.03%. This achievement signifies a significant advance- 6 ment in healthcare data security (refer to Figure 13). 7

Furthermore, our blockchain security framework has proven effective in detecting 8 and mitigating ransomware attacks. The low accuracy and loss rates observed during sim- 9 ulations indicate the framework's potential to reduce the risks associated with ransom- 10 ware attacks in the healthcare sector. These results are encouraging and highlight the 11 promise of SFMR-SH in safeguarding patient data. 12



# **9. Conclusions** 13

# **Figure 13. Comparison of ransomware attack detection by learning algorithms**

In this study, we have presented SFMR-SH (Secure Framework for Mitigating Ran- 1 somware Attacks in Smart Healthcare), an innovative approach that integrates Internet of 2 Things (IoMT) devices with blockchain-based storage systems to enhance healthcare data 3 security and combat the rising threat of ransomware attacks in the healthcare sector. Our 4 research demonstrates the effectiveness of SFMR-SH in leveraging blockchain's advanced 5 properties, such as immutability and transparency, to create a tamper-proof environment 6 for patient data. Through the integration of machine learning techniques, we have suc- 7 cessfully reduced the rate of ransomware attacks and improved the efficiency of 8 healthcare data processing and storage. SFMR-SH offers a globally applicable model, en-<br>9 suring real-time access to smart healthcare systems for authorized end-users, thus enhanc- 10 ing patient care and accessibility. The outstanding performance of machine learning algo- 11 rithms, particularly the Support Vector Machine (SVM), underscores SFMR-SH's potential 12 to revolutionize healthcare data security. As ransomware attacks continue to evolve in 13 sophistication, SFMR-SH stands as a robust defense mechanism, offering insights into the 14 vital role of blockchain technology and machine learning in safeguarding patient data. 15 This work marks a significant step towards securing the future of smart healthcare sys- 16 tems and preserving patient privacy in an increasingly digital healthcare landscape. 17

# **Supplementary Materials** 19

Not applicable. 20

# **Author Contributions** 21

For research articles with several authors, a short paragraph specifying their individual contribu- 22 tions must be provided. The following statements should be used "Conceptualization, J.A. and I.A.; 23 methodology, J.A.; software, I.A.; validation, J.A., and I.A.; formal analysis, J.A.; investigation, I.A.; 24 resources, I.A.; data curation, J.A.; writing—original draft preparation, I.A.; writing—review and 25 editing, J.A.; visualization, I.A.; project administration, I.A. All authors have read and agreed to the 26 published version of the manuscript. 27

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### **Ethical approval** 32

This article does not contain any studies with human participants or animals performed by 33 any of the authors. 34

# **Conflicts of Interest** 35

The authors declare that there is no conflict of interest in the research. 36

# **Data Availability Statement** 37

All data generated or analyzed during this study are included in this article. 38

#### **References** 39

- [1]. Alam, S., Shuaib, M., Ahmad, S., Jayakody, D. N. K., Muthanna, A., Bharany, S., & Elgendy, I. A. (2022). Blockchain-based 40 solutions supporting reliable healthcare for fog computing and internet of medical things (IoMT) integration. Sustainabil- 41 ity, 14(22), 15312. 42
	-

- [2]. Alabdulatif, A., Khalil, I., & Saidur Rahman, M. (2022). Security of Blockchain and AI-Empowered Smart Healthcare: Ap- 1 plication-Based Analysis. Applied Sciences, 12(21), 11039. 2
- [3]. Namasudra, S., Sharma, P., Crespo, R. G., & Shanmuganathan, V. (2022). Blockchain-based medical certificate generation 3 and verification for IoT-based healthcare systems. IEEE Consumer Electronics Magazine, 12(2), 83-93. 4
- [4]. Mohurle, S., & Patil, M. (2017). A brief study of wannacry threat: Ransomware attack 2017. *International journal of advanced* 5 *research in computer science*, *8*(5), 1938-1940. 6
- [5]. Ch, R., Srivastava, G., Nagasree, Y. L. V., Ponugumati, A., & Ramachandran, S. (2022). Robust cyber-physical system ena- 7 bled smart healthcare unit using blockchain technology. Electronics, 11(19), 3070. 8
- [6]. Antwi, M., Adnane, A., Ahmad, F., Hussain, R., ur Rehman, M. H., & Kerrache, C. A. (2021). The case of HyperLedger 9 Fabric as a blockchain solution for healthcare applications. Blockchain: Research and Applications, 2(1), 100012. 10
- [7]. Wazid, M., Das, A. K., Mohd, N., & Park, Y. (2022). Healthcare 5.0 security framework: applications, issues and future 11 research directions. IEEE Access. 12
- [8]. Reshmi, T. R. (2021). Information security breaches due to ransomware attacks-a systematic literature review. *International* 13 *Journal of Information Management Data Insights*, *1*(2), 100013. 14
- [9]. Kara, I., & Aydos, M. (2022). The rise of ransomware: Forensic analysis for windows based ransomware attacks. *Expert* 15 *Systems with Applications, 190, 116198.* 16
- [10]. Maigida, A. M., Abdulhamid, S. I. M., Olalere, M., Alhassan, J. K., Chiroma, H., & Dada, E. G. (2019). Systematic literature 17 review and metadata analysis of ransomware attacks and detection mechanisms. Journal of Reliable Intelligent Environ- 18 ments, 5, 67-89. 19
- [11]. Maigida, A. M., Abdulhamid, S. I. M., Olalere, M., Alhassan, J. K., Chiroma, H., & Dada, E. G. (2019). Systematic literature 20 review and metadata analysis of ransomware attacks and detection mechanisms. Journal of Reliable Intelligent Environ- 21 ments, 5, 67-89. 22
- [12]. Mukati, A. Blockchain Technology In Healthcare Services. 23
- [13]. Wazid, M., Das, A. K., & Shetty, S. (2022). BSFR-SH: Blockchain-enabled security framework against ransomware attacks 24 for Smart Healthcare. IEEE Transactions on Consumer Electronics, 69(1), 18-28. 25
- [14]. Thamer, N., & Alubady, R. (2021, April). A survey of ransomware attacks for healthcare systems: Risks, challenges, solu- 26 tions and opportunity of research. In 2021 1st Babylon International Conference on Information Technology and Science 27 (BICITS) (pp. 210-216). IEEE. 28
- [15]. Tariq, U., Ullah, I., Yousuf Uddin, M., & Kwon, S. J. (2022). An Effective Self-Configurable Ransomware Prevention Tech- 29 nique for IoMT. Sensors, 22(21), 8516.  $\qquad \qquad$  30
- [16]. Thamer, N., & Alubady, R. (2021, April). A survey of ransomware attacks for healthcare systems: Risks, challenges, solu- 31 tions and opportunity of research. In 2021 1st Babylon International Conference on Information Technology and Science 32 (BICITS) (pp. 210-216). IEEE. 33
- [17]. Namasudra, S., Sharma, P., Crespo, R. G., & Shanmuganathan, V. (2022). Blockchain-based medical certificate generation 34 and verification for IoT-based healthcare systems. IEEE Consumer Electronics Magazine, 12(2), 83-93. 35
- [18]. Liu, H., Crespo, R. G., & Martínez, O. S. (2020, July). Enhancing privacy and data security across healthcare applications 36 using blockchain and distributed ledger concepts. In Healthcare (Vol. 8, No. 3, p. 243). MDPI. 37
- [19]. Zakaria, W. Z., Abdollah, M. F., Mohd, O., Yassin, S. W. M. S. M., & Ariffin, A. (2022). RENTAKA: A Novel Machine 38 Learning Framework for Crypto-Ransomware Pre-encryption Detection. International Journal of Advanced Computer Sci- 39 ence and Applications, 13(5). 40
- [20]. Battineni, G., Sagaro, G. G., Chinatalapudi, N., & Amenta, F. (2020). Applications of machine learning predictive models in 41 the chronic disease diagnosis. Journal of personalized medicine, 10(2), 21. 42
- [21]. Asharf, J., Moustafa, N., Khurshid, H., Debie, E., Haider, W., & Wahab, A. (2020). A review of intrusion detection systems 43 using machine and deep learning in internet of things: Challenges, solutions and future directions. Electronics, 9(7), 1177. 44
- [22]. Kumar, S., Bharti, A. K., & Amin, R. (2021). Decentralized secure storage of medical records using Blockchain and IPFS: A 45 comparative analysis with future directions. Security and Privacy, 4(5), e162. 46
- [23]. Dorogush, A. V., Ershov, V., & Gulin, A. (2018). CatBoost: gradient boosting with categorical features support. arXiv pre- 47 print arXiv:1810.11363. 48
- [24]. Attaran, M. (2022). Blockchain technology in healthcare: Challenges and opportunities. International Journal of Healthcare 49 Management, 15(1), 70-83. 50
- [25]. Pan, B. (2018, February). Application of XGBoost algorithm in hourly PM2. 5 concentration prediction. In IOP conference 51 series: earth and environmental science (Vol. 113, p. 012127). IOP publishing. 52
- [26]. Petkovic, D., Altman, R., Wong, M., & Vigil, A. (2018). Improving the explainability of Random Forest classifier–user cen- 53 tered approach. In Pacific symposium on biocomputing 2018: proceedings of the pacific symposium (pp. 204-215). 54
- [27]. Quasim, M. T., Algarni, F., Radwan, A. A. E., & Alshmrani, G. M. M. (2020, July). A blockchain based secured healthcare 55 framework. In 2020 International Conference on Computational Performance Evaluation (ComPE) (pp. 386-391). IEEE. 56
- [28]. [Online]. Available:Support Vector Machine (SVM) Algorithm Javatpoint 57
- [29]. Tariq, N., Qamar, A., Asim, M., & Khan, F. A. (2020). Blockchain and smart healthcare security: a survey. Procedia Com- 58 puter Science, 175, 615-620. 59



[32]. [Online]. BitcoinHeistRansomwareAddressDataset (kaggle.com) 6



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