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DLSDHMS: Design of a deep learning-based analysis model for secure and distributed hospital management using context-aware sidechains

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A B S T R A C T

Designing an efficient hospital management solution requires the integration of multidomain operations that include secure storage, alert system modelling, infrastructure management, staff management, report analysis, and feedback-based learning tasks. Existing hospital management models are either highly complex or do not incorporate comprehensive deep learning analysis, which limits their deployment capabilities. Moreover, most of these models use mutable storage solutions, which restricts their trust levels under multi-patient to multi-doctor mapping scenarios. To overcome these issues, this article proposes the design of a novel deep Learning-based analysis model for secure and distributed hospital management via context-aware sidechains. The model initially collects large-scale information sets from different hospital entities via an IoT-based network and stores the information on context-sensitive sidechains. These context-sensitive sidechains store information sets related to Medicine Management, Doctor Management, Insurance and Billing Management, and Appointment Management operations. These chains are optimized via an Iterative Genetic Algorithm (IGA) that assists in improving storage and retrieval performance via intelligent merging and splitting operations. Information stored on these chains is processed via a combination of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), that assist in identifying patient-level diseases and issues. The information obtained from these classifiers is updated on the central repository and assists in the pre-emption of diseases for other patients. Due to these integrations, the proposed model is capable of reducing computational delay by 3.5 % and reducing storage cost by 8.3 % when compared to other blockchain-based deployments. The model is also able to pre-empt patient issues with 9.3 % higher accuracy and 4.8 % higher precision, which makes it useful for real-time clinical deployments.

1. Introduction

Despite a number of challenges that need to be overcome first, the healthcare sector is starting to focus more on the potential advantages of using Internet of Things (IoT) solutions. Despite the fact that there are many challenges to overcome, this is happening. A growing number of monitoring devices with one or more sensors that are connected to the IoT are available [1–7]. These innovations offer a workable remedy for long-term health monitoring and assist in addressing the shortage of medical specialists. Solutions for the

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healthcare industry could be created before the IoT, but a sizable number of obstacles still need to be found and overcome [8–11]. This is true even if sensor networks and autonomous systems are widely used. Usability, safety, storage support, and communication security issues are all included in this problem domain. As clinical data is quickly incorporated into various healthcare systems, it is anticipated that there will be an increase in the amount of health information that may be available electronically [12]. This benefits not only the overall cost of therapy but also the standard of care given. In particular, as more sensors are utilized for longer periods of time, the amount of data that must be examined and securely kept increases proportionately in order to meet all applicable compliance and clinical requirements. This presents a significant barrier. The availability of enormous amounts of data is crucial for data processing and analysis [13,14]. Fog computing designs are frequently taken into account from an infrastructure perspective, in addition to the conventional method of interfacing with cloud systems [15]. This is because fog computing architectures offer a level of data processing and storage that is intermediate between the hundreds or thousands of IoT sensors and devices and the cloud [16,17]. These solutions not only do away with the need for additional bandwidth but also enable quick response in the case of a potentially life-threatening medical emergency on the premises. The paper [18] provides a fog computing-based fault-tolerant data processing layer as an illustration. Additionally [19,20], offers a framework for signal quality-aware data analysis of IoT device data. Recently, it was suggested to employ battery-free wireless sensors for health monitoring applications [21] or to use biofuel cells to power biosensors on their own [22]. Given the challenges posed by the energy consumption needs for wearable IoT devices, this suggestion was given. Information security is essential due to the private and delicate nature of the data these applications carry. Applications for the IoT may employ a network security strategy like the one outlined in Refs. [23,24]. Contrasting viewpoints are provided in Ref. [25], which suggests utilizing intelligent systems to maintain trust boundaries in hostile industrial IoT environments. This paper also proposes a fault-tolerant design for wearable IoT health data sensors. In Ref. [24], a fault-tolerant approach is suggested for wearable IoT health data sensors. Artificial intelligence-based solutions for intrusion detection are put out from the perspective of computer networks [26]. In Ref. [27], the authors explain how to use machine learning and enormous data processing to deter criminals from accessing delicate IoT devices, including those found in hospitals. Since the volume of data gathered during continuous monitoring from a high number of sensors and unstructured data rises constantly, big data strategies and analytics must be taken into account [28]. The move from EDA to IoT eHealth, as well as the growing variety and volume of created data and the implications for clinical operations and procedures, are all thoroughly studied in Ref. [29]. In Ref. [30] provides a thorough assessment of how data on chronic diseases and health monitoring are integrated, and it also describes many of the anticipated future advancements.

In addition to these developments, recent advancements in optimization techniques have also played a significant role in enhancing the capabilities of IoT-based healthcare systems. Two such metaheuristic algorithms, the Crow Search Algorithm, and the Giant Trevally Algorithm, have emerged as promising approaches for optimizing various aspects of IoT-enabled healthcare systems. These algorithms bring novel perspectives to the optimization of data processing, resource allocation, and network management within the healthcare domain.

In [31] Crow Search Algorithm is inspired by the foraging behavior of crows and is known for its ability to explore complex search spaces efficiently. It has been applied to problems such as feature selection in medical data analysis and resource allocation in healthcare networks.

On the other hand, the Giant Trevally Algorithm draws inspiration from the hunting behavior of giant trevally fish and is particularly suited for solving optimization problems in dynamic and uncertain environments [32]. Its adaptability and ability to handle real-time changes make it a valuable tool for optimizing healthcare systems that must respond to evolving patient needs and environmental conditions.

These emerging metaheuristic algorithms, alongside the ongoing advancements in IoT technology, promise to further enhance the efficiency, scalability, and reliability of healthcare systems, ultimately improving the quality of patient care and addressing the evolving challenges in the healthcare sector.

Big data is used as the lens through which this inquiry is presented. Concentric computing is recommended as a solution to issues with both big data analytics and the IoT in the article [31]. In Ref. [32], which discusses large data analytics for the Internet of Things Nano sensor data, might have the solutions to your questions. The foundation for the development of a wide variety of new

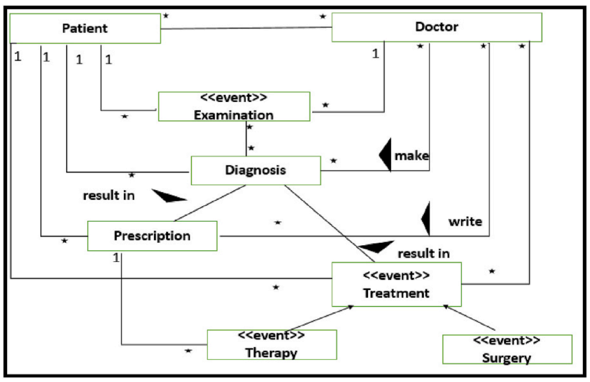

Fig. 1. Design of the typical Hospital Management Model.

applications is laid by fusing the sensor and device networks of the Internet of Things with AI paradigms [33–40].

Thus, it can be observed that hospital management modeling is a multidomain task that involves the design of patient management, infrastructure management, doctor management, alert management, storage optimization, and analysis modules. These modules are built using multiple deep learning and machine learning models, which involve a high level of complexity during deployment and analysis operations. A typical healthcare management model that showcases the deployment of these entities can be observed in Fig. 1, where * indicates many and 1 indicates 1. Patients and doctors are linked by different events. These events include examination, diagnosis, prescription changes, treatment modifications, therapeutic amendments, surgery changes, etc.

A graph model is used to connect all of these events, which helps in tracking various real-time event changes. These modifications enable the models to carry out alert activities, which are used to enhance patient care services. These models can be scaled according to their internal design characteristics and are relevant to a wide range of hospital administration scenarios. In the following section of this work, a survey of these models is presented in terms of the deployment-specific nuances, functional advantages, application-specific limits, and context-specific future research possibilities. Based on this debate, it can be seen that the following constraints exist in current models:

- The majority of these models were created for implementation in a single hospital, which limits their capacity to scale.
- Distributed models perform poorly in terms of security and privacy, and they complicate deployment.
- The majority of models do not use distributed processing, which restricts their capacity for prognosis advice and report analysis for various patient kinds.

Here are several bioinspired models that can be considered for optimization:

1. Ant Colony Optimization (ACO): ACO is a bioinspired optimization algorithm inspired by the foraging behavior of ants. In the context of hospital management, ACO can be applied to optimize the routing of alerts and feedback within the system. It can help in finding the most efficient paths for information flow, ensuring timely responses to critical events, and reducing delays in alert propagation.
2. Genetic Algorithms (GA): Genetic algorithms are inspired by natural selection and genetic evolution. They can be used to further optimize the proposed Iterative Genetic Algorithm (IGA) for context-sensitive sidechain optimization. GA can help in fine-tuning the parameters and strategies used in IGA, leading to better storage and retrieval performance.
3. Neural Networks Inspired by Biological Neurons: While the abstract mentions the use of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), there is room to explore more advanced neural network architectures inspired by the human brain. For instance, Spiking Neural Networks (SNNs) mimic the spiking behavior of neurons and can be applied to more accurately model complex patterns and temporal relationships in patient data.
4. Swarm Intelligence: Inspired by the collective behavior of social insects like bees and termites, swarm intelligence algorithms like Particle Swarm Optimization (PSO) can be used for optimizing the parameters and configurations of the deep learning models. PSO can assist in finding the optimal hyperparameters for RNNs and CNNs, leading to improved disease identification accuracy.
5. Immunological Algorithms: These algorithms are inspired by the human immune system's ability to identify and defend against pathogens. In the context of hospital management, immunological algorithms can be applied to enhance the security of the system. They can help detect and respond to potential security threats and breaches in real-time, ensuring the integrity and confidentiality of patient data.
6. Bioinspired Data Compression: Bioinspired data compression techniques, such as DNA-based compression algorithms, can be explored to further reduce storage costs. These algorithms mimic the way genetic information is compactly encoded and can be applied to compress and store large-scale information sets more efficiently.

By integrating these bioinspired models into the proposed hospital management system, you can enhance its capabilities in terms of optimization, security, and data analysis. These models can work synergistically with the deep learning components to create a comprehensive and highly efficient healthcare management solution.

1.1. Genetic algorithm

In the context of this multifaceted exploration of IoT and healthcare management, it is essential to introduce Genetic Algorithms (GAs). GAs are a class of computational techniques inspired by the process of natural selection and genetic evolution. They are employed to address optimization and search problems across diverse domains. GAs operate by iteratively evolving a population of potential solutions, allowing them to undergo processes of selection, crossover, mutation, and adaptation to generate increasingly optimal solutions to complex problems.

The inclusion of GAs in this paper is particularly noteworthy as they play a pivotal role in optimizing context-sensitive sidechains through an Iterative Genetic Algorithm (IGA). This process enhances the storage and retrieval performance by intelligently merging and splitting information stored in these sidechains. The integration of GAs exemplifies the commitment to advanced computational techniques in crafting an innovative and efficient solution for secure and distributed hospital management.

1.2. Motivation for using Genetic Algorithms

GAs stand as one of the earliest and most enduring metaheuristic optimization techniques, and their integration into the proposed research framework is underpinned by several compelling motivations.

First and foremost, GAs excel in solving complex optimization problems that involve a high degree of uncertainty, non-linearity, and combinatorial complexity. These characteristics are often inherent in real-world applications, particularly in the context of healthcare management. The intricate nature of hospital management operations, including secure storage, alert system modeling, staff management, and report analysis, necessitates the need for a versatile optimization approach capable of accommodating multifaceted and dynamic requirements. GAs, with their ability to explore vast solution spaces and adapt to evolving problem landscapes, offer a robust framework for tackling the intricacies of hospital management.

Furthermore, the adoption of GAs aligns with the broader objective of enhancing the efficiency and effectiveness of hospital management through intelligent optimization. In this context, GAs play a pivotal role in optimizing context-sensitive sidechains, which are fundamental to the proposed deep learning-based analysis model. The iterative nature of GAs allows for continuous refinement of storage and retrieval processes within these sidechains. As a result, the model can dynamically adapt to changing data patterns and user requirements, thus improving both storage and retrieval performance. This adaptability is essential in the healthcare domain, where data volumes and access patterns can vary significantly over time.

Moreover, GAs offer a degree of parallelism and exploration-exploitation balance that is well-suited for addressing the challenges posed by distributed hospital management. In a context where information from different hospital entities is collected via an IoT-based network and stored on context-sensitive sidechains, the optimization of these chains requires a method that can efficiently explore alternative configurations while exploiting promising solutions. GAs achieve this by maintaining a diverse population of potential solutions and iteratively evolving them, thereby ensuring a robust exploration of the solution space.

Incorporating GAs into the proposed model also reflects a commitment to harnessing state-of-the-art techniques for enhancing computational efficiency. By reducing computational delay by 3.5 % and storage costs by 8.3 % compared to other blockchain-based deployments, the utilization of GAs directly contributes to resource optimization, which is a crucial consideration in healthcare settings.

In summary, the decision to integrate Genetic Algorithms into the research framework is motivated by their proven efficacy in addressing complex optimization challenges, adaptability to dynamic problem landscapes, and capacity to parallelize and balance exploration and exploitation. This utilization represents a strategic choice aimed at enhancing the efficiency, adaptability, and resource optimization of secure and distributed hospital management, ultimately contributing to improved healthcare outcomes.

Section 3 describes the construction of a revolutionary deep learning-based analysis model for secure and distributed hospital management via context-aware sidechains to get around these restrictions. The key component of the suggested paradigm is a distributed blockchain architecture that makes use of context-specific sidechains. A Genetic Algorithm Model (GA) is used to manage these sidechains and helps to adjust chain length in accordance with the network's security and quality of service needs. The approach can combine data transparency, record immutability, communication traceability, and distributed processing across various hospitals thanks to the use of sidechains. This model includes a report analysis layer based on recurrent neural networks (RNN) and convolutional neural networks (CNN) that can identify various health issues using transfer learning analysis. In order to deploy a thorough hospital management model for various uses, the model also incorporates management layers for patients, receptionists, doctors, staff, hospital infrastructure, and medicines. In section 4, this model's performance is assessed and contrasted with other cutting-edge techniques. The security, quality of service (QoS), and scalability of this performance are assessed for deployments of various sizes. Finally, this study offers suggestions for ways to further enhance the performance of the proposed model as well as some application-specific findings.

2. Related work

There are many hospital data management models, each with deployment-specific properties. For instance Refs. [5,6], suggests using Prototype Management Applications and Electronic Health Record Management to manage hospital resources during pandemics like COVID-19. This study suggests using Prototype Management Application with Electronic Health Record Management. This study suggests using a prototype management application with electronic health record management. The models' scalability must be assessed for a variety of diseases and sensors.

This determines model performance. This stage is crucial for model evaluation. In Ref. [7] explores this paradigm and its ramifications and presents an interface for several wearable sensors that scan diverse characteristics for temporal analysis. Sensors analyze parameters temporally. Discussing its effects. This model's effects are also explored. The model rates hospitals in distributed processing systems using AHP and VIKOR.

These methods compare hospitals. Because of this method, the research in Refs. [8,9] proposes using a Genetic Algorithm for Out-Patient Experience Management (GAPEM) with RFIDs and other sensors, as well as a Nonlinear Stochastic Programming (NSP) method to allocate resources to different types of patients. The research suggests that combining these models is necessary to offer patients the best care and efficiently manage hospital resources.

Extensions to these models [10,11] suggest using Data Envelopment Analysis (DEA) and Supply Chain Management (SCM) optimizations to improve hospital management under various real-time patient monitoring applications. This improves hospital patient care. This improves patient care at the institution. This improves patient care at the facility where it is done. Bioinspired approaches should be used to enhance these models for real-time continuous optimization. This ensures optimal results. This will help us achieve the greatest results. This will help us achieve the best possible results.

Hybrid Neural-Symbolic Systems (HNSS) and Threshold Control Policy Optimization (TCPO) via a state-dependent Markovian arrival model reduce patient wait times and improve hospital resource efficiency for multiple and distributed deployments [13,14]. Discuss similar models. Hospital management models should use Packet Wavelet Transfer (PWT) to reduce patient wait times. It maximizes resource use and increases feedback ratings for a wide range of patients in different categories. This maximizes resource use. Models suggest Bottleneck Simulations using finite and infinite-horizon Markov Decision Processes (MDP) to lower PWT [15,16]. These models estimate frequent usage patterns and balance department loads to improve patient experiences. This enhances patient care.

The models must be expanded to include Patient Tracking with Long Range Wide-Area Network (LoRaWAN) [17], Deep Learning for Imputation of Missing Values in Patient Records [18], Multiple Objective Tabu Search (MTS) to solve Hospital Department Layout Tasks (HDLTs) [19], and Fluid Queueing Approximation (FQA) [20] for dynamic allocation of hospital and medical resources in response to large-scale requirements and multiple hospital scenarios. These models aim to solve hospital problems and simplify patient and resource management. To accurately analyze these models [21,22], programs must be implemented. Researchers optimize Resuscitation-team Activation (RA) and hospital power systems by estimating operational resilience under real-time use cases.

Recent research [23,24] suggests using Explainable Machine Learning Predictions (EMLP) and Grey Relational Analysis (GRA) to estimate and optimize Medical Service Quality in single hospital deployments. Both methods forecast using machine learning. Both strategies aim to better estimate medical service quality. These strategies, meant to boost managerial performance, will help.

These models reduce unnecessary duplication in hospital operations. This will help make and implement optimal decisions for managing a wide range of physical infrastructure. For various application scenarios, academics have proposed discrete-time with finite-horizon models. Markov decision process (DT FH MDP) [25], Post-discharge Intervention Processes to reduce readmissions, IoT design allows sensors, embedded devices, and other "things" to sense, process, and communicate in tiny devices.

IoT-assisted ECG monitoring with secure data transfer is recommended for cardiovascular health monitoring [26]. IoT sensors, Arduino boards, Android phones, Bluetooth, cloud servers, and other devices are recommended for real-time ECG Signal Strength Analysis (SSA). LAC and LS-IoT secure data transport. MIT-BIH and Physio Net Challenge ECG data are analyzed and validated in real time. The Internet of Things-assisted ECG monitoring device may improve unsupervised diagnosis. E-healthcare solutions require a wireless body area network (WBAN) enabled by wireless communication and medical sensor technology.

Medical sensors in WBAN [27] transfer patient health data to a remote medical server through PDA or mobile device. Due to the sensor network's power, storage, and processing, WBAN aggregates real-time data to reduce communication overhead. WBAN transmits sensitive health data. Remote health monitoring systems use our bilinear pairing-based secure privacy-preserving data aggregation (SPPDA) approach. SPPDA provides data integrity and authenticity in the WBAN using the ElGamal cryptosystem's homomorphic features and aggregate signature mechanism.

Wireless body area networks for remote patient monitoring (M-Health) allow remote health monitoring. In Refs. [28,29], it claims that ICU physiologic data can be analyzed using revolutionary methods. We designed and evaluated IRIS for ICU physiologic monitoring, clinical judgment, and caregiver alarms. Methods: The neuro-intensive care unit's IRIS system processed ICP and EEG data transmitted to a server. 26 patients were monitored for burst suppression, four for intracranial pressure, and 364 for IRIS with continuous EEG. Algorithms can detect ICP rise, BSRs, and damaged or disconnected EEG electrodes. Our API sent password-protected smartphone notifications to hospital employees.

Alarm throttling and user-defined thresholds detect ICP changes. BSR trends and platform neurologists worked well together. The technique identified 95 % of faulty EEG electrodes in 93 % less time. The findings may be utilized to construct a real-time platform that can monitor and analyze ICU data in real time and feed caregivers with crucial information, relieving manual staff. Translational medical data analytics lowers healthcare expenditures and improves patient outcomes.

IoT interest is expanding rapidly. IoT-enabled health care allows convenient remote monitoring. In Ref. [30] health data is massive. IoT has increased data production. Medical records must be scrupulously maintained for usage. Cloud-based IoT e-health is recommended. This e-Health platform simplifies cloudlet-based data access. A healthcare data management system stores large amounts of health data and responds to client queries. NoSQL stores medical data. The proposed paradigm evaluates data transmission time, energy consumption, query response time, and data packet loss. Comparing our results to those of established cloud-based e-health solutions showed that our technique was better.

IoT remote monitoring solutions use device-to-cloud networks, according to Ref. [31]. Remote patient monitoring systems use low-resource devices to track patients outside of clinical settings and transfer the data to a trusted healthcare provider's cloud backend for processing and decision-making. Measurements contain patient data, requiring access management and trustworthy processing. Even if this challenge were overcome in software utilizing attribute-based encryption and completely homomorphic encryption, client and server computing costs would rise. Secure Remote Monitoring (SRM), a trustworthy and efficient remote monitoring framework, uses Intel SGX, the latest hardware-based trustworthy computing technology.

Health monitoring and remote diagnostics have helped e-health systems spread [32]. Managing the e-health ecosystem and protecting personal data are the main drawbacks. Data that is not consolidated, replicated, and moved around many e-health service providers causes the first. Centralized systems may leak sensitive data. Blockchain allows large, decentralized commercial platforms to protect user privacy and data access. Our comprehensive solution can transition traditional e-health systems to blockchain. Relational and blockchain file databases are compared. How to handle massive e-health data differs.

Analysis and execution improved data transport, access management, and storage. Remote health monitoring devices can transfer EEG data using optical chaos [33]. Our approach masks the EEG signal before sending it via the optical fibre using semiconductor laser-generated optical chaos. Optisystem analyses and rescales 14-channel Emotiv headset EEG data for the experiment. Additive masking blends EEG data with chaos, making it easy to understand. EEG signal propagation is studied using chaotic optical fibre data. Controlling linear defects in optical fiber may improve long-distance communication security. If transmission and receiving parameters match, EEG signals can be combined and subtracted to reconstitute the original signal.

Cyber-physical systems (CPS) [34] can communicate medical data from mobile devices and biomedical sensors to m-Health servers. This study's hierarchical mobile health system begins with a sensor network that collects vital signals. The mobile computing network analyzes and routes remote data, followed by the back-end network, which examines remote data and the patient's medical history. This architecture creates a second-tier physical layer security mechanism and evaluates its network performance. Comparing end-to-end latency of two communication methods. All neighbors are alerted. Eavesdropper location is also discussed. Broadcasting to the nearest neighbor yields the longest secure transmission distance and the lowest mean latency.

Wearable health monitoring technologies have transformed the medical sector worldwide [35] because they provide reliable and quick information on physical tests like pain, heart rate, and blood glucose level, which helps detect delicate cardiac abnormalities. The Internet of Medical Things (IoMT) allows doctors and patients to communicate directly. These algorithms track limbs, rural healthcare, e-health applications, mobile apps, heart sounds, driver stress, cardiac issues, heart attacks, and breast cancer. To help diagnose cancer, heart attacks, and excessive blood pressure early, the IoMT environment must be clear. We conclude with healthcare IoMT security issues.

The IoT-based health system may quickly diagnose patients based on recorded health data. If cloud data is altered or deleted due to an attack or power outage, doctors may misdiagnose patients. Verify the patient's cloud-stored health data [36]. Due to their modest processing power, IoT-based health sensors make data integrity verification challenging. This paper presents a safe IoT-based health storage system. Data authenticators and integrity checks on edge servers reduce computation costs and third-party verifier administrative labour. The suggested remedy improves performance and security.

According to research [37], healthcare technology has many potential and challenges. "M-health"—the creation of wireless body area networks (WBANs) for remote patient monitoring—is a reliable and cost-effective solution to improve healthcare efficiency and quality. Medical data gathered when developing m-health solutions may impede mobile networks. Due of medical data's sensitivity and D2D sensor interactions, security issues occur. Healthcare institutions risk patient privacy breaches. This study recommends certificateless generalized signcryption (CLGSC) for M-health D2D data transfer security. We present a novel, efficient CLGSC primitive for encryption, signatures, and signcryption. This method seeks invulnerability and concealment. In Table 1, we have explained the contributions of existing models.

As Per studies, innovative healthcare technology is increasing [38]. Integrating healthcare technologies raises many challenges. Healthcare must take precedence over threats, network congestion, and device failures. We want to use technology to monitor wandering patients' safety and determine if they violate hospital rules or other patients' privacy. Our approach includes SDN, WLAN, and patient wearables. WLANs are readily available, making our approach affordable. WLAN is commonly utilized for Internet access because it is open and may have security issues. SDN, which prioritizes monitoring services, may solve some of these concerns. A security application controlled host connection tracked patient position in real-time and prevented hospital network breaches using an SDN controller.

Ad-hoc networks are increasing [39] LPWAN and WBAN are increasingly used for emergency location tracking and health monitoring. LPWANs can use sensors and personal devices to activate real-time IoT devices and emergency alarm systems. This could improve military networks and applications and soldier and field worker health. Sensors and other devices that provide data to a central server must use low-power components to extend battery life. Inference systems save data and energy, but accuracy may suffer.

Many service providers restrict users' remote data access, posing security and privacy risks [40]. Wearable data's sensitivity and diversity complicate matters. Most systems have substantial processing and communication costs and are subject to known attacks,

Table 1
Summary of existing work for quick reference to readers.

Related Works	Contributions
Existing Hospital Management Models	- Address various aspects of hospital management but often lack comprehensive deep learning analysis. - May use mutable storage solutions.
Fog Computing in Healthcare [18]	- Introduces fault-tolerant data processing based on fog computing. - Enhances data processing and storage for healthcare applications.
Signal Quality-Aware IoT Data Analysis [19,20]	- Proposes a framework for signal quality-aware data analysis of IoT device data. - Focuses on data quality for IoT applications.
Battery-Free Wireless Sensors [21]	- Suggests the use of battery-free wireless sensors for health monitoring. - Addresses energy consumption challenges in wearable IoT devices.
Information Security in IoT [23,24]	- Offers network security strategies for IoT applications. - Emphasizes information security in IoT ecosystems.
AI-Based Intrusion Detection [26]	- Discusses AI-based solutions for intrusion detection in computer networks. - Enhances security in IoT environments.
Big Data Analytics in Healthcare [28]	- Advocates for the adoption of big data strategies and analytics. - Deals with the challenges of processing large volumes of healthcare data.
Converging IoT and AI [33–40]	- Explores the integration of IoT sensor networks with AI paradigms. - Lays the foundation for innovative healthcare applications.
Current Study	- Introduces a novel deep learning-based analysis model for secure and distributed hospital management. - Utilizes Genetic Algorithms to optimize context-sensitive sidechains. - Reduces computational delay by 3.5 % and storage costs by 8.3 % compared to other blockchain-based deployments. - Achieves 9.3 % higher accuracy and 4.8 % higher precision in pre-empting patient issues. - Provides a comprehensive solution for hospital management with deep learning analysis and secure storage.

limiting their real-world uses. This study recommends cloud-based medical data authentication. User and wearable sensor node create a secure session key after mutual verification. Using an AVISPA tool and the Real-Or-Random (ROR) concept, session keys can be safeguarded.

A reliable, secure, and privacy-protected system that can keep up with fast-expanding digital storage technologies [41–44] is essential. IoMT, or personalized patient-centric care, is now considered the greatest solution since it employs technology to improve sickness detection, eliminate errors, and lower healthcare expenses. It also lets users manage their prescriptions, medical histories, and doctor visits to stay healthy.

Electronic medical records [45–47], administrative expenditures, and data shortages are IoMT implementation obstacles. BCT uses cutting-edge encryption to avoid IoMT security issues. This system uses blockchain technology's lower costs, faster processing, automation, immutability, almost impossible data loss, permanence, removal of middlemen, decentralization of consensus, legitimate access to health data, data storage, accrual-based reimbursement mechanisms, and medical supply chain efficiency. The research addresses cloud computing, IoMT, and blockchain (BC) convergence difficulties and prerequisites. Methodically evaluate cloud storage, IoMT, and blockchain. Real-time remote health one-to-one care frameworks require core features [48–50].

Due to their intrinsic properties, most of these types can only be deployed in single hospitals. These models lack distributed processing, which limits report analysis and prognosis advice for distinct patient types. The next section presents a deep learning-based analysis methodology for safe and remote hospital management via context-aware sidechains to solve these shortcomings. The model's performance was evaluated across application kinds and compared against state-of-the-art methodologies in several deployment circumstances.

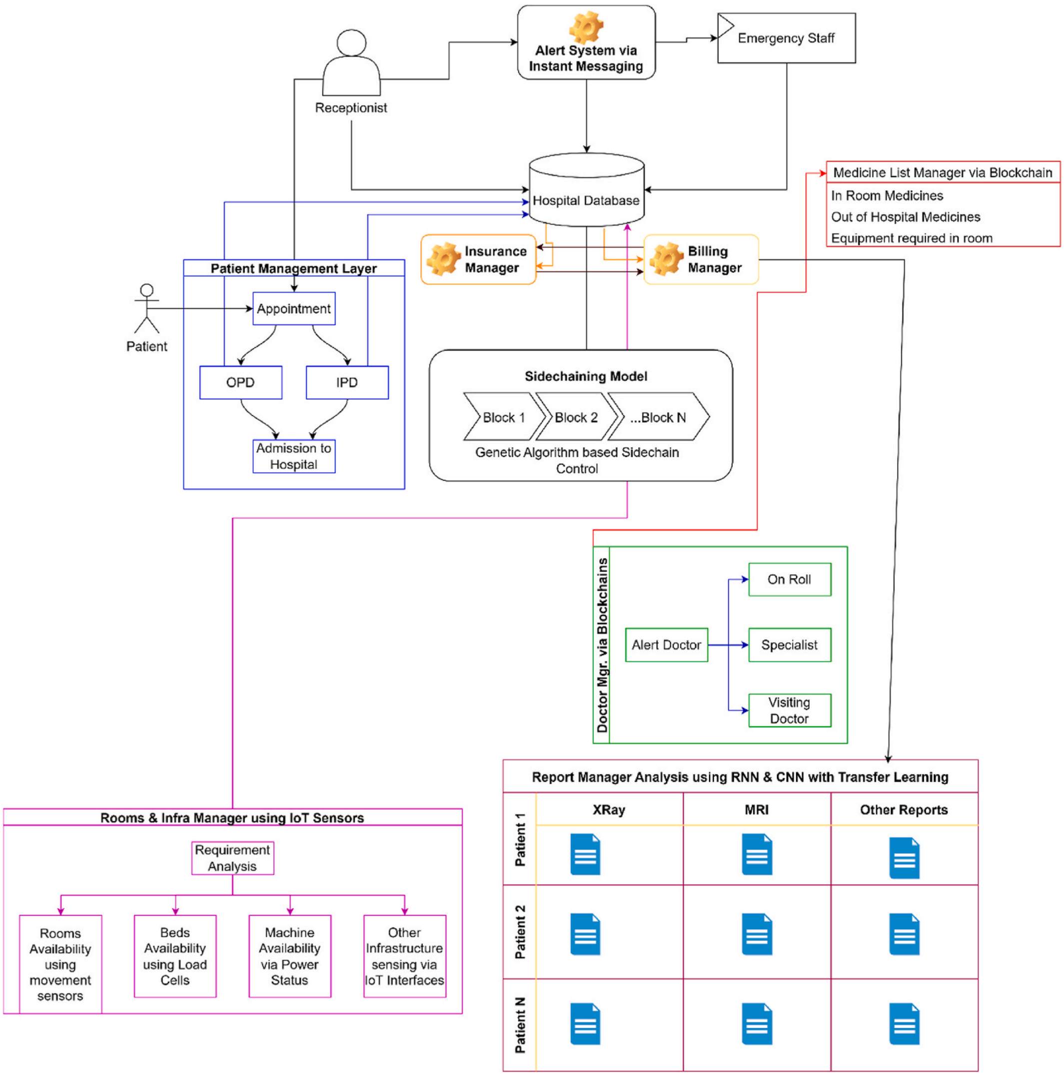

Fig. 2. The flow of the proposed Hospital Management Model with different processes.

3. Design of the proposed deep learning-based analysis model for secure and distributed hospital management via context-aware sidechains

The broad study of existing hospital management models reveals that their deployment potential is constrained by the fact that they are either extremely complex or do not include thorough deep-learning analyses. Additionally, the majority of these models employ changeable storage options, which limits their degrees of trust in scenarios involving the mapping of several patients to multiple doctors. This work offers the construction of a novel deep learning-based analysis model for secure and distributed hospital management using context-aware sidechains as a solution to these problems. An IoT-based network is used by the model to initially gather enormous data sets from various hospital entities, which are then stored on context-sensitive sidechains. These context-sensitive sidechains hold data sets pertaining to the activities of managing prescription drugs, doctors, insurance and billing, and appointments. An IGA is used to optimize these chains, which helps to enhance storage and retrieval performance through clever merging and splitting procedures. RNNs and CNNs are used in tandem to process the data recorded on these chains in order to identify illnesses and other problems at the patient level. The data gathered from these classifiers is updated in the central repository and helps other patients avoid contracting diseases.

As shown in Fig. 2, the model deployment is started by gathering massive information sets from various IoT sensors. These include the availability of rooms (obtained through movement sensors), beds (obtained through load cells), scanning and operational machinery (obtained through respective power status levels), doctors and other staff (obtained through schedules and in-out status), and medications (obtained through stock management sensing interfaces).

All this information is stored on a Proof-of-Work (PoW) based blockchain, which has a block structure as depicted in Table 2, as follows.

This block structure stores sidechain information, nonce values, the current hash, the previous block hashes, the timestamp at which the information was stored, the IP address of the sensor, the data sensed by the sensor, its metadata (which is determined by the content stored on the chain, the type of sensor, and various information types), and the data sensed by the sensor. By modifying the metadata fields, the same blocks are also utilized to store all sets of information linked to hospitals. The following fields are reported in Table 3:

$$D(New) = N * [D(Nonce) + D(Hash)] + (N-1) * D(Verify) + D(Write) \tag{1}$$

This delay is evaluated via equation (1) where $D(New)$ represents the delay needed to add a new block, $D(Nonce), D(Hash)$, $D(Verify)$, and $D(Write)$ represents delays needed for the generation of a nonce number, hashing delays, verification delays, and block writing delays for N blocks. These delays increase exponentially with an increase in the value of N, due to which an intelligent GA-based sidechaining model is used to handle the blocks. This sidechaining model segregates existing blockchains into multiple parts *or* merges these chains depending on their access patterns. This GA model works via the following process,

- To initialize the GA-based sidechaining process, set the following constants,
  - o Total GA iterations used for optimizations of sidechains (N_i)
  - o Total GA solutions to be iterated for efficient sidechaining (N_s)
  - o Rate at which the model learns (L_r)
  - o Current number of sidechains (N_{sc})
- Generate the N_s sidechain configurations as per the following process,
  - o Select a stochastic chain from the list of sidechains via equation (2),

$$S_{sel} = STOCH(1, N_{sc}) \tag{2}$$

o Create N_d dummy blocks and emulate the block addition process for S_{sel}.
o Identify its fitness levels.

$$f = \sum_{i=1}^{S_{sel}} \frac{D(New)_i}{Max(D(New))} + \frac{E(New)_i}{Max(E(New))} + \frac{SC(New)_i}{Max(SC(New))} \tag{3}$$

From equation (3), E *and* SC represents the energy needed and storage cost needed for adding blocks.

- Store the fitness levels for each solution, and then calculate the iteration fitness threshold via equation (4),

$$f_{th} = \sum_{i=1}^{N_s} f_i * \frac{L_r}{N_s} \tag{4}$$

Table 2
Block structure used for storage operations.

Prev. Hash	Timestamp	Sensor IP	Sensed Data
Meta Data	Sidechain Information	Nonce	Current Hash

Table 3
Meta Data for different fields.

Hospital Related Field	Meta Data Sets
Room Availability	Room Number, Total Capacity, Current Number of Patients
Beds Availability	Room Number, Bed Status
Equipment Availability	Equipment ID, current location, contact details of the person for the equipment
Doctor Status	Doctor contact details, current in-time, schedule of individual Doctors
Staff Status	Staff contact details, current in-time, schedule of individual Staff members and their shift status
Medicine Status	Medicine details, Current Stock, Last Quantity Sold, Last Quantity Purchased, In-room or external Medicine status, Location and Contact Details
Patient Reports	Report Parameter Names, Parameter Values, Inferences
Billing Information	Patient Details, Admission Date, Exit Date, Item-wise and Department-wise Bills, Contact Details
Insurance Information	Patient Details, Insurance company details, Claim Process, Current Claim Status

Based on this flexible blockchain structure, any kind of information can be stored on the chains. But as the number of blocks increases, the delay needed to add new blocks increases exponentially, which limits its performance levels.

- Regenerate solutions with $f > f_{th}$, and repeat this process for N_i iterations
- At the end of the final iteration, select a solution with minimum fitness levels
- Perform this task of solution selection again for N_i iterations, and identify the selected sidechain during each of the iterations.

Once this process is completed, then select the top $N = L_r * N_{sc}$ sidechains, which are commonly occurring across all iterations. Estimate the minimum and maximum fitness for these sidechains, and then estimate the decision threshold via equation (5),

$$d_{th} = \frac{Max(f)}{Min(f)} \tag{5}$$

The sidechain with minimum fitness levels is split into 2 equal parts if $d_{th} > 2$, while the top 2 sidechains with maximum fitness levels are merged if $d_{th} > 1.5$, while, the sidechains are not modified if $d_{th} \leq 1.5$, which indicates that there is not even 50 % change in delay, energy and storage cost between minimum and maximum fitness chains. After these operations, the sidechain configuration with minimum fitness levels is used for the storage of new blocks. Due to this, the model is capable of reducing mining delay, reducing energy consumption, and minimizing storage costs under real-time use cases.

The data stored on these blockchains are processed via a set of CNN and RNN both of which work on different report types. The CNN Model works on MRIs, and other image-based reports, while RNNs work on single-dimensional data samples. The CNNs and RNNs are initially trained as per the Doctor's inputs and are used later for pre-emption operations. Reports from multiple patients and multiple departments are aggregated, and their manual inferences are converted into different disease classes. For instance, the Electrocardiogram (ECG) reports are categorized as Normal, Myopathy, Valve Leakage, Arrhythmia, etc., depending upon inference done by doctors. Multidimensional reports, along with their inferences, are used to train a CNN, which is depicted in Fig. 3, where a combination of Convolutional Layers (for feature extraction), Max Pooling Layers (for feature selection), Drop Out Layers (for variance maximization), and Fully Connected Neural Network (FCNN) (for final classification) are used to train the network under different report types. Individual CNNs are trained for each type of report, which assists in selective classification as per the treatments given to different patients.

$$.Conv_{out_{i,j}} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} \sum_{b=-\frac{n}{2}}^{\frac{n}{2}} Scan(i-a, j-b) * ReLU\left(\frac{m}{2}+a, \frac{n}{2}+b\right) \tag{6}$$

The CNN Model initially generates convolutional feature sets via equation (6) where m, n represents convolutional window sizes, $Scan$ represents the multidimensional scan, while a, b represents stride sizes for the convolutional operations.

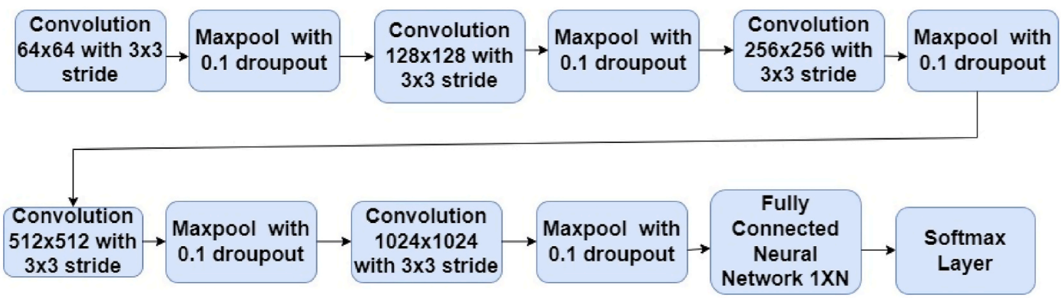

Fig. 3. Structure of the CNN model used for processing multidimensional data samples.

These features are activated via a Rectilinear Unit (ReLU) based layer, which assists in retaining positive features. These features are further selected via a Max Pooling layer, that estimates a feature threshold.

$$f_{th} = \left(\frac{1}{X_k} * \sum_{x \in X_k} x^{p_k} \right)^{1/p_k} \tag{7}$$

From equation (7) as follows where, X, p represents feature value and its respective variance levels. Convolutional features with values more than f_{th} are retained for further operations. Out of these features, lower 10 % variance feature sets are removed via a dropout layer, which assists in the reduction of low variance feature sets. This process of convolution, max pooling, and dropout is repeated for different window and stride sizes. Extracted feature sets are classified into output disease classes (c_{out}) via a SoftMax-based activation function.

$$c_{out} = SoftMax\left(\sum_{i=1}^{N_f} f_i * w_i + b \right) \tag{8}$$

From equation (8), N_f represents a number of extracted features, f, w *and* b represent feature values, their weights and respective biases. Based on this process, all multidimensional information sets are classified into scan-specific disease classes. This process is repeated for each scan type and is extended via the application of a Recurrent Neural Network, this model works as per Fig. 4 and uses a Long-Short-Term Memory (LSTM) for extraction of different feature sets.

The RNN model uses a combination of multiple LSTMs for the augmented extraction of feature sets. This LSTM works as per Fig. 5 and uses a combination of tangent and variance maximization functions for the estimation of different feature sets.

This model inputs scanned values and estimates an initialization vector. via equation (9),

$$i = var\left(x_{in} * U^i + h_{t-1} * W^i\right) \tag{9}$$

In equation (9), x_{in} represents input scan values, h represents the activation matrix, var represents variance levels, while U *and* W represent activation hyperparameters for the LSTM process. The initialization features are cascaded with functional features and output features, which are evaluated as per equations (10) and (11) as follows,

$$f = var\left(x_{in} * U^f + h_{t-1} * W^f\right) \tag{10}$$

$$o = var(x_{in} * U^o + h_{t-1} * W^o) \tag{11}$$

Both these feature sets are combined with a convolutional metric which is estimated as per equation (12),

$$C_t^{'} = tanh(x_{in} * U^g + h_{t-1} * W^g) \tag{12}$$

The final output features from LSTM are extracted via equation (13),

$$T_{out} = var\left(f_t * x_{in}(t-1) + i * C_t^{'}\right) \tag{13}$$

Based on the output features, a new activation metric is generated via equation (14),

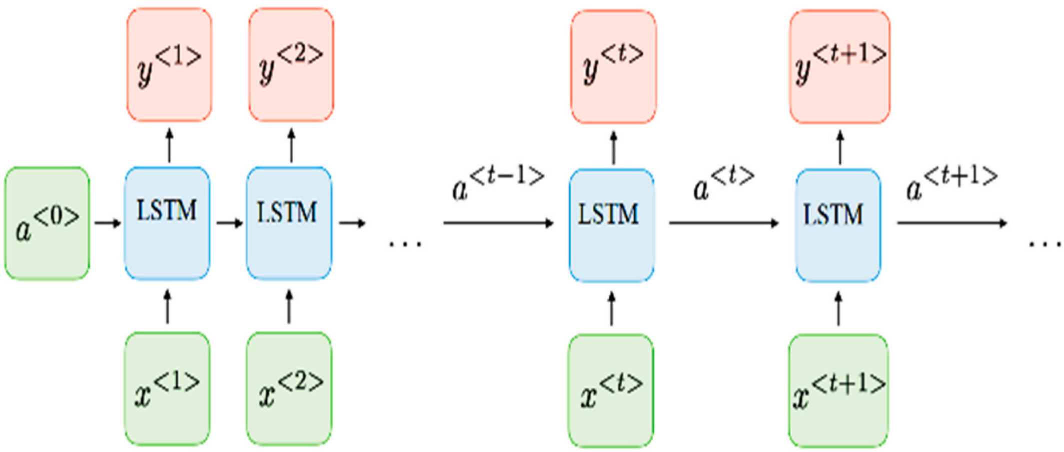

Fig. 4. RNN for analysis of single-dimensional scans.

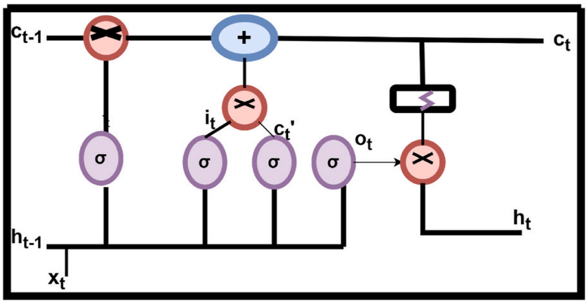

Fig. 5. LSTM Model used for the analysis.

$$h_{out} = \tanh(T_{out}) * o \tag{14}$$

The process is iteratively continued for different RNN layers and output classes.

$$C_{out} = purelin\left(\sum_{i=1}^{N} xout_i * W_i\right) \tag{15}$$

It is estimated via equation (15) where, *purelin* represents a purely linear activation function, while $xout = T_{out}$ for the final LSTM layer, and w_i represents RNN weights that are tuned by a hyperparameter tuning process. The trained models are evaluated for every new patient scan, and their result sets are recommended to doctors for better hospital management efficiency under large-scale deployments. In the case of emergency-based disease classes (like brain strokes, heart attacks, etc.), an alert system is initiated, and doctors are immediately informed directly by the scanning units. This assists in saving the patient's life, via the provision of immediate treatment under real-time scenarios.

$$C = \frac{N_f \sum_{i=1}^{N_f} x_i y_i - \sum_{i=1}^{N_f} x_i \sum_{i=1}^{N_f} y_i}{\sqrt{N_f\left[\sum x^2 - x'^2\right]\left[\sum y^2 - y'^2\right]}} \tag{16}$$

For all new patients, a feature-level correlation is estimated via equation (16) where x, y represent current features and new features, while x' *and* y' represent their mean values for N_f features. These features are added to the database if $C<$ 0.999, which indicates that the new feature sets are different from existing feature sets. Due to this, the model is able to incrementally learn, and improve its pre-emption performance for different disease types. The model was tested under different simulation conditions, and its performance was compared with standard hospital management methods in the next section of this paper.

4. Result analysis and comparisons

The suggested solution first stores several hospital-related entities on a Proof-of-Work (PoW) based blockchain. An intelligent genetic algorithm helps in merging and splitting of these chains according to their mining delays, energy levels, and storage costs. These entity blocks are separated into several smaller chains. In order to help prevent various diseases, the data stored on these sidechains is further analyzed using a combination of CNN (for multidimensional datasets) and RNN (for single-dimension datasets). Based on these pre-emptions, timely notifications are created, assisting in the prompt treatment of high-priority disorders. The report-

Table 4
Delay needed for storage operations.

NR	D (ms) FQA [20]	D (ms) DT FH MDP [25]	D (ms) SSA [26]	D (ms) DLSD HMS
1k	16.50	14.20	10.50	6.87
5k	36.50	19.40	39.20	15.85
10k	49.20	39.20	54.07	23.74
15k	59.20	55.60	68.42	30.54
20k	70.32	60.75	82.77	35.64
30k	81.44	71.42	97.12	41.66
50k	92.56	82.09	111.47	47.69
70k	114.80	103.43	140.17	59.73
90k	125.92	114.10	154.52	65.76
100k	137.04	124.77	168.87	71.78
150k	148.16	135.44	183.22	77.80
200k	159.28	146.11	197.57	83.83
250k	170.40	156.78	211.92	89.85

based datasets are updated with the use of an incremental learning layer, which helps the CNN and RNN models be continually modified for better pre-emption performance in clinical scenarios. These activities enable the model to improve the accuracy (A) and precision (P) of pre-emption procedures while lowering storage cost (SC), energy needed for storage (ES), and delay needed for storage operations (DS).

The proposed model was simulated on the following datasets to verify its performance:

- Hospital Triage and Patient History Data, which you can find at https://www.kaggle.com/datasets/maalona/hospital-triage-and-patient-history-data
- The CORGIS Dataset Project, which can be accessed at https://corgis-edu.github.io/corgis/csv/hospitals/
- The Centers for Medicare and Medicaid Services, which can be accessed at https://data.cms.gov/provider-data/topics/hospitals.

Together, these sets made up a total of 1 million records, of which 70 % were utilized to train the blockchain, CNN, and RNN models, and 15 % were used for both training and validation. Performance was compared to industry-standard hospital management models used for real-time deployments, including FQA [20], DT FH MDP [25], and SSA [26]. Based on this strategy, the delay needed for storage operations was evaluated with respect of the Number of Records (NR) and can be observed from Table 4 as follows.

Based on this evaluation, and Fig. 6, it can be observed that the proposed model showcased 19.5 % faster performance than FQA [18], 14.9 % faster performance than DTFH MDP [23], and 28.4 % faster performance than SSA [26], which makes it useful for high-speed hospital management scenarios. The reason for this enhancement is use of contextual sidechains that are controlled by the GA model, and assists in optimizing delay needed for storage and retrieval operations. Similarly, the energy consumed during these operations can be observed from Table 5 as follows.

Based on this evaluation and Fig. 7, it can be observed that the proposed model showcased a 28.3 % lower energy consumption than FQA [20], a 9.5 % lower energy consumption than DTFH MDP [25], and an 18.5 % lower energy consumption than SSA [26], which makes it useful for high network lifetime hospital management scenarios. The reason for this enhancement is the use of energy levels during the formation of contextual sidechains that are controlled by the GA model and assists in optimizing energy needed for storage and retrieval operations. Similarly, the storage cost needed during these operations can be observed from Table 6 as follows.

Based on this evaluation, and Fig. 8, it can be observed that the proposed model showcased 24.3 % lower storage cost than FQA [20], 15.2 % lower storage cost than DTFH MDP [25], and 30.4 % lower storage cost than SSA [26], which makes the model useful for highly cost-effective scenarios. The reason for this reduction in cost is due to use of storage cost during the formation of fitness function used by the GA model, and assists in optimizing storage needed for storage and retrieval operations. Similarly, the accuracy of pre-emption for different disease types can be observed from Table 7 as follows.

Based on this evaluation, and Fig. 9, it can be observed that the proposed model showcased 8.5 % higher pre-emption accuracy than FQA [20], 3.9 % higher pre-emption accuracy than DTFH MDP [25], and 4.8 % higher pre-emption accuracy than SSA [26], which makes the model useful for highly accurate clinical scenarios.

The reason for this improvement in accuracy is use of different CNNs and RNNs for each scan type, which makes the model highly efficient even in presence of multiple disease types. Similarly, the precision of pre-emption for different disease types can be observed from Table 8 as follows.

Based on this evaluation, and Fig. 10, it can be observed that the proposed model showcased 2.9 % higher pre-emption precision than FQA [20], 7.6 % higher pre-emption precision than DTFH MDP [25], and 4.5 % higher pre-emption precision than SSA [26], which makes the model useful for highly precise clinical scenarios. The reason for this improvement in precision is use of different CNNs and RNNs for each scan type, which makes the model highly precise even in the presence of multiple disease types. Due to these enhancements, the model is capable of deployment for a large variety of hospital scenarios.

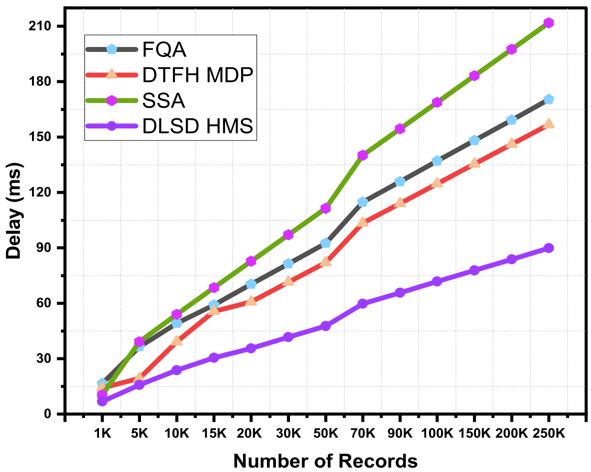

Fig. 6. Delay needed for storage operations.

Table 5
Energy needed for storage operations.

NR	E (mJ) FQA [20]	E (mJ) DT FH MDP [25]	E (mJ) SSA [26]	E (mJ) DLSD HMS
1k	23.50	25.40	16.50	13.08
5k	32.30	29.50	24.50	17.26
10k	36.70	31.33	28.10	19.23
15k	41.10	33.38	32.10	21.32
20k	45.50	35.43	36.10	23.41
30k	49.90	37.48	40.10	25.50
50k	54.30	39.53	44.10	27.59
70k	63.10	43.63	52.10	31.77
90k	67.50	45.68	56.10	33.86
100k	71.90	47.73	60.10	35.95
150k	76.30	49.78	64.10	38.04
200k	80.70	51.83	68.10	40.13
250k	85.10	53.88	72.10	42.22

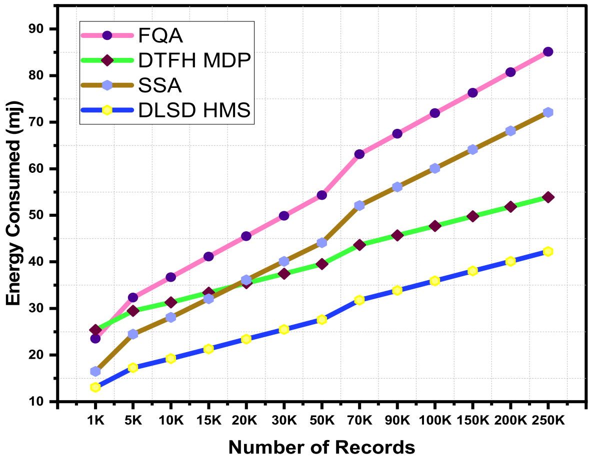

Fig. 7. Energy needed for storage operations.

Table 6
Cost needed for storage operations.

NR	SC (MB) FQA [20]	SC (MB) DT FH MDP [25]	SC (MB) SSA [26]	SC (MB) DLSD HMS
1k	26.67	26.40	18.00	13.30
5k	45.87	32.60	42.47	22.07
10k	57.27	47.02	54.78	28.65
15k	66.87	59.32	67.01	34.57
20k	77.21	64.12	79.25	39.37
30k	87.56	72.60	91.48	44.77
50k	97.91	81.08	103.71	50.19
70k	118.60	98.04	128.18	61.00
90k	128.95	106.52	140.41	66.41
100k	139.29	115.00	152.65	71.82
150k	149.64	123.48	164.88	77.23
200k	159.99	131.96	177.11	82.64
250k	170.33	140.44	189.35	88.05

5. Conclusion

The proposed concept first keeps track of several hospital-related entities on a blockchain powered by PoW. Based on the mining delays, energy consumption, and storage costs of these links, a clever genetic algorithm helps merge and split them. These entity blocks are split up into multiple smaller chains using a genetic process. The data kept on these sidechains is further processed, assisting in the prevention of various diseases, with the aid of a combination of CNN (for multidimensional datasets) and RNN (for single-dimension datasets). These pre-emptions result in prompt alerts that facilitate the prompt treatment of high-priority disorders. The CNN and RNN models are continuously enhanced by using an incremental learning layer in order to increase pre-emption performance in clinical

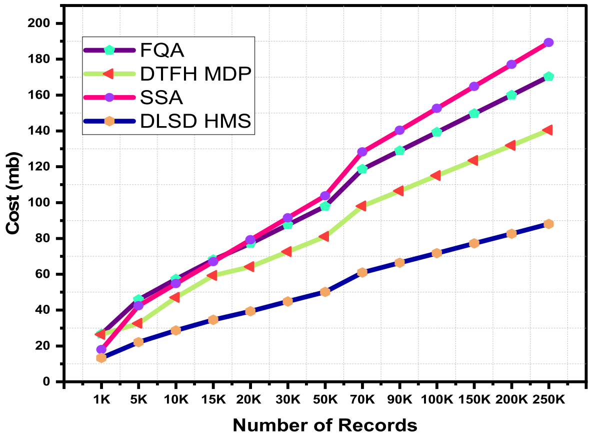

Fig. 8. Cost needed for storage operations.

Table 7
Accuracy achieved during the hospital management operations.

NR	A (%) FQA [20]	A (%) DTFH MDP [25]	A (%) SSA [26]	A (%) DLSD HMS
1k	90.50	91.30	91.90	96.50
5k	90.53	91.90	92.50	97.20
10k	90.59	92.17	92.60	97.50
15k	90.68	92.47	92.75	97.90
20k	90.72	92.77	92.91	98.10
30k	90.74	93.07	93.14	98.30
50k	90.78	93.37	93.33	98.40
70k	90.87	93.97	93.70	98.65
90k	90.91	94.27	93.89	98.75
100k	90.95	94.57	94.07	99.20
150k	90.99	94.87	94.26	99.30
200k	91.04	95.17	94.44	99.40
250k	91.08	95.47	94.63	99.50

scenarios. The suggested model outperformed FQA [20], DTFH MDP [25], and SSA [26] by 19.5 %, 14.9 %, and 28.4 % respectively during evaluation, making it effective for high-speed hospital management scenarios. This improvement is the result of the introduction of contextual sidechains, which are controlled by the GA model and assist in lowering the amount of time needed for storage and retrieval activities. Moreover, it was discovered that the suggested model used 28.3 % less energy than FQA [20], 9.5 % less energy than DTFH MDP [25], and 18.5 % less energy than SSA [26], making it useful for high network lifespan hospital management situations. This enhancement uses energy levels during the generation of contextual sidechains, which are under the control of the GA model, to more effectively manage the energy needed for storage and retrieval operations. The proposed model can be used in situations where cost-effectiveness is a major priority because its storage costs were shown to be 24.3 % cheaper than those of FQA [20], 15.2 % lower than those of DTFH MDP [25], and 30.4 % lower than those of SSA [26]. The GA model's use of storage cost in building its fitness function, which aids in optimizing the amount of storage needed for store and retrieval activities, can be credited with this cost decrease.

The suggested model outperformed FQA [20], DTFH MDP [25], and SSA [26] by 8.5 %, 3.9 %, and 4.8 %, respectively, during pre-emption performance comparisons, demonstrating the model's use for highly accurate clinical scenarios. The boost in accuracy is due to the employment of different CNNs and RNNs for each type of scan. Due to this, the model is incredibly powerful even in the presence of multiple disease types. The suggested model showed pre-emption accuracy that was consistently 2.9 % higher than FQA [20], 7.6 % higher than DTFH MDP [25], and 4.5 % higher than SSA [26], making the model for extremely precise clinical settings. The model is quite accurate even when there are numerous different illness kinds present because different CNNs and RNNs are employed for each type of scan. This tactic has led to this increase in precision levels. These changes have enabled the model to be used for a variety of hospital scenarios.

Larger hospital networks will need to use the model in the future, and its effectiveness can be increased by incorporating low-complexity bioinspired models for blockchain administration and update operations. To further maximize pre-emption performance for various use cases, it is also advised that Gated Recurrent Units (GRUs), Autoencoders (AEs), and other deep learning approaches be included for different use cases.

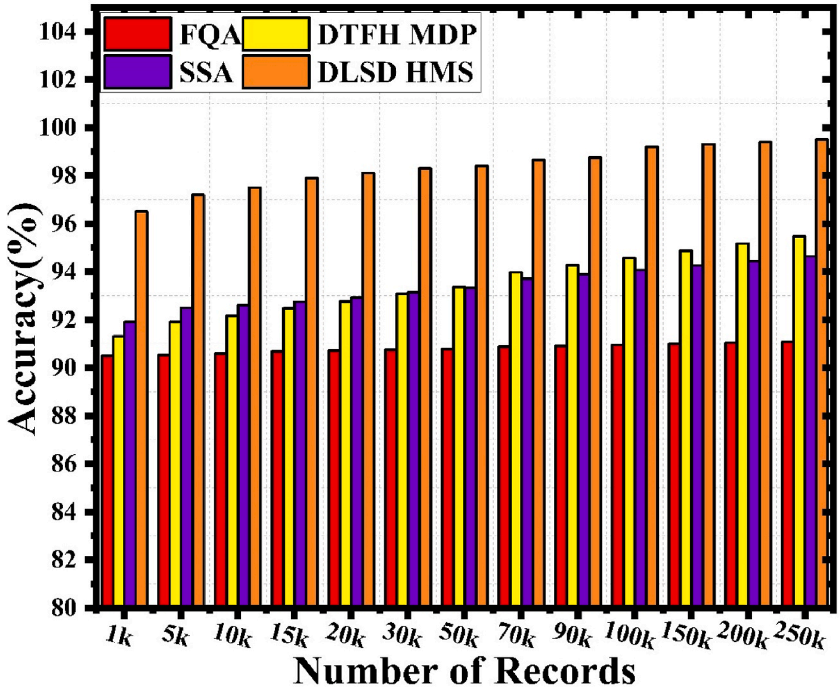

Fig. 9. Accuracy achieved during the hospital management operations.

Table 8
Precision achieved during the hospital management operations.

NR	P (%) FQA [20]	P (%) DTFH MDP [25]	P (%) SSA [26]	P (%) DLSD HMS
1k	84.94	83.62	85.38	89.85
5k	85.50	83.70	85.73	90.37
10k	85.77	83.74	85.88	90.57
15k	86.05	83.78	86.05	90.75
20k	86.32	83.82	86.23	90.88
30k	86.60	83.86	86.41	91.05
50k	86.88	83.90	86.58	91.20
70k	87.43	83.98	86.92	91.59
90k	87.71	84.01	87.09	91.77
100k	87.99	84.05	87.26	91.96
150k	88.26	84.09	87.43	92.14
200k	88.54	84.13	87.60	92.32
250k	88.82	84.17	87.77	92.50

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Data availability statement

Data used for the research is available at//www.kaggle.com/datasets/maalona/hospital-triage-and-patient-history-data, https://corgis-edu.github.io/corgis/csv/hospitals/, https://data.cms.gov/provider-data/topics/hospitals.

CRediT authorship contribution statement

Vonteru Srikanth Reddy: Writing – original draft. **Kumar Debasis:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

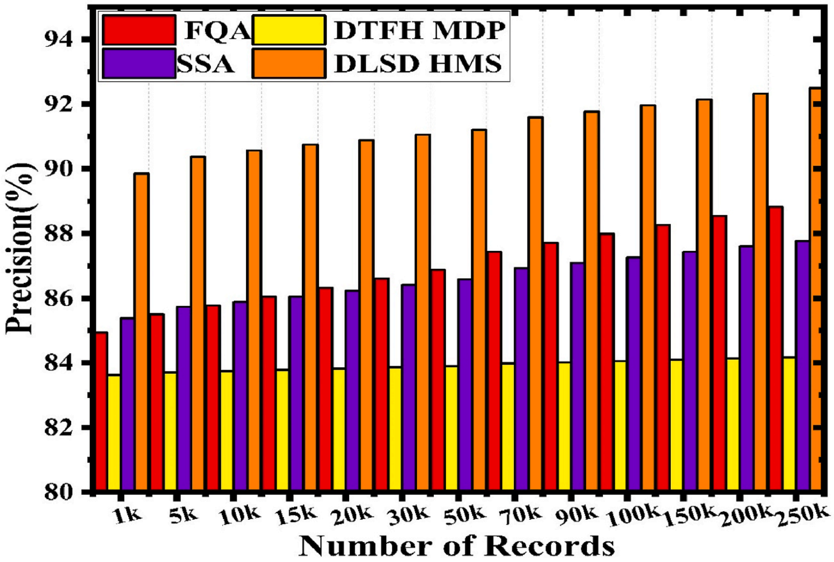

Fig. 10. Precision achieved during the hospital management operations.

influence the work reported in this paper.

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