PENINSULA PUBLISHING LLC

**SHIFRA**

Vol. **(2025)**, 2025, **pp**. 118–125
ISSN: 3078-3186

Research Article

# Secure and Fault-Tolerant IoT-Based Healthcare System for Reliable Decision-Making

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**ARTICLE INFO**

Article History

Received 1 Dec 2024

Revised: 21 Jan 2025
Accepted 21 Feb 2025
Published 10 Mar 2025

Keywords

IoT-based Healthcare,

Fault-Tolerant Systems,

Data Security,

Decision-Making Algorithms,

Fog Computing.

**ABSTRACT**

Internet of Things (IoT) integration has revolutionized healthcare, offering personalized medical care through remote patient monitoring and telemedicine. However, challenges remain in critical healthcare scenarios, such as data security vulnerabilities and system failures. This paper proposes an IoT-based healthcare system that is fault-tolerant and secure. As part of the proposed Fault-Tolerant Data Management (FTDM), advanced encryption techniques, fault-tolerant data management, and intelligent algorithms will safeguard patient data and guarantee system resilience. Utilizing a fault-tolerant system with two levels enhances data management, reduces energy consumption, and minimizes execution time. Based on simulations using iFogSim, the results indicate significant reductions in energy consumption, network usage, execution time, and fault tolerance compared with existing approaches. IoT-enabled healthcare systems can be deployed in resource-constrained environments with greater security and reliability based on the results of this study.

## 1. INTRODUCTION

Many research fields have witnessed rapid technological development during this decade. Sports, healthcare, industry, and our environment have all been adversely affected by the Internet of Things (IoT), which is one of the most recent developments in technology [1], [2]. The Internet of Things allows for remote management and seamless delivery of medical care. Providing remote healthcare to patients is one of the most important aspects of their care. It is being researched how intensive methods can be used to develop new applications in telemedicine and medicinal sciences [3]. As telemedicine research has grown in the research domain, the Internet of Things has played a significant role [4], [5], [6]. ITPD (Interaction, Things, Process, Data) is often considered the key defining parameter for IoT sectors. Ray [5] gave a presentation on ITPD in 2014. Mobile technologies, such as Wi-Fi, Bluetooth, low energy, and NFC, are some of the ways in which users interact with systems (e.g., smartphone apps). Wearables collect data through hardware, cloud processing, and raw sensor data from the environment through sensor interventions. IoT-enabled technology is effectively managed and engaged with patients through the process.

An IoT environment is one where everything around us is connected to the internet and communicates with one another. An example of an internet-connected device is an intelligent oven, a smart healthcare device, a smart home appliance, a smartwatch, a smart keg, or a drone. Thousands of IoT devices generate data every second, generating huge amounts of information [7]. Health care is a prominent application of IoT devices due to their ability to manage patients and diseases. There is also a need for better management due to the limited number of medical staff and facilities available [8], [9]. Communication costs will rise, however, as more devices are connected on a large scale. A growing workload is causing traditional clouds to face difficulties with bandwidth, energy consumption, robustness, delay, and latency [10]. Cloud computing has been brought to a new level of efficiency and effectiveness by introducing a new paradigm called fog

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DOI: https://doi.org/10.70470/SHIFRA/2025/008

computing, which targets bandwidth, delay, and latency problems. [11]. Since fog computing involves so many connections, it suffers from efficiency issues as a new way to organize device connections.
The Internet of Things (IoT) has revolutionized healthcare by making it more efficient, timely, and personalized. IoT networks, however, also present challenges, such as data security vulnerabilities and system failures, and require reliable decision-making in high-stakes situations. To enhance the effectiveness of IoT-based healthcare systems, security and fault tolerance must be ensured. Using innovative solutions to safeguard patient data and maintain system resilience, the proposed model addresses these challenges. The research aims to create a robust and dependable IoT-driven healthcare ecosystem using advanced encryption techniques, fault-tolerant mechanisms, and intelligent decision-making algorithms[12]. The advancement of medical technology will improve patient outcomes, support healthcare providers, and ensure a more secure and reliable future for patients and healthcare providers.

## 2. RELATED WORK

A low-energy, low-latency fog computing scheme is proposed in [13]. Multiple fog nodes were used to provide the authors with a decision on the offloading of tasks using an optimization algorithm. Although this scheme solves the problems of latency and energy consumption, it does not address the problems of data management, task management, or fault tolerance. Scheduling scheme Greedy Knapsack Scheduling (GKS) consumes a minimum amount of energy and has low latency. As a result of the GKS scheme, fog-based IoT applications can reduce latency and maximize energy efficiency. Despite reducing latency and minimizing energy consumption, the GKS scheme does not resolve the failure of nodes and tasks. Likewise, the GKS Scheme is not tailored to any particular field of healthcare, such as the Internet of Things. Using a data chunking technique [14] proposes improving fog computing security and reducing latency by converting data into chunks. The purpose of chunking data is to protect it from malicious users and save bandwidth on the network. As part of an IoT environment, data must be reliable and fault-tolerant so that they can survive failures on edge servers. Still, these factors are not specifically taken into account by the technique.
In [15], an IoT edge architecture is proposed based on cloud, fog, mist, and dew distributions. A processing power and distance parameter was taken into account when designing the architecture for IoT devices. With this architecture, IoT devices can repeat data at the edge of the network, improving the overall system's reliability[16]. Through IoT, a system for monitoring healthcare was proposed that connects patients to the internet [17]. Neither scheme is fault-tolerant, nor does it have any bandwidth limitations. Using fog computing for healthcare IoT devices, [18] proposed a fault-tolerant technique for increasing network reliability and processing speed. The authors used RCA schemes based on Random Variable Neighbor Search (RVNS) to choose the patient data to be analyzed randomly. As a result of high receiving data rates or other problems, the authors used fault-tolerant techniques to maintain connectivity. Considering the critical nature of healthcare, the data collection mechanism proposed in the proposal is inefficient. The authors are proposing a real-time monitoring system for sink data [19]. A single Gateway for healthcare monitoring systems contains many data points, making it hard to monitor a large data set at a bottleneck with just one sink node.
Among other things, mHealth makes use of the core utility of mobile phones, voice [22] and short messaging services (SMS), as well as complex functionalities and applications such as general packet radio services (GPRS), 3G and 4G mobile telecommunications systems, global positioning systems (GPS), and Bluetooth technology [20]. Nonetheless, mobile technology has been introduced rapidly and widely to healthcare, resulting in mHealth. MHealth can provide healthcare services to patients by combining sensor networks and information. Telemedicine applications provide healthcare services that should be highlighted by a comprehensive literature review, as should mHealth applications. Despite the extensive literature on telemedicine, risk management remains challenging when mHealth is used to improve healthcare services [21]. Healthcare costs are increasing, and the global population is ageing, making it impossible to provide common healthcare through telemedicine networks [22].

## 3. METHODOLOGY

A fault-tolerant healthcare system based on the Internet of Things is shown in Figure 1. BSN-Care's basic architecture [23] can be improved to make fault-tolerant decisions. Through cellular networks like LTE-A/CDMA, BSN care will be based on a data-driven approach where data will be received from a local processing unit (LPU). The original article in BSN-Care [23] provides more details regarding the process of data collection. Using a single sensor, BSN-Care makes decisions about possible actions. A decision-making approach is proposed that considers data from other sensors as well as the BP sensor under abnormal circumstances. Using this method, false positives or false negatives made by BSN care can be corrected. The system will also handle the case when a sensor's data is not available to BSN Care for decision-making.
The proposed system utilizes machine learning to make fault-tolerant decisions. Through the use of support vector machines, the system learns the patient's normal behaviour from the sensor data. A decision-making module determines if any sensor data is missing from every new record sent from the server, for instance. An anomaly in a patient's records is detected by comparing it to the normal behaviour pattern of that patient. As soon as an anomaly in the record is detected,

correlations between its different parameters are generated. Figure 1 illustrates the treatment of incomplete new records (i.e., those with missing data) as permanent models (red). The complete greatest is created in this way, and the decision-making process continues as if the record were complete.

### 3.1 Anomaly Detection Process

This proposed system uses incoming records from the real system to create a model based on which any anomalies can be detected in a patient's behaviour. Consequently, the framework cannot model the normal behaviour of the data until there are enough records. Whenever the system receives data from a user, it considers it normal and labels it 'Normal'. Data only from the assigned class is used for the characterization of normal behaviour. OC-SVM classifiers were used to generate normal behaviour [24]. As part of our semi-supervised classification strategy, we formulate the normal behaviour and detect deviations from it using a modified classification.

In order to formulate OC-SVM, we require the following data from the system. Let $X = \{x_1, x_2, x_3, \cdots, x_n\}$ m represents a set of real-time streaming instances labelled 'Normal'. Sensors capture n parameters for a given instance, with m instances per instance. $K : R^n \rightarrow H$ transforms input data into the structures interplanetary $H$. Utilizing the OC-SVM, we construct a model of normal behaviour based on the minimum distance between points within one class:

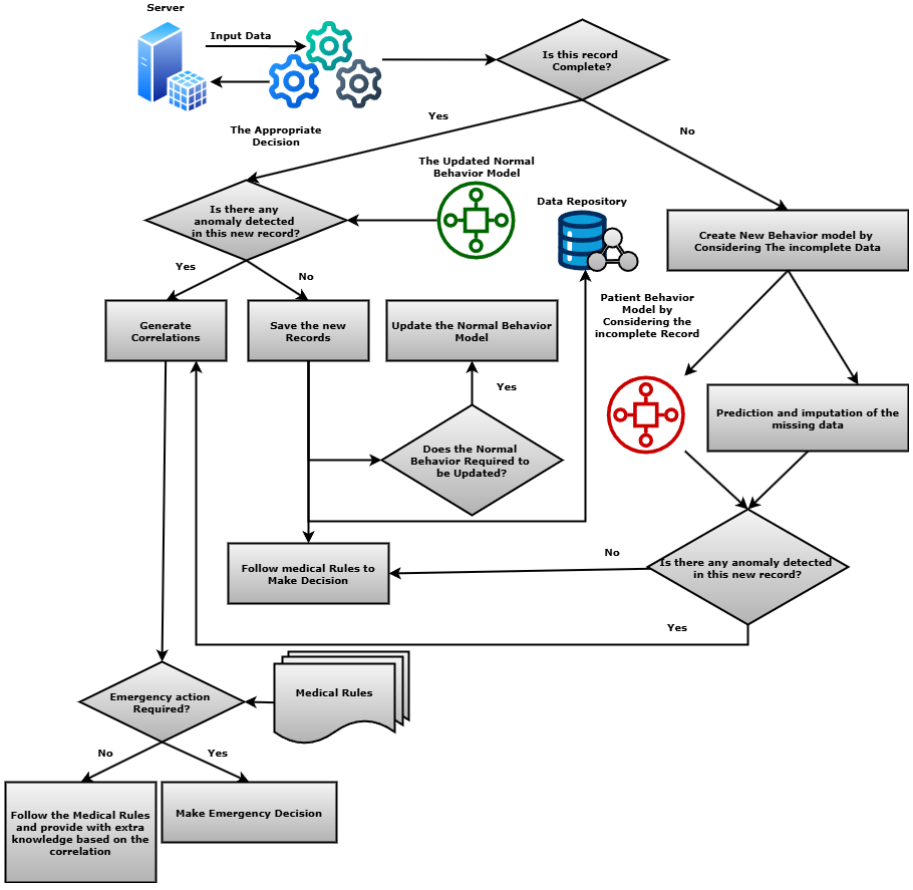


Fig. 1. Process flowchart for making decisions.

$$\min_{w,b,\delta,\rho} F(w,b,\delta,\rho)^n = \frac{1}{2}||w||^2 + \frac{1}{vn}\sum_{i=1}^{n}\delta_i - \rho \quad (1)$$

$$Subject\ to : \left(w^T K(x_i)\right) \geq \rho - \delta_i, \quad i = 1, \ldots, n \quad (2)$$

This parameter balances the experienced risk minimization with the relaxation parameter $\delta_i \geq 0$. Based on these two parameters, the decision distance separates points associated with normal behaviour from those associated with abnormal behaviour. In $v \in ]0,1]$ and $vn$ upper and lower bounds are set on how many out-of-class training examples are used as support vectors. To separate data between classes, here is how to determine the optimal hyperplane:

$$\min_{\alpha} Q(\alpha) = \frac{1}{2}\sum_{i,j}^{n}\alpha_i\alpha_j K\left(x_i, x_j\right) \quad (3)$$

$$Subject\ to: 0 \le \alpha_i \le \frac{1}{vn}, \sum_{i}^{n} \alpha_i = 1 \quad (4)$$

An example $I$ is influenced by $\alpha_i$. Here are the components of the decision function:

$$f(x) = sign\left(\left(w, K(x)\right) - \rho\right) \quad (5)$$

Sign functions are derivatives of absolute value functions$(-1, +1)$. $\rho$ is assumed by

$$\rho = \sum_{j=0}^{n} \alpha_i K\left(x_i, x_j\right) \quad (6)$$

### 3.2 Missing Data Prediction Algorithm

Missing data in sensor-based systems occurs when one or more variables are not observed within a given period. This paper proposes a two-step process for imputed missing data. To begin with, we use the nearest neighbour algorithm to select the closest record that has the same incomplete information as the current record. Using the nearest neighbour algorithm, the missing record's dimension is reduced. Missing variables aren't directly predicted from the nearest record as the system uses healthcare data, where any change can have a significant impact on the outcome. We impute data using Arc values, which represent the rate of change between two variables. To calculate $Arc$, follow these steps:

$$V_j = \sum_{i=0}^{\xi-1} (x_{i+1} - x_i) \quad j = 0, \ldots, \xi - 1 \quad (7)$$

$$Arc_{i+} = \frac{\sum_{k=0}^{\psi} V_k}{\psi}\ if\ (V_k \ge 0) i = 1, \ldots, \xi \quad (8)$$

$$Arc_{i-} = \frac{\sum_{k=0}^{\psi} V_k}{\phi}\ if\ (V_k < 0) i = 1, \ldots, \xi \quad (9)$$

An example of $V_j$ is when a value is different from another. In this chart, you will find the total number of records, the positive change, and the negative change. In $Arc_{i+}$ positive differences are averaged over time. $Arc_{i-}$ measures the average rate at which negative differences change

An Arc's positive or negative changes determine if we have missed any values. In order to calculate the missing values, the algorithm uses the following equations based on whether the new records have increased or decreased values:

$$X_{Miss} = X_{NR} + \left(Arc_{X-} * \frac{|Y_{MR} - Y_{NR}|}{Arc_{y+}}\right) \quad (10)$$

$$X_{Miss} = X_{NR} + \left(Arc_{X-} * \frac{|Y_{MR} - Y_{NR}|}{Arc_{y-}}\right) \quad (11)$$

An $X_{miss}$ indicates the absence of a value, while an $X.Y$ indicates that a variable is highly correlated with $X$ and $Y_{MR}$ indicates the absence of a value for $Y$. An $X_{NR}, Y_{NR}$ the record lacks both $X$ and $Y$ values. This value gives the average change rate of variable Y.

### 3.3 Correlation Measures

A new dataset is analyzed to identify the potential causes of anomalies when an anomaly is detected, and correlations between parameters are measured. We can identify the relationship between a parameter and other parameters through correlation measures, i.e., how a parameter change is related to a parameter change. Experts and machines can interpret correlations in specific scenarios based on prior knowledge, even though correlation does not imply causality [25]. The proposed system produces X and Y readings from motion sensors and blood pressure sensors, respectively. In the case of motion-blood pressure interaction, blood pressure-movement interaction, motion-blood pressure interaction, motion-blood pressure interaction, motion-blood pressure interaction, motion and blood pressure interaction, motion-blood pressure interaction, or motion and blood pressure interaction, motion and blood pressure interact, or a third variable influences both blood pressure and motion. Two variables are correlated using Pearson correlation coefficients in this study. In terms of Pearson's correlation coefficient $r_{xy}$, random variables X and Y have the following relationship:

$$r_{xy} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})\,(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (12)$$

### 3.4 Evolution Matrix

The basic event simulation functionality of CloudSim was leveraged for implementing iFogSim architecture [26]. As with data centres, CloudSim entities communicate with one another by sending messages (sending events). CloudSim handles

events between iFogSim's Fog computing components in this way. An overview of the main classes of iFogSim can be found here. In this section, we explain how these classes interact. Simulated entities and services are used to implement iFogSim. Firstly, we describe the iFogsim classes that represent architectural elements.

## 4. RESULT AND DISCUSSION

Energy consumption results for the proposed model are significantly better than those for the existing GKS strategy, as shown in Figure 2. Comparing the proposed strategy to the GKS strategy, 2.58 % less energy is consumed. Several factors contribute to this improvement, such as the proposed strategy's approach, which only re-executes failed tasks. Existing strategies restart task execution from the system's initial stage whenever there is a failure.

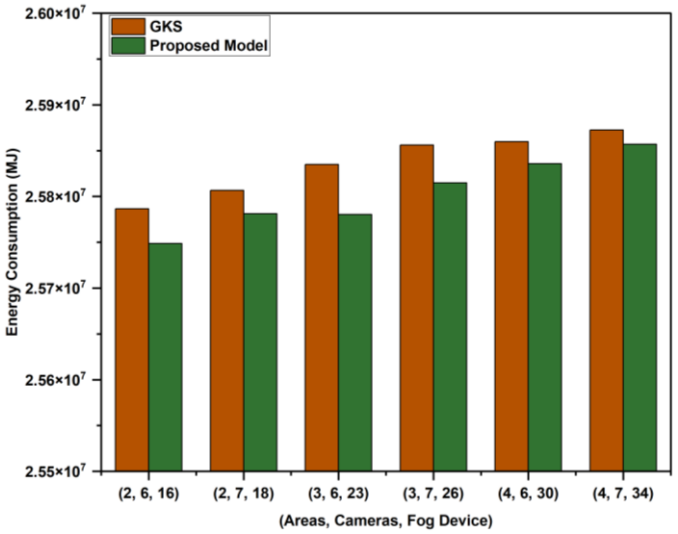


Fig. 2. Comparison of proposed with existing models in terms of energy consumption.

Compared to the existing GKS strategy, the proposed model strategy shows significant improvements. In comparison to the GKS strategy, the proposed strategy achieves a 4.3% reduction in execution costs as shown in Figure 3. Optimal utilization of minimal resources is achieved through the proposed strategy's fault-tolerance mechanism.

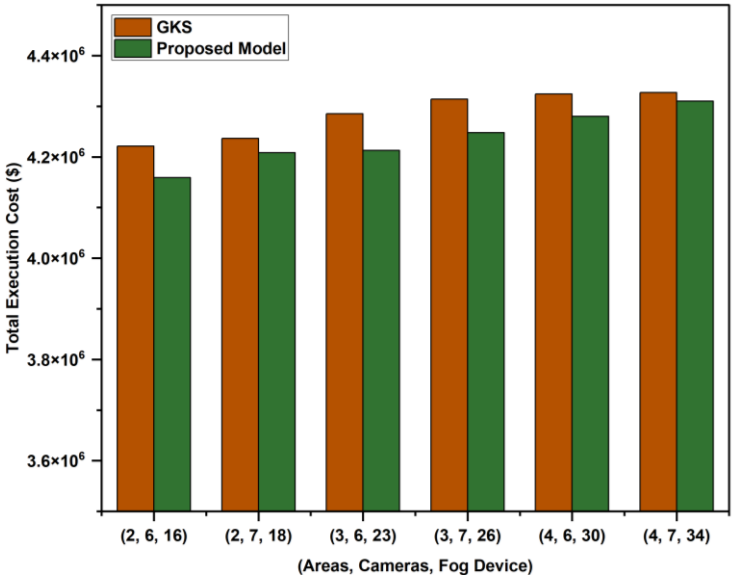


Fig. 3. Performance of proposed model with the existing model in terms of cost of execution.

As shown in Figure 4, the proposed strategy provides significant improvements over the existing GKS strategy. A comparison between the proposed and the GKS strategy reveals a 25.09% reduction in network usage. A reduction in communication costs can be attributed to the proposal's fewer nodes, resulting in fewer communications.

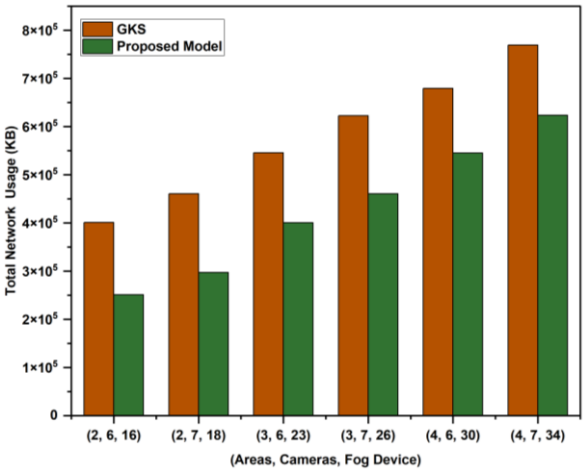


Fig. 4. Performance analysis of a proposed model with an existing model based on network usage.

A comparison of the proposed strategy with the current GKS strategy is shown in Figure 5. Compared to the current network delay, the proposed approach reduces it by 22.9%. As a result of the fault-tolerant mechanism used in the proposed strategy, failed tasks are immediately re-executed. This mechanism is missing from the GKS strategy, which results in higher network delays. This leads to an effective reduction of network delay as a result of the proposed strategy.

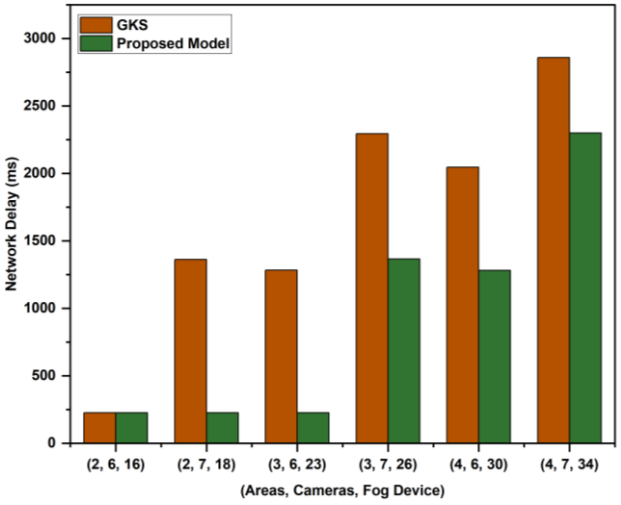


Fig. 5. Performance of proposed model with existing model for network delay.

According to Figure 6, the proposed strategy results in a marked improvement in execution time. Because the proposed approach requires fewer executions, the overall task execution time is minimized by reducing the number of executions.

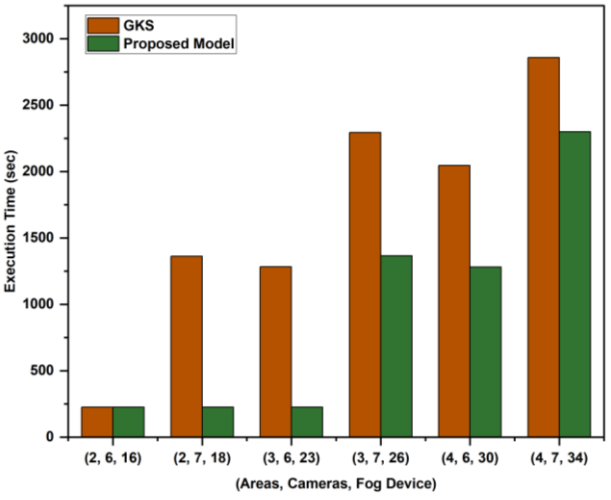


Fig. 6. Performance Analysis of the proposed model with existing model based on execution time.

## 5. CONCLUSION

Research in this area addresses critical challenges such as data reliability, system failures, and decision-making under abnormal circumstances in IoT-based healthcare systems. With Fault-Tolerant Data Management (FTDM), IoT healthcare systems will be able to operate more efficiently in fog computing environments by reducing energy consumption, network usage, execution costs, and latency. Based on simulation results, the proposed model is more efficient and resilient than existing approaches. The system ensures reliable decision-making for the benefit of patients by incorporating machine learning techniques for anomaly detection and leveraging fault-tolerant mechanisms. These results demonstrate that this approach is not only secure but also cost-effective, which makes it ideal for low-resource healthcare environments. Additional privacy and security techniques can be explored in future work, as well as optimizing the model for large-scale deployment.

## Funding:

No external funding or financial support was provided by any commercial or governmental agency for this study. The research was independently managed by the authors.

## Conflicts of Interest:

The authors declare that there are no conflicts of interest.

## Acknowledgment:

The authors would like to thank their institutions for the continuous moral and institutional support received during the course of this work.

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