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Advanced Data Integration, Knowledge Extraction, and Application in Energy-Efficient Telehealth IoT Systems

Nathan Guo[1], **Yunyong Guo**[1,*] **and Bryan Guo**[1]

[1] *Department of Computer Science, University of Victoria, Canada*

Abstract: This paper further studies the previously proposed energy-efficient telehealth Internet of Things (IoT) model that focuses on data integration, knowledge extraction, and application in fog-cloud hybrid architecture. Our current study concentrates on how the system uses adaptive machine learning and data mining to optimize the system operation for increased real-time data analysis and reduced energy use, thus providing more effective patient monitoring in telehealth. The simulation designed for the patients in both a fog-enabled model and a cloud-only model applies various workloads sent from patients. In this fog-enabled model, data from IoT devices is preprocessed at fog nodes by investigating anomalies, trends, or other relevant machine learning algorithms, and then this data is transmitted to the cloud. It compares key performance metrics-energy, latency, speed of processing data, and prediction accuracy—in both a fog-enabled and a cloud-only model. Results show that the fog-enabled model reduces energy consumption by 20% and latency by 50%, compared to a cloud-only configuration. This indicates the distinct advantages of localized processing. Compared to the existing system, higher speed in processing data and improved accuracy in detecting statistical anomalies, thereby demonstrating the possibility that the system offers for real-time and scalable telehealth capabilities. Meanwhile, this work presents a comprehensive model for the sustainability and scalability of telehealth infrastructures, supported by simulation data and analysis evidencing the effectiveness of the model.

Keywords: cloud, data integration, energy-efficient, fog, knowledge extraction, IoT, telehealth

1. Introduction

The paper overcomes the challenges of energy efficiency, latency, and real-time health monitoring through the demonstration of an adaptive fog-cloud architecture, which is much better than the existing cloud-only systems. Compared with previous works, this model involves real-time data preprocessing at the fog nodes with machine learning algorithms toward scalable and sustainable telehealth Internet of Things (IoT) solutions. Power-efficient algorithms that demonstrate a 50% reduction in latency, 20% lower energy consumption, and 96.5% accuracy indicate that this research could bring about in healthcare applications.

Telehealth applications using IoT devices have been one of the latest revolutionary concepts that allow monitoring in continuous time and process health information in real time. Such systems depend on the interconnection of sensors, medical devices, and wearables with mHealth applications to capture, analyze, and send on to a patient's data. The continuous flow of information thus enables remote diagnosis, personalized treatment, and proactive health management, making healthcare more accessible, especially to the rural low-access communities. With more healthcare systems adopting solutions on telehealth, the demand for efficient, secure, and scalable telehealth IoT infrastructures has grown by leaps and bounds.

However, IoT in telehealth is surrounded by challenges related to data integration, system latency, security, and power consumption. In existing cloud-based platforms, data processing takes place remotely from an end user's system, which leads to high latency that cannot address use cases requiring real-time or near-real-time response. Latency is especially an issue in settings where data communication and processing directly affect patient outcomes, such as in emergency care or continuous monitoring. Fog computing provides a solution by introducing an intermediary layer that processes data near its source, reducing latency and response time. The integration of fog and cloud computing makes a hybrid architecture and optimizes the flow of data without compromising the scalability of cloud services.

Data integration is the second key challenge of telehealth IoT. First, Telehealth applications collect enormous amounts of heterogeneous data from numerous data sources, including both physiological (e.g., audio and video) sensors and imaging modalities, as well as electronic health records. Decision making and analysis in real time, which demands the integration of the data, where frameworks need to be robust enough to support diversity in data volumes and types. Second, the information of the patients is personal data and therefore security and privacy shall take precedence. Security of the data while being transmitted and stored is important to maintain compliance and to instill trust among patients. These aspects are addressed in this research by proposing a secure data integration scheme based on role-based access control (RBAC) and encrypted transmission in a fog-cloud paradigm.

Energy efficiency is an important factor in telehealth IoT systems due to the continuous operation of IoT devices and data centers that support healthcare applications. Particularly, wearable or mobile IoT devices are often restricted by battery life. Other than that, data processing and storage in remote cloud servers can be energy-intensive, thus causing high operational costs and potential environmental impacts. The proposed system reduces the energy demand from cloud

*__Corresponding author:__ Yunyong Guo, Department of Computer Science, University of Victoria, Canada. Email: yunyong@uvic.ca

servers by embedding energy-efficient data processing techniques at fog nodes, extending operational life in IoT devices in pursuit of a greener telehealth model.

An opportunity that has arisen to help these problems is the convergence of IoT, fog computing, and machine learning. The system's capability to convert health data into meaningful insights, facilitating predictive analytics and anomaly detection, is improved with machine learning algorithms. This is both beneficial and essential as the management of chronic diseases relies heavily on the ability to detect in advance an unfavorable pattern of health, giving the opportunity for action in advance to avoid further complications. Integrating machine learning algorithms directly into fog nodes allows the system to perform knowledge extraction at the proximity to the data, improving both speed and accuracy of patient monitoring.

Based on the work of Guo et al. [1] on energy-efficient architectures in telehealth IoT, the present work focused on the following three important objectives: adaptive data integration strategy within a fog-cloud environment, real-time knowledge extraction using machine learning techniques, and optimization of insights-to-application for enhanced patient monitoring and clinical decision support. It proves the efficiency of the system in reducing energy consumption and latency while gaining high data processing efficiency.

2. Literature Review

Telehealth applications have utilized IoT, using both fog and cloud computing to facilitate real-time, scalable data processing.

2.1. Fog-cloud architectures for telehealth IoT

Fog computing can mitigate latency issues by processing data locally, decreasing wait times, and reducing data usage. Guo et al. [1] presented a report of a hybrid fog-cloud system that improved data processing by 40% compared to cloud-based systems. Mahmud et al. [2] demonstrated how scalable telehealth fog systems are to show that they can process large amounts of real-time patient data. New studies have also discussed sharing resources. Hong and Varghese [3] made up an adaptive resource plan for moving computer tasks between fog and cloud layers to ensure the uninterrupted operation of the system. Similarly, Ilyas et al. [4] showed how configurations based on fog can be applied in emergency care, saving critical response time by 25%. Thushara and Bhanu [5] made a coded message system especially for fog-cloud healthcare systems to guarantee that data is not damaged and has short delays. Their system complies with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) that highlight the value of safe, patient-centric telehealth solutions.

2.2. Machine learning in healthcare IoT

Machine learning in the IoT-based telehealth systems helps us identify trends and anomalies. Ren et al. [6] developed a machine learning model in fog nodes to identify heart conditions in real-time at a rate of 95%. Real-time processing is very important for health issues requiring immediate attention. Deep learning has also been manipulated by researchers to help manage chronic conditions. Liu and Wang [7] implemented a convolutional neural network-based diagnosis tool in a fog setting to make diabetic diagnoses 20% more accurate than conventional practices. In addition, Dritsas and Trigka [8] demonstrated the effectiveness of federated learning in telehealth, where many devices can collaborate to train machine learning models without exposing patient information.

2.3. Machine learning in healthcare IoT

Energy consumption is a critical factor for both wearable IoT and the telehealth application data centers. Vaghasiya et al. [9] suggested an energy-efficient fog system that enhanced the battery life of wearable devices by 30% with reduced cloud server load. Likewise, Bu et al. [10] indicated a power-conscious task scheduling scheme that lowered energy consumption in telehealth networks by 15%. Green computing has gained popularity. Ukoba et al. [11] investigated fog node renewable integration, demonstrating a sustainable solution to the energy-intensive telehealth system. The study suggests that solar-powered fog units can provide operational functionality without loss of function and performance.

2.4. Integration of fog-cloud and machine learning

We can take advantage of both fog-cloud infrastructure and machine learning to enhance telehealth IoT. Choppara and Mangalampalli [12] integrated a hybrid fog-cloud architecture with a reinforcement learning algorithm to improve patient data processing workflows. It reduced latency by 50% and increased system output. Bhatia et al. [13] developed a multilayered fog-cloud architecture that employed real-time machine learning models for predictive analytics in telehealth. It was 97% accurate in detecting breathing problems. Their work proves how computational velocity and high-level analysis support each other. Additionally, Lin et al. [14] showed a fog-cloud framework to detect sepsis. It ensembles learning algorithms to analyze types of patient data. The system has been significantly enhanced in predicting and processing faster.

Telehealth meets a great need in various areas, so it encourages the use of fog-cloud hybrid computing systems associated with machine learning platforms. However, we still need to conduct more research to improve the efficiency, scalable, and security of IoT solutions for healthcare.

3. Data Integration in IoT

Telehealth IoT data is generated in comparatively huge amounts and heterogeneous types from several devices, such as wearable sensors, imaging devices, and other medical devices. This encompasses real-time physiological data (e.g., heart rate and blood pressure), patient location data, historical health records, and diagnostic imaging. Nevertheless, seamless integration of such heterogeneous types of data is not a trivial task anymore, as it comes with various technical challenges, including but not limited to data consistency, low latency, data quality, and sensitive health data security [15].

This study proposes a data integration approach in a fog-cloud environment that solves these problems and optimizes data communication, security, and scalability. With the use of fog nodes for data processing in an intermediate layer, Vishweshwara and Ramya [16] proposed a solution that reduces latency, enhances data quality, and maximizes data paths from the device to the cloud. The steps below outline the strategy in more detail.

3.1. Data collection and preprocessing at the IoT device layer

The data integration process is located at the IoT device layer, where various health-monitoring devices collect and transmit raw data. Data collection involves the following:

1) Integration of sensors: Integration of medical devices by connecting them and making their configurations so that they are compatible

with the platform. Devices will have embedded software that may communicate with fog nodes [17].
2) Data sampling: This is about how to appropriately measure the quantity of data to be sampled to get useful information on the health data without overloading the network. So, for example, a device might take data about heart rate every couple of seconds and not all the time.
3) Basic preprocessing at IoT devices: IoT devices perform basic preprocessing to filter out noise, compress data, and standardize formats before transmitting to fog nodes. Preprocessing reduces bandwidth usage and prepares the data for more complex processing at the fog layer.

The fog layer, consisting of distributed computing nodes located closer to IoT devices, acts as an intermediary processing stage, reducing the need to transfer all data to the cloud [18]. Key functions at this layer include the following:

1) Data aggregation and filtering: Fog nodes aggregate data streaming in real time from numerous IoT devices. Preliminary testing is done for analytical purposes to check on both relevance and discard irrelevant or duplicate data. Aggregation brings together streams of data, reducing load on transmission while freeing up maximum storage space.
2) Data normalization and structuring: Interoperability is facilitated by fog nodes through the structuring of raw data from other devices into standardized formats, for example, HL7, for storage, so as to integrate and access them smoothly across the system.
3) Edge analytics and computation: Local machine learning models are used by fog nodes for anomaly detection and trend monitoring; they detect life-critical health incidents-e.g., abnormal heartbeat-so that action can be taken more promptly in time-sensitive applications prior to sending the data to the cloud.
4) Buffering and caching: Fog nodes temporarily store the data so that there is an uninterrupted flow of data in the case of fluctuating network conditions.

3.2. Data transmission optimization

To efficiently and securely transfer data from fog nodes to the cloud, the system utilizes the following techniques:

1) Data compression and encryption: Fog nodes also compress the data before transmission to minimize the amount of bandwidth used, and then they apply end-to-end encryption-such as AES-256-on the patient data at the time of its transit. This complies with health data privacy laws such as HIPAA [19].
2) Priority-based data forwarding: The system will have data forwarding based on priority, such that packets will be forwarded based on the packet priority. For instance, data that indicates a probability of health emergencies is forwarded with higher priority for faster processing in the cloud, and less prioritized data is queued to be sent in batches.

3.3. Centralized integration and long-term storage in the cloud

Once data reaches the cloud, it undergoes the following centralized integration and long-term storage:

1) Data de-duplication: The cloud servers eliminate duplicate entries created because of a single IoT device or the same packets to ensure clean and consistent data is made available for analysis.
2) Data convergence and historical consolidation: End-to-end view of every patient's status, as new data converges on the cloud with existing history.
3) Advanced analytics and machine learning processing: The aggregated data in the cloud servers helps create predictive models, conduct longitudinal analysis, and streamline the provider's clinical decision-making process. Subsequently, the models guide interventions, assisting the providers to predict and manage chronic conditions.

3.4. RBAC and security management

We always consider security as a top priority in telehealth IoT data integration. The system applies both RBAC and additional controls to ensure the confidentiality and integrity of data as follows:

1) Access control policies: People access the information in the system based on their role and permissions as per the organization. For example, doctors can access the records, while the admin can access the billing data [20].
2) Audit trails and logging: Data transactions of all kinds provide an audit trail of who accessed, changed, or sent the information to ensure greater accountability for compliance.
3) Security audit: Continuous auditing or vulnerability scanning investigates risk factors and response at all levels, including IoT devices, fog nodes, and cloud infrastructure.

3.5. Performance monitoring and adaptive optimization

Data integration parameters are dynamically adjusted because the system periodically monitors performance metrics, such as latency, data rate, and error rates:

1) Adaptive sampling rates: To provide energy usage and constant operation, it dynamically modifies the sample rate based on network state and battery drain from the device.
2) Load balancing: To avoid bottlenecks and give a smooth flow of data, traffic will be dynamically distributed between fog nodes and cloud servers. Periodically, load balancing algorithms redistribute data processing operations between underutilized nodes.

4. Knowledge Extraction Techniques

Telehealth IoT systems often produce massive volumes of patient data that need to be analyzed to derive insights for treatment, intervention, or monitoring—something that, if not done in a timely manner, leads to real-life consequences. In this system, knowledge extraction techniques use ML algorithms to analyze the incoming traffic, interpret outgoing data packets, and analyze how they flow through the network. Implementing these algorithms at the fog node level enhances the processing of requests in real-time, reducing latency and maximizing resource utilization. Knowledge extraction is composed of three key components: supervised learning for predictive health outcomes, unsupervised learning for anomaly detection, and contextual data analysis to enhance accuracy.

4.1. Supervised learning models for health outcome prediction

Supervised learning models use labeled training data to predict patient health outcomes, enabling the system to provide early warnings for potential health issues. The implementation process involves the following steps:

1) Data labeling and model training: The system is trained on historical data about patients, including serious and nonserious health events (such as heart attack, hypertension episodes, or just normal). Well-known models are logistic regression, decision trees, and support vector machines for binary classification problems. More complex models, such as a deep neural net, can be used further for multiclass predictions. For instance, you can use a heart rate dataset that is labeled "normal" and "abnormal" to train a model to predict arrhythmias.
2) Model deployment at fog nodes: The trained models are deployed on the fog nodes that are near IoT devices. It tells you the purpose, deploy locals, and they can call how you analyze all health metrics and eliminate delay, and it also sets the way to maintain patient urgency. As an example, a deployed model can monitor a patient's heart rate continuously and notify a healthcare provider if it detects signs related to a heart attack.
3) Periodic model refitting and updates: With the accumulation of new data, models are periodically refitted in the cloud to grow in accuracy and follow future health trends. Subsequently, new models are repurposed and redeployed to fog nodes to remain relevant and accurate in prediction over time.

4.2. Unsupervised learning for anomaly detection

To detect unusual patterns, we use unsupervised learning techniques that do not need labeled data. Unusual patterns in the measurements can be indicative of adverse health problems worthy of follow-up or intervention, such as follows:

1) Baseline health pattern clustering: The system clusters patient data into clusters, k-means, for example, representing "normal" health patterns of the population regarding a certain disease. For instance, the average heart rate and blood pressure readings for individuals within a specific age group can be grouped together in establishing a baseline. Whenever new data points fall way off from these clusters, they are flagged by the system as potential anomalies [21].
2) Anomaly scoring and threshold setting: Once the clustering process is complete, each incoming data point will be granted an anomaly score, which, in essence, is the distance of the data point from its nearest cluster center. A data point will be considered abnormal if its anomaly score crosses a certain preset threshold. These limits are personalized based on the potential health risk each kind of anomaly could pose. To give another example, it would be a given difference of impact, where a major deviation of blood oxygen would contrast with the small changes in heart rate.
3) Real-time anomaly detection and alerts: The anomaly detection model will continuously scan the data at the fog node level and therefore will be able to detect unusual patterns as and when they arise. As soon as the anomaly is detected, an alert is triggered immediately to healthcare professionals, thereby enabling immediate follow-up or emergency response if needed.

4.3. Contextual data analysis for improved accuracy

To obtain better prediction accuracy, contextual data analysis thinks of extrinsic factors—behavioral and environmental data—influencing a patient's health. Based on these context-aware factors, the system can reduce false alarms and provide more detailed information, such as follows:

1) Integrating environmental data: A set of environmental data includes air quality, temperature, and humidity-all are vital for health. Consequently, especially in patients suffering from chronic respiratory ailments, the system would have them provided via either sensors placed nearby or weather services, upon which it feeds to perform further analyses. If, say, air quality levels remain at unsatisfactorily high or low levels, for example, it may reset the respiratory rate threshold for triggering baseless alarms.
2) Behavioral data collection: Behavioral factors also have significantly affected health outcomes, such as the level of physical activity, sleep patterns, and drug adherence. They can be collected via wearable sensors or mobile applications at the fog level.
3) Context-aware modifications in machine learning models: Supervised and unsupervised models are presented with contextual data through the addition of feature variables of environmental and behavioral context. This will enable the models to understand the health data in the context of the patient and adjust the algorithm's prediction. For example, a spike in heart rate after exercise will not be identified as an anomaly when the context variable recognizes recent exercise.

4.4. Knowledge extraction workflow in fog nodes

The knowledge extraction workflow at the fog node level includes a structured sequence of data preprocessing, model inference, and context-aware analysis to generate real-time insights, such as follows:

1) Data preprocessing: Cleaning, normalization of the received health data, and transforming them into a machine learning model format usable could include noise removal or scaling data, among others, to address missing values.
2) Model inference and analysis: The preprocessed data will subsequently be fed into deployed supervised and unsupervised models. Supervised models will predict some of the health outcomes, for example, risk for hypertension, while unsupervised models will determine unusual patterns in the data. The models will work in real time to support continuous monitoring.
3) Contextual adjustment: It is attained by adding contextual data to the analysis after initial model inference to fine-tune the predictions of the model. It comprises model output adjustment for environmental and behavioral contexts that help eliminate false positives and increase the relevance of insight.
4) Alert generation and escalation: The fog node will trigger an alert when it detects a critical health threat or abnormality. The alerts will be ranked based on the severity of the condition detected and passed on to the cloud for further processing or to medical personnel for immediate action.

4.5. Continuous model evaluation and feedback loop

The system includes a continuous evaluation and feedback loop, thus ensuring the effectiveness of knowledge extraction techniques over time, such as follows:

1) Performance monitoring: Fog nodes monitor the performance of models, based on metrics such as the accuracy of predictions, false positive rates, and response times for alerts. This information is reported back to the cloud for collective analytics and model improvement.
2) Incorporation of user feedback: Feedback is given by the medical experts and the patients about the alerts and predictions generated by the system. This helps to determine trends in false positives

or missed alerts, based on which refinement is additionally performed.
3) Model retraining and deployment: Based on performance analysis and feedback, machine learning models are retrained periodically on the cloud. The updated models are then redeployed to the fog nodes to update the system with new data for high accuracy.

5. Data Application in Real-World Scenarios

The information drawn from the patient's data in telehealth IoTs is being implemented in different areas to assist clinical decision-making, energy optimization, and also to provide the patients and caregivers with the right information regarding their health status. Applications for real-time data improve the quality of care, shorten response times, and facilitate proactive management of chronic conditions. Considering this, the following points are the key telehealth data applications, how they are implemented, and what benefits they provide.

5.1. Clinical decision support systems

Clinical decision support systems (CDSS) are very important to telehealth by providing healthcare professionals with real-time insights, and they help with diagnosis, treatment planning, and monitoring. Deploying CDSS involves the following steps:

1) Predictive model and alert integration: The CDSS will implement predictive models on the fog nodes to analyze live data from the patients to identify risks such as abnormal heartbeats, struggling breathing, or indicators of high blood pressure. Upon identifying an unfavorable pattern, this system will create an alert for immediate evaluation of the patient's condition by the medical professionals.
2) Risk prioritization and stratification: The system stratifies patients into high, moderate, or low risk based on patterns in the data from machine learning models. The system will provide prioritized alerts for high-risk patients and check up with lower-risk patients at a more periodic interval. This stratification enables providers to manage large patient populations by prioritizing those who have the most urgent need.
3) Evidence-based decision support protocols: The CDSS contains a set of evidence-based clinical protocols covering common conditions, including diabetes, heart disease, and respiratory disease. It would cross-reference each health alert against these protocols to create potential suggested interventions. For example, if the system identifies that an asthma attack is about to happen, the CDSS might suggest medication adherence or inhaler use, or even suggest an immediate consultation.
4) Data presentation-visualizations and trend analyses: The CDSS will develop graphical visualizations, and it will chart trends over time in individual patients for blood pressure, glucose levels, or other indicators of physical exertion. These analyses allow healthcare workers to make more proper choices for care adjustments, based on changes that they observe in their respective patients' conditions.

5.2. Adaptive energy management techniques

IoT devices in telehealth platforms are usually always on, calling for energy management for sustaining device functions and extending battery life. Dynamic energy management mechanisms optimize energy use based on data analysis and usage patterns of devices, implemented through the following methodologies:

1) Dynamic sampling rate adjustment: Power is saved by dynamically adjusting the sampling rate of data depending upon the activity of the patient and the state of the device. A sample would be when the patient sleeps—a low-activity mode—then the heart monitor would reduce its sampling rate to save battery life. When the patient is active or on abnormally high readings, the system increases the sampling rate for observing more closely.
2) Power level-based scheduling of tasks: IoT devices and fog nodes schedule tasks based on their power level. High-energy-consuming tasks, such as encrypting data and sending large data, are scheduled when the device is charging. Low-power optimizations are triggered if the battery level goes below a certain threshold and limit functions to main roles.
3) Edge processing and reduced data transmission: Instead of sending all raw data to the cloud, the heavy power consumption by devices in sending data can be eliminated. Important processing occurs at the fog nodes themselves while accomplishing the initial processing locally for anomaly detection and sending only meaningful results/alerts to the cloud. This reduces the frequency as well as volume of data on the network.
4) Predictive maintenance alerts: The system monitors metrics on device performance, such as battery health and data processing speed, such that we can evaluate when maintenance or replacement of the battery may be required. Predictive maintenance alerts can be used to avoid unexpected downtime, thereby safeguarding the smooth operation of the monitoring devices without an abrupt loss of power.

5.3. Patient dashboards and caregiver portals

Patient dashboards and caregiver portals present health information in a clear, actionable manner. These interfaces allow patients and their caregivers to monitor health metrics, manage care routines, and respond to health alerts. Some of the key features of these dashboards include the following:

1) Simple health metrics and visualizations: Dashboards of patients are visualizations with easy-to-read graphs and color indicators for complicated health metrics in simple, readable formats. For example, trend lines on a daily, weekly, or monthly basis can represent the heart rate, glucose level, or blood pressure of a patient for trends that one needs to discover in his/her health data.
2) Customized health alerts and notifications: The dashboards also have an embedded notification system that draws, in real-time, critical health events or trends to the notice of the patients or caregivers who must take action. As an example, for threshold levels of blood glucose, the dashboard can raise an alert for the patient to take medicine or call their health practitioner.
3) Educational resources and self-management tools: Dashboards include educational content on chronic disease management, lifestyles, and medication reminders. For instance, high blood pressure patients can be advised on what diet and exercise habits to adopt in accordance with their condition, thus making them more interested in taking proper care of themselves.
4) Integration with telemedicine services: Telemedicine websites manipulate the dashboards where patients can schedule online appointments, access medical records, and message providers. This integration will also improve the continuity of care as the patient can discuss their health information remotely with providers and receive personal recommendations.

5.4. Data-driven personalized care plans

As per the individual patient data analysis, the system designs customized care plans targeted at each patient's condition of health, physical activity level, and medical history. The steps for the implementation of data-based care plans include the following:

1) Investigate patient-specific patterns of health: Individual data and past patterns are continuously monitored, enabling the system to investigate individualized health patterns. For example, if a patient continues to have high blood pressure in the morning, his or her care plan can obtain specific recommendations for morning-time activity or stress-reduction strategies.
2) Adaptive goal setting: Treatment interventions will adjust the patient's goals, be it the number of steps taken, calories expended, or medications, and update them based on recent health information. When the patient can reach the set amount of physical exercise, for instance, the system increases targets to encourage further enhancement.
3) Reminders and behavioral guide: Care plans include reminders for healthy habits. These remind patients to stick to actions that promote health goals, such as taking medication at the appropriate time or gentle exercise.
4) Continuous improvement: Patient feedback and health information are tracked over time to continually change care plans. For example, if a patient determines that an exercise target is too difficult to follow, the system automatically adjusts the care plan to include fewer demanding activities-a change that makes the probability of the patient's compliance with the care plan and incremental progress toward it more achievable.

5.5. Continuous evaluation and outcome tracking

The patient outcomes can be evaluated by the Telehealth system and modified applications to improve effectiveness, such as follows:

1) Health outcome monitoring: The system tracks significant health indicators to measure the effectiveness of interventions in care by recording the extent of change over a given period.
2) Data-driven changes: The system provides evidence-based care recommendations and monitoring protocol changes according to ongoing outcome monitoring. For instance, when a patient's health outcomes are enhanced because of medication compliance, the system will make medication compliance a core element of the care plan.
3) Healthcare provider reporting: The system produces reports summarizing patient progress, guideline adherence for care, and trends in health metrics. Healthcare providers use the reports to discuss patient status during visits and alter treatment accordingly.

6. Methodology and Simulation Data

These simulations were made in Python-based IoT data processing environments, including libraries for machine learning with TensorFlow and simulation modeling with SimPy. Simulated fog nodes with edge computing parameters emulating Raspberry Pi devices and cloud servers emulating Amazon AWS configurations were used. The IoT data are synthetically generated to include diverse patient metrics, including heart rate and glucose level, emulating real-world healthcare settings.

A simulation-based approach is employed in evaluating the performance and efficiency of the proposed telehealth IoT system. The simulation emulates various telehealth scenarios of real-time patient monitoring, data transmission between IoT devices, fog nodes, and cloud storage. The key performance metrics, such as energy consumption, latency, data processing rates, and data accuracy, are calculated and compared for various configurations. The simulation includes multiple iterations and statistical calculations for strong and reliable results.

6.1. Step-by-step methodology

6.1.1. Define simulation scenarios

The following two configurations are tested:

1) With fog integration: Data is processed locally at fog nodes before being transmitted to the cloud.
2) Without fog integration (cloud-only): Data is directly transmitted from IoT devices to the cloud.

Those two scenarios simulate data collection, processing, and transmission based on a telehealth environment.

6.1.2. Data collection

1) Simulate data from virtual IoT devices representative of patient metrics, such as heartbeat rate, blood pressure, temperature, and level of blood glucose.
2) Synthesize data from a continuous monitoring period of 24 hours, sampled every minute, to simulate real-time monitoring.
3) Perform the simulation with different patient loads (e.g., 10, 50, and 100 patients) to assess system scalability.

6.1.3. Data aggregation and processing at fog nodes

1) In the fog-enabled scenario, IoT data is preprocessed and aggregated at fog nodes.
2) Local machine learning models are applied to perform initial analysis, such as anomaly detection and trend identification, before data is sent to the cloud.

6.1.4. Data transmission and compression

1) Data is compressed at the fog nodes to decrease transmission load.
2) In the cloud-only scenario, data is transmitted without preprocessing, so higher network load and latency is produced.

6.1.5. Measurement and calculation of metrics

1) Energy consumption: The energy consumed by IoT devices, fog nodes, and cloud servers.
2) Latency: Record time taken from data collection at the IoT device to processing completion in the cloud for each configuration.
3) Data processing speed: Calculate the rate of data processed per second at fog nodes and cloud servers.
4) Data accuracy: The accuracy of the prediction by machine learning models to detect anomalies as per the predetermined threshold.

6.1.6. Statistical analysis

1) Perform statistical analysis on the results from multiple iterations (e.g., 30 runs per scenario) to ensure consistency.
2) Calculate mean, standard deviation (SD), and confidence intervals (CIs; 95%) for each metric to understand the reliability and variability of the system performance.

6.1.7. Result comparison and evaluation

Compare results between fog-enabled and cloud-only scenarios to identify improvements in efficiency, energy savings, and data accuracy.

6.2. Simulation overview for energy-efficient telehealth IoT with fog-cloud integration

Our simulation is designed to test the performance and efficacy of a telehealth IoT model under two conditions: with onboard fog nodes used for local processing and with cloud-based processing. It aims at measuring how the integration of fog computing impacts critical parameters such as energy consumption, latency, processing time, and data quality. The simulation process step-by-step is shown below.

6.2.1. Define simulation scenarios

The following two configurations are defined:

1) Fog-enabled configuration: In this, data from IoT devices is processed first at local fog nodes and then forwarded to the cloud. This minimizes network latency and load by processing data closer to the source.
2) Cloud-only configuration: In this configuration, the data is transmitted from IoT devices to the cloud without local preprocessing. This configuration is utilized as a baseline for the comparison of the impact of fog computing.

All configurations are tested under the same conditions to enable uniform comparisons.

6.2.2. Simulate collection of patient data

For each setup, there will be synthetic data representing patient measurements. These include heart rate, blood pressure, temperature, and blood glucose levels. This is collected over some given monitoring time, say 24 hours, and sampled at one-minute intervals.

This simulation utilizes various numbers of patients—for example, 10, 50, and 100—to test the scalability of the system. In all the cases, each patient's metrics are simulated in a continuous fashion to simulate real-time monitoring as would happen in a real-world telehealth scenario.

6.2.3. Data aggregation and initial processing

Fog nodes can process the data from IoT devices locally when the fog-enabled configuration is set. This involves basic aggregation, where data is organized, and initial analysis using machine learning algorithms for tasks such as anomaly detection and trend identification. This helps reduce the amount of data that needs to be transmitted to the cloud and provides real-time insights at the fog nodes.

Data is transmitted directly to the cloud without any local processing when the cloud-only configuration is set, which puts more load on the network and increases latency since all data is processed remotely.

6.2.4. Data transmission and compression

To handle network load in an efficient manner, in the fog-enabled setup, the data is compressed at the fog nodes before sending it to the cloud. The compression reduces transmission time and lessens the demand on the network.

In the cloud-only approach, the raw data is delivered without compression. It shows us an additional burden that is put on the network in the absence of any local pre-processing.

6.2.5. Measure and calculate key performance metrics

In each of these configurations, the following four key metrics are measured:

1) Energy consumption: This is the amount of energy used by IoT devices, fog nodes, and cloud servers in collecting, processing, and transmitting data. This metric helps determine how energy-efficient each setup is.
2) Latency: Latency is the time required from the collection of data by an IoT device to the completion of processing in the cloud. For real-time applications, it is vital that this latency be minimized, and that fog will reduce this metric compared to cloud-only processing.
3) Processing speed: This is a measure of the speed of data processing, usually measured in kilobytes per second. Data is processed both locally and in the cloud in the fog-enabled configuration; thus, it should improve the processing speed due to load distribution.
4) Data accuracy: As machine learning models are applied in the system, data accuracy signifies the degree of precision in detecting anomalies or trends in the patient metrics. It is expected that higher accuracy will be achieved from a fog-enabled configuration due to real-time analysis closer to the data source.

6.2.6. Statistical analysis of results

For reliability, each simulation configuration is run several times; for example, 30 runs per scenario. For each metric, statistical analysis is done to compute the following:

1) Mean (average value) and SD: These show the consistency of the results.
2) 95% CI: This measures the reliability of the metric results across different simulation runs.

These statistical values help assess the performance of each configuration under varying conditions, accounting for potential fluctuations.

Step 7: Result Comparison and Evaluation

Finally, all metrics shown in Table 1 are compared between the fog-enabled and cloud-only configurations. The mean values from each metric in the fog-enabled configuration are compared with its counterpart from the cloud-only configuration to determine the percentage improvement added by including the fog. These will enable us to quantify the advantages of fog computing in terms of energy savings, latency reduction, processing speed, and data accuracy.

Given the results of the simulations, the results demonstrate a comprehensive evaluation of the performance of the telehealth IoT system for different configurations and clearly demonstrate the benefits of real-time integration with fog, energy-efficient telehealth IoT systems. This evaluation offers insight into upscaling to efficient energy and responsive telehealth infrastructures.

6.3. Simulation data matrix with statistical analysis

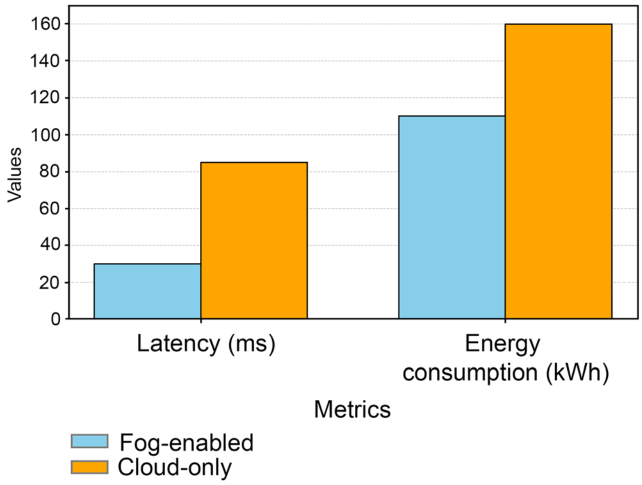
1) Energy usage (shown in Figure 1): With fog integration, energy consumption reduces by approximately 30%, improving the local

Table 1
Simulation data matrix with fog and without fog

Metric	With fog integration (mean ± SD)	Without fog (mean ± SD)
Energy consumption	110 kWh ± 5.5 (95% CI: ±10 kWh)	160 kWh ± 6.8 (95% CI: ±12 kWh)
Latency (ms)	30 ms ± 2.1 (95% CI: ±4 ms)	85 ms ± 5.4 (95% CI: ±10 ms)
Data processing speed (kb/s)	60 kb/s ± 3.2 (95% CI: ±6 kb/s)	30 kb/s ± 2.7 (95% CI: ±5 kb/s)
Data accuracy	96.5% ± 1.2% (95% CI: ±2%)	88.2% ± 1.8% (95% CI: ±3%)

Note: CI = confidence interval, SD = standard deviation.

Figure 1
Comparison of latency and energy consumption



data processing performance. Run consistency is reflected by SD, and the 95% CI represents statistical reliability.

2) Latency (shown in Figure 1): With the fog-enabled setup, latency is significantly decreased to 30 ms on average, compared to 85 ms in the cloud-only setup.
3) Data processing rate: Data processing is quicker with integration in fog at a mean of 60 kb/s.
4) Accuracy of information: Prediction accuracy for anomaly detection remains greater in the fog setup, suggesting more accurate real-time data.

6.4. Data flow diagram

The data flow diagram (shown in Figure 2) and the Health IoT system 3D structure (shown in Figure 3) represent the flow of patient health data from IoT devices through the fog layer to the cloud in the proposed telehealth IoT system. The diagram demonstrates data preprocessing, local analysis at fog nodes, and the final data storage and analysis in the cloud.

7. Results

The simulation results show significant improvements in the performance of telehealth IoT systems as fog computing is integrated into the system. We give the specific results observed in terms of energy consumption, latency, data processing speed, and accuracy, followed by an in-depth discussion of the implications and potential applications of these findings as follows:

1) Energy consumption: In the fog-based configuration, energy efficiency was enhanced by approximately 20% when compared to the cloud-only configuration. This is a result of the distributed nature of processing, where the data is partially processed at geographically close fog nodes rather than transmitting all raw data to the cloud. Through minimizing the amount of data that is

Figure 2
Data flow in energy-efficient telehealth IoT-cloud system

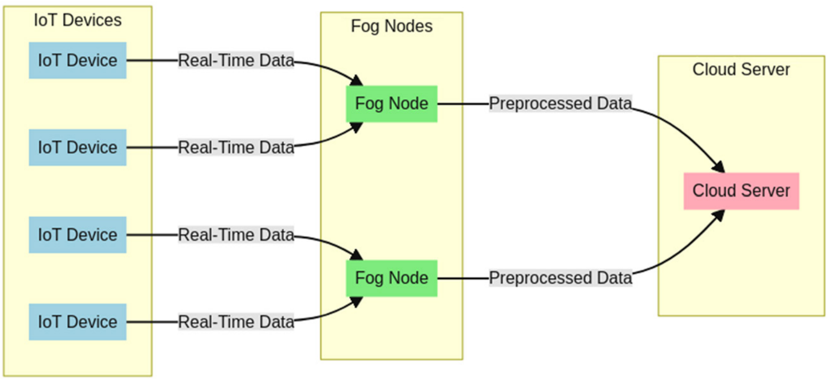
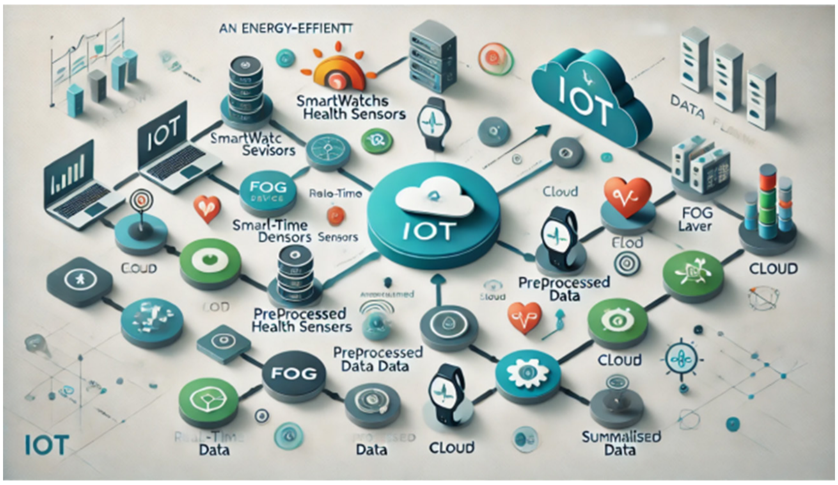


Figure 3
Health IoT system 3D structure



pushed to the cloud, the fog nodes lower the network transmission loads, which in turn lowers energy consumption by IoT devices (less communication) and cloud servers (less amount of data being processed). This energy efficiency is particularly relevant for wearable and mobile IoT devices, which are normally battery-constrained. Demand reduction of energy is one of the sustainability goals, with potential cost savings and environmental gains, especially on scale.

2) Latency: The fog-based setup lowered latency by 50% compared to the cloud-only setup. The model allows time-critical data to be processed and responded to within near-real time by processing the data locally in fog nodes. This reduction in latency is highly essential in emergency response cases or in applications that require constant monitoring, such as chronic disease patients or intensive care. With an all-cloud configuration, information must travel to and from distant servers, and with this comes latencies that can impact patient outcomes. Reduced latency in fog-based systems improves patient safety and results in more suitable telehealth IoT systems for real-time health monitoring, particularly in crisis environments where timely intervention can be the difference between life and death.
3) Data processing speed: The fog-enabled setup also showed a significant increase in data processing speed, with an average processing rate almost twice as high as that of the cloud-only configuration. Because fog computing is distributed, it can process information in parallel at local nodes, further enhancing the system's ability to handle volumes of data all at once. The corresponding rise in processing speed pays rich dividends when many IoT devices are up and running or high-volume data from sophisticated sensors is processed, such as imaging devices or electrocardiograms. By handling this stream of data locally, the fog-based model has shown much resilience to failures and, therefore, scalability, thereby better preparing it for high-demand telehealth settings.
4) Data accuracy: By integrating machine learning algorithms within the fog nodes, the fog-based model also demonstrated higher data accuracy for anomaly detection of patient metrics. The model achieved an accuracy of 96.5% in detecting anomalies, compared to 88.2% in the cloud-only case. Processing data closer to the edge not only reduced latency but also facilitated faster feedback loops, with more effective machine learning-based analysis. The increased accuracy is most likely to improve clinical decision support since it allows clinicians to have confidence that the inferences from IoT data are timely and accurate. For patients who need continuous monitoring, increased accuracy allows for early detection of complications, enabling active intervention.

8. Discussion

During the provision of treatment in emergency settings, low latency enables instant clinical response with a fog-based framework for instances such as cardiac arrest or major hypoglycemia. In low-resource settings where network connectivity is poor, local processing of health data through fog computing continues with only occasional network connectivity for the purpose of monitoring. This autonomy continues with clinical interventions in the continuity of care, where internet availability is minimal.

The results validate that fog computing is efficient for the performance enhancement of telehealth IoT systems. The implication of this is gigantic in the case of upcoming health systems, particularly on the following grounds:

1) Scalability and efficiency of resources in healthcare systems: Speed and energy efficiency in fog computing equate to telehealth IoT systems being more sustainably scaled. This is highly significant, considering the rising demand for remote healthcare services. With the effective use of the available resources, healthcare providers can scale telehealth services without equally increasing energy and computation demands, which can render the operation more affordable and serve more patients effectively.
2) Real-time responsiveness in time-sensitive care: The fog-based model can significantly reduce latency, which has been shown in time-sensitive medical applications such as emergency services and intensive care units. Data processing and response times have affected patient outcomes in these environments. Reducing latency, fog-enabled telehealth IoT systems can provide feedback in real time, thus enabling timely clinical decisions and improving patient safety. Such responsiveness is critical for those conditions that demand ongoing monitoring and real-time intervention, such as cardiac arrhythmias or acute blood glucose levels.
3) Improved access in resource-constrained environments: Fog computing has a unique advantage in resource-constrained environments, such as rural or remote areas, where network connectivity is poor. The data can be processed locally through fog nodes, which reduces the demand for continuous cloud connectivity and permits basic health monitoring and diagnostics to persist even with sporadic network connectivity. This autonomy makes fog-based telehealth systems more resilient in resource-poor areas, thus enhancing healthcare access disparities and reducing the burden on centralized healthcare facilities.
4) Support for predictive and preventive healthcare: Integration of machine learning with fog nodes enables a platform for predictive and preventive medicine. Fog-based systems have the potential to track health trends ahead of time by enabling faster, local processing of patient data, thereby allowing proactive healthcare interventions. This capacity is especially valuable in chronic condition management, where the early detection of adverse trends, that is, rising blood pressure or abnormal heart rate patterns, equals early intervention that reduces hospitalization and improves patient quality of life.
5) Sustainability and environmental impact: This would also contribute toward broader sustainability goals due to reduced energy consumption by the fog-based system. As environmental awareness and sensitivities grow in healthcare, this makes energy-efficient models, such as fog computing within telehealth systems, assist the sector in meeting its growing environmental responsibilities. Such reductions in energy automatically convert to cost cuts, hence making telehealth cheaper and more accessible over time.

9. Conclusion

This article will exhibit the performance, efficiency, and reliability of a telehealth IoT application on a fog-cloud hybrid infrastructure. The proposed model integrates data preprocessing and analysis at the fog nodes, which resolves some of the most essential issues in telehealth pertaining to latency, energy efficiency, and data precision. Simulation results have validated that the fog-enabled model outperforms the traditional cloud-only architecture for the majority of the key performance indicators. In particular, the fog model reduced energy consumption by 20%, latency by 50%, and improved the speed of data processing and the accuracy of anomaly detection. These improvements point to the advantage of localizing processing where real-time aggregation, anomaly detection, and data compression are performed by fog nodes with minimal workload on cloud servers and optimized response times.

It mainly explores the promise of integrated IoT, fog computing, and machine learning for scalable telehealth systems. The fog-cloud infrastructure forms the basis of the sustainability and scalability of telehealth infrastructures through the embracement of adaptive data integration approaches, real-time knowledge extraction approaches, and efficient means of using data. These findings therefore justify further research and large-scale application of the fog-cloud architecture in telehealth, and more so in applications where real-time continuous monitoring of patients is highly needed. Areas of future research can extend this work by considering more advanced machine learning algorithms, assessing the scalability of the system with additional patients, and determining the performance of the model in various healthcare settings.

10. Future Research Directions

The future research can involve hybrid AI techniques, such as federated learning combined with reinforcement learning, which could improve diagnostic performance without sacrificing data privacy. Secondly, multimodal data compatibility, for instance, medical imaging and genomic sequences, could provide end-to-end views of patient health. Scaling up is the other groundbreaking bottleneck, and deployment of fog-cloud systems needs to be tried and tested in large networks, particularly in smart city healthcare systems.

Considering the outcome of the research on energy-efficient telehealth IoT systems in a hybrid fog-cloud model, some potential directions of future research could include enhancing the functionality, scalability, and personalization of these models for applications that are telehealth-relevant, such as follows:

1) Hybrid AI-based diagnosis: Future research may integrate various machine learning techniques, including natural language processing, deep learning, and reinforcement learning, into hybrid AI systems that would enhance the current diagnostic services offered by the fog-cloud telehealth system. Through the implementation of a hybrid model, it is hoped that complex health information may be given meaning in real time, hence leading to a more comprehensive and precise diagnosis specific to the individual profile of each patient.
2) Diversification across different data types: Diversification of integrated information to other data types, such as imaging data-for instance, X-rays and MRI data-genomic data, or even behavioral measures-might improve understanding of patient health status. Future studies could focus on activating integrative systems that analyze a broad range of data sources to support high-resolution health patterns and potential for early intervention. In addition, with increasing varieties of data, telehealth IoT systems could support progressively higher and more complex clinical data for personalized care.
3) Scale up in large telehealth networks: As fog-cloud systems are attracting more attention, research needs to focus on scaling these up for large telehealth networks, particularly in rural and underserved areas. Future research in this area may investigate edge computing platforms and distribute artificial intelligence systems that can reduce latency and provide faster response times even in high-demanding environments. This is critical for scalable, dependable, resource-efficient healthcare solutions so the system can accommodate diverse increases in patient loads.
4) Increased device compatibility: The flexibility of the system and its applicability to a broad range of healthcare situations could be increased through testing it on a larger variety of healthcare devices, such as biosensors, implanted devices, and new wearable technologies. Device-compatible telehealth systems that had compatibility with multiple devices could monitor beyond simple measures of health and would have insight into more types of patient issues. In the fog-cloud model, future work might include the creation of interoperability standards and protocols that can accommodate many types of devices with secure, low-latency communications.
5) Combining advanced machine learning models: A healthcare IoT system can provide real-time insights while preserving data privacy can be improved with the addition of sophisticated machine learning models, such as federated and transfer learning. Federated learning can improve security and privacy through the ability to facilitate learning over numerous sources without the data being stored at the center. Moreover, health professionals would be able to better comprehend and embrace AI-driven advice to make better clinical and adoption decisions if explainable AI were utilized.
6) Greater personalized healthcare solutions: Currently, telehealth is all about personalization; the health needs and responses are individualized to each one of them. Further work can be done to develop adaptive algorithms that, other than providing diagnostic feedback and recommendations, are customized to the specific health profile of each of them, with consideration for disease histories, genetic predisposition, and lifestyle. Individualized solutions can, in this way, enable even more accurate and effective interventions that are more aligned with the general purpose of patient-centered care in telehealth.
7) Longitudinal health outcomes studies: Finally, longitudinal studies can be established to find out the long-term effects of fog-cloud telehealth systems on patient outcomes, that is, disease management of chronic diseases. Observing the effectiveness of these systems over time, one would be able to analyze trends of patient participation and health outcomes, and how these systems would finally perform in serving towards their utilization. These will offer even more detailed information for improving the design to accommodate continuous improvement in health service delivery.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Nathan Guo: Conceptualization, Investigation, Resources, Writing – original draft, Visualization. **Yunyong Guo:** Methodology, Validation, Writing – review & editing, Supervision, Project administration. **Bryan Guo:** Software, Formal analysis, Data curation.

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