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Cloud Computing-Based Data Processing and Energy Management Modeling in IoT Healthcare Systems

Sai Sathish Kethu[1], Durai Rajesh Natarajan[2], Sreekar Peddi[3] and R. Hemnath[4*]

[1]*NeuraFlash, Georgia, USA*
[2]*Estrada Consulting Inc, California, USA*
[3]*Tek Leaders, Texas, USA*
[4]*Kaamadhenu Arts and Science College, Sathyamangalam, India*

**Corresponding author*

Abstract

The use of cloud computing for healthcare IoT is a new way of configuring data processing and management, facilitating real-time processing and data-driven decision-making. Data privacy, energy consumption, and computational efficiency are obstacles that will not fade anytime soon. This paper takes a holistic approach that integrates cloud computing for scalable data storage, energy-centered models for optimizing energy use, and advanced data processing approaches, (including Random Forest for feature selection, and Principal Component Analysis (PCA) for the extractive of features). The expectation is to provide a generational advancement in analyzing data related to healthcare, by creating energy sustainability, data security through cloud infrastructure, while using the cloud for advanced processing capabilities. The experimental results of the investigation show promising properties of improvement in reductions in energy consumption, storage gains, and overall system performance.

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Keywords

Cloud Computing, Health Care, Random Forest, Principal Component Analysis, Energy-based Models.

Introduction

The IoT devices to healthcare systems to facilitate unprecedented advancements (1). These advancements enable continuous monitoring of various health metrics in patients (2). Such devices include wearable sensors and medical monitoring devices, which produce massive amounts of data from real-time snapshots of a patient's health state (3). On the contrary, efficient and accurate processing and analysis of this data remain important challenges to clinicians and researchers (4). Cloud computing comes in to offer a scalable environment for storage, processing, and real-time access to data so that professionals are aided in the effective monitoring of patients and making informed decisions (5).

One of the main driving forces for more efficient data processing in healthcare is the magnitude and diversity of generated IoT data (6). But the management of the data doesn't only include these tasks; relevant information extraction from the data is also a critical area of challenge (7). Therefore, techniques like feature selection (e.g., Random Forest) and feature extraction (e.g., Principal Component Analysis) become very important in improving data quality for analysis through dimensionality reduction and focusing only on significant features (8). Furthermore, energy efficient solutions such as energy management modeling are also necessary for the sustainable operation of such devices without compromising performance in the growing trend of energy conservation in IoT devices (9).

Adverse issues overshadowed the global adoption despite the merits of IoT in healthcare (10). Major concerning environmental energy consumption of IoT devices (11). Most of the healthcare IoT devices are battery operated rendering it a primary consideration in energy efficiency when it comes to long-term usage (12). The other problem is on the data generated by these devices it is overwhelming, requiring sophisticated algorithms and cloud resources for storage and real-time analysis (13). Data privacy and security of sensitive patient information are the other issues requiring robust systems for managing and securing health data (14).

Solutions to these problems can be approached using the cloud computing approach to data processing integrated with smart energy management techniques. Use energy-based models for optimizing energy consumption to IoT devices, additionally leverage cloud infrastructure for scalable data storage and analysis. Healthcare systems will be able to achieve high resource utilization without compromising the security and privacy of patient data. Furthermore, using machine learning algorithms for analysis of the data will ensure well-predictive power thus improving overall efficiency of healthcare services as well as informed decision-making. The framework is thus sustainable and very efficient making it a very worthy avenue into the future development of IoT-enabled healthcare systems.

Problem Statement

The proposed work addresses key challenges in IoT-based healthcare systems, such as energy efficiency, data processing, and privacy concerns (15). By integrating cloud computing for scalable data storage and processing, it ensures efficient management of large datasets (16). The energy-based models optimize power usage for IoT devices, which is crucial for battery-powered systems (17).

Feature selection and PCA improve computational efficiency by processing only relevant data, enhancing accuracy (18). The cloud infrastructure ensures secure storage and real-time analysis of healthcare data while maintaining patient privacy (19). This approach boosts operational efficiency, resource utilization, and sustainability, ultimately improving patient care and supporting informed clinical decisions (20).

Objectives

- Assessing the role of cloud computing in nursing and facilitating healthcare systems to allow storage and processing of data at a scale.
- Evaluating the influence of energy-based models (in relation to impact on power utilization) for the optimization of power consumption in battery-powered IoT devices within the healthcare industry.
- Appraising the influence of feature selection (Random Forest) and feature extraction (PCA) on data processing efficiency.
- Examining the scalability, security and real-time accessibility of healthcare data stored in the cloud.
- Presenting suggestions for improving efficiencies in operation, resource utilization, and sustainable developments in the context of IoT within healthcare systems.

Tunnel engineering involves numerous hazards, lengthy construction times, and the risk of high costs, thus, safety and operational efficiency are key considerations. Tunnel boring machines (TBMs) are indispensable, as they routinely collect massive quantities of operational and monitoring data, which is important to enhancing safety and operational efficiency. (21) propose a hybrid data mining approach for automating the real-time processing of TBM operational data based on association rule mining, decision tree classification, and neural network models. The system assesses TBM data parameters, detects anomalies, classifies geological formations, and predicts the rate of penetration (ROP). This approach was applied on a tunnel project in China, which has been instrumental in improving safety management and operational efficiency and is very effective and accurate in facilitating TBM data mining (22).

AI model that facilitates the early detection and diagnosis of neurological disorders through the integration of PSP Net for detailed feature extraction, Hilbert-Huang Transform (HHT) for analyzing non-stationary signals, and fuzzy logic for the treatment of uncertainty associated with the data (23). The system improves a clinician's ability to accurately diagnose disorders by simulating both recognition of spatial characteristics by PSP Net, Beaking down ambiguous signals using HHT analysis for improved study or detailed analysis, and activating a fuzzifier to enhance the model discriminant function (24). The system was able to make decisions with impressive results of 95% accuracy, 92% precision and 94% recall in decision making as a model, thus bettering prior methods and facilitated usability as a clinical variant standard for neurologic disorders (25). The new AI model represents a notable step forward in the fusion of hybrid approaches for AI-based diagnostic tools for neurologic disorders, which may assist healthcare employed personnel or professionals with accurate, quick decision making (26).

Prediction model for cardiovascular disease (CVD) in rheumatoid arthritis (RA) patients who are at an elevated risk of CVD (27). We examined the stability of biomarkers over 10-20 years using innovative biobanking approaches to evaluate lipid profiles, inflammatory markers, and disease-specific markers for RA, such as disease activity (28). We develop predictive models for patients with RA, which integrate traditional risk factors and RA-specific markers, with longitudinally obtained data. We include advanced technologies for risk estimation and patient monitoring, such as wearables, telemedicine, and omics data (29). Ultimately, our goal is to enhance cardiovascular risk prediction based on RA, which has the potential to personalize treatments and improve outcomes (30).

Security issues of cloud computing in health care and proposes a comprehensive security management solution (31). The proposed framework includes four components (i.e., risk assessment, security implementation, continuous monitoring, and compliance management) to address the risks faced regarding unauthorized access and theft of sensitive patient data (32). The proposed framework also utilizes modern security technologies (i.e., blockchain and multifactor authentication) to bolster security in a health care cloud computing environment (33). The framework utilizes robust risk assessments and measures associated with authentication, encryption, and intrusion detection systems that allow for early detection of a security breach and will ensure compliance with applicable regulations (34). Exemplary case studies offered by organizations such as Mayo Clinic and Cleveland Clinic also demonstrated how the solutions offered in the framework provide for instances of secure integration of cloud computing (35). The implementation of the proposed solution would afford health care providers with both enhanced patient care and improved operational efficiency while protecting the sensitive health care data (36).

Merged Cyber Security Risk Management (m-CSRM) method, capable of addressing the growing and evolving challenges of cybersecurity threats and the increasingly complex cyber infrastructures (37). The m-CSRM method, unlike previous threat modelling approaches that did not combine context data and intelligence related to emerging attack patterns, was designed to systematically understand what the critical assets are through the use of a fuzzy set-based decision support system (38). It proposes that Machine Learning (ML) can be beneficial in understanding risk types, and can automatically process risks through an automated tool (39). Results showed that m-CSRM provided a high success rate of 82.13% and was an alternative to existing methods in managing cybersecurity risk. The method offers a better way to provide dynamic and clear attribution of the cyber threat landscape (40).

Workload forecasting in intelligent cloud computing systems which combines the Backpropagation neural network algorithm with game theory (41). By leveraging game theory's underlying principles, the proposed approach aligns cloud users and service providers to offer the best possible outcome for resource allocation and service delivery that benefits both parties through Service Level Agreements (SLAs) in terms of Nash equilibrium (42). The proposed idea was validated through the analysis of experimental real-world data, showcasing how the method can benefit the improvement of cloud operations and strategic alignment. The process aims to ensure seamless implementation for both cloud providers and practitioners focusing on (1) the scalability of cloud resource, (2) security of cloud usage, and (3) usability of cloud services. The method will provide a significant improvement to cloud resource management for all industries (43).

Collaborative computing systems by examining the range of attacks against the systems, as well as concerns related to data privacy protection. Emerging technologies such as federated learning and cloud-edge collaborative computing systems are employed in this research to build a multinational validation framework by checking the multi-national architectures that considered and did not consider attacks.

The crux of the research is the End-to-end privacy-preserving deep learning (E2EPPDL) approach, which is used to classify attack episodes without reducing privacy. The effectiveness of the system is validated using metrics such as Time, Node Count, Routing Count, and Data Delivery Ratio, demonstrating that systems can be effective while preserving privacy in the face of attacks (44).

The Internet of Things (IoT) is reshaping contemporary industries, specifically within the domains of enterprise information management and supply chain optimization. However, the integration of IoT technology into our current manufacturing infrastructures can prove to be problematic--most notably in the areas of inventory cost control and job-shop scheduling (JSP), given it seeks a path to optimal productivity within complicated conditions and rapidly evolving constraints (45). Innovative methodology to tackle the challenges of JSP by applying a Heterogeneous Genetic Algorithm (HGA) and Hybrid Particle Swarm Optimization (HPSO). HGA overcomes limitations of conventional Genetic Algorithms (GA) by means of deploying some aspects of the immune response, including memory and variations within the mutation function, to avoiding premature convergence while fostering broader exploration. HPSO is manufactured to specifically improve job sequencing into minimizing production time, whereby an amalgam of incorporating relations, as coined by PSO as evolutionary intelligence, with genetic operator's capabilities (46). The combination of capabilities allows HPSO to extract the advantages of conducting explorations using global attraction and implementing proper planning since searching via traditional PSO has limitations when it comes to JSPs intricate nature. Not only has this research contributed to the field via hybridization of genetic algorithms into HPSOs as well modifying programmable optimization functions, the developed mechanics modestly improve costs, are on-schedule and on-time efficiencies while also introducing a double-chain encoding form for machine selection and sequence job assignment. Finally, the procedures are validated through empirical studies which suggest HGA and HPSO significantly outperformed their traditional counterparts (47).

Heart disease monitoring system using Internet of Medical Things (IoMT) with blockchain by making use of both BS-THA and OA-CNN approaches for heart disease prediction (48). The proposed system allows the doctors and patients to register to the application, establish keys for privacy, and safely upload ECG (Electrocardiogram) and PCG (Phonocardiogram) data to the InterPlanetary File System (IPFS) for hashing, and then store on the blockchain for secure access (49). By using MAC (Message Authentication Code) verification, signal preprocessing, spectrum analysis, and the consequences of the arrhythmia, the proposed system can extract elements and classify heart disease. In fact, the classification system takes ECG and PCG as wavelet components and uses the feature extraction through Durbin's Prediction Counting Algorithms DPCA to classify the two signal types to an impressive accuracy of 98.32% - a considerably better predictive accuracy than existing models of heart disease (50).

Smart education management platform that leverages cloud computing and artificial intelligence (AI) to improve educational services. The platform invests AI into the final intelligent application results for automation of educational tasks and personalization experiences, while utilizing a service-oriented architecture (SOA) to maintain flexibility, scalability, and efficiency of the data management routines (51).

The platform is supported by a server cluster managed by Hadoop for processing and storage of big data. The remote learning aspect of the platform allows for large scale access to data and efficiencies of managing concurrently accessed resources. Stress-testing has shown the reliability of the platform when under heavy loads. AI-generated platform features such as recommendation engines and predictive analytics support an effective user-centered experience. With the completion of implementation and testing, the platform has the potential to change educational management and service delivery (52).

Adopting improvements to IoT security, which will involve identification of critical nodes and performance of vulnerability assessments in the IoT domain, and finally the identification of security measures which will improve the performance of the system. Following the identification of critical nodes within IoT systems using a quantitative approach, the vulnerability assessment was performed extensively. The proposed security options, including systems of intrusion detection, encryption, access control, and maintenance of continuous security audits, were assessed comprehensively as well, resulting in an understanding of systems that had significant improvements (53). The study outcomes suggest that identification of nodes and security measures developed to alleviate risk were 95% accurate, and risk was reduced by 85%, and established full compliance across all levels of regulatory standards. The study concludes that the integration of multiple security solutions is imperative to maintain a secure and reliable IoT system related to health for seniors, while maintaining patient data safety and the performance of the system (54).

Cloud computing difficulties by proposing a hybrid of Resource Allocation and Task Scheduling through the Improved Bat Optimization Algorithm (IBOA) and Modified Social Group Optimization (MSGO). In IBOA, the weight assignment is dynamic, complemented with a speed update formula to enhance scalability.

MSGO enhances the acquiring phase to improve aspects of task scheduling (55). Multiple setups were used to run simulations with IBOA and MSGO, and the results such as response time, resource utilization, and energy consumption were compared to the existing methods. The proposed methods produced an energy consumption of for 100 tasks, surpassed the energy efficiency of the Multi-Objective Task Scheduling Grey Wolf Optimization (MOTSGWO) method (56).

The implementation of Robotic Process Automation (RPA) into cost accounting and financial systems to improve efficacies and financial accuracy. By automating repetitive tasks, RPA decreased processing time by 95 percent, increased cost allocation accuracy to 99.5 percent, and improved errors down to 5 percent from other operations (57). The implementation involved identifying processes, designing step functions, creating and developing RPA solutions, and measuring and evaluating RPA's performance. The results support the underlying idea that RPA has a significant impact on systems within a finance function, as RPA allows for improved, cleaner, consistent, scalable, and error-free financial optimization, all while improving operational efficacy and financial accuracy in systems that may have multiple moving parts (58).

Combination forecasting approach as a solution to the issues of forecasting nonlinear and non-constant character in manufacturing time series data. The proposed process consists of three parts: (i) linear modelling using ARIMA, (ii) nonlinear modelling with a Bi-GRU approach for the error series generated by the linear model, and (iii) linear and nonlinear modelling combined into a hybrid method to improve forecasting accuracy (59). Six real-world time series are analyzed, and forecasting performance is evaluated with MSE, MAPE and MAE error measurements. The results show the performance of the hybrid method is superior to existing models MAE of 10.3, MAPE of 17.5 and MSE of 26.3 and display significant threshold improvements in forecasting effectiveness (60).

Attention is paid to the use of artificial intelligence (AI) with machine learning for detecting financial fraud in Internet of Things (IoT) environments. Artificial intelligence systems can accurately detect suspicious behavior in data streams from IoT devices through anomaly detection, clustering, and supervised and unsupervised learning. These fraud detection systems have models that receive training using previous historical transaction data to conceptualize what is valid and not valid financial transactions. In our research, we are addressing how these models can rely on retraining in order to increase the reliability in IoT environments - and our paper focuses on the methodology, datasets needed, and evaluative metrics needed for measuring success. To ensure reliability in models, adaptive learning, retraining, and automatic reactive processes are metrics that could be included in these fraud detection systems (61).

The usage of artificial intelligence (AI), powered by machine learning, to detect financial fraud in the Internet of Things (IoT). AI can detect anomalies and deviations from "normal" transactions or behavior using anomaly detection, clustering, supervised and unsupervised learning models/system. These models are trained to differentiate between legitimate and fraudulent transactions, based on historical transaction data, for the real time analysis and identification of actions from data streams, originating from IoT devices. Our investigation centers on explaining the method, data sets, and evaluation metrics. The study emphasizes the need for adaptive, or dynamic, learning, retraining the model/algorithms frequently, and augmenting with automatic, reaction mechanisms to develop reliable fraud detection models/systems in IoT (62).

The combination of attribute-based encryption (ABE), big data analytics, and cloud computing to improve security around financial data in the digital age. It begins with an overview of ciphertext-policy ABE (CP-ABE) and key-policy ABE (KP-ABE), focusing on how they allow access control of encrypted data at a fine-grain level. We show how ABE can provide data scalability and confidentiality with cloud computing.

In addition, the use of big data analytics can provide anomaly detection, predictive analytics, and active transaction monitoring to improve security for financial institutions. This article emphasizes the utility of big data in fraud detection, risk management focused on controls in the financial industry, and compliance for regulatory risk with market volatility. We present case studies for how financial institutions can adopt these technologies and mitigate risks, improve data security, and meet legal and ethical responsibilities to their customers (63).

Investigates the opportunities and challenges involved in the empirical studies of modern financial datasets (including structured and unstructured data), with a special reference to the use of modern machine learning methods and algorithms. Traditional modeling techniques have limitations in high-dimensional and complex space modeling, which compromise both model usability and assumptions around inaccuracies with scalability. Gradient Boosting Decision Trees (GBDT) is used with ALBERT and is ultimately tuned by the Firefly Algorithm integrated into a cloud-based high-performance framework provides scalability, processing in real-time, and improved security. This hybrid modeling strategy enhances both the accuracy and efficiency of the analysis of financial data over every step and phase of this research, while effectively addressing some of the scalability and accuracy issues of traditional approaches for real-time settings.

Materials and Methods

Figure 1 presents the schematic diagram of the operations carried out to optimize data processing and energy management for an IoT healthcare system. Data are traversed from medical monitoring tools and a tiny wearable gadget. Then, cleaning of the dataset involves filling in the missing values, removing noise, or correcting inconsistencies. The feature selection process is based on Random Forest (RF) to recognize the most compatible variables. It creates new features through dimensionality reduction using Principal Component Analysis (PCA) but retains some key information. Energy management modeling is thus followed by power optimization according to device activities. Lastly, processed data, together with performance metrics, is kept in the cloud for scalability, accessibility, and real-time analysis.

Data Collection

In the Data Collection step, an extensive set of IoT healthcare devices is employed to gather continuous data from the patient. Such devices include wearable sensors, medical monitoring tools, and patient tracking systems that have specific functionalities for monitoring vital health parameters such as heart rate, blood pressure, body temperature, glucose levels, and other important physiological parameters. The real-time data collected from such devices build a dynamic and ongoing image of the patient's health status. Consistent monitoring enables the early detection of health anomalies by healthcare practitioners, under whom timely and informed interventions take place. Data from these devices are usually very accurate and reliable so that the healthcare system may respond adequately and promptly to any changes in patient status. This dataset forms the crux of the subsequent processing, analysis, and predictive modelling that underpin decision-making and offer scope for better patient outcomes in any healthcare environment.

Data Cleaning

Raw data coming from IoT-based healthcare is not without its share of problems, such as inconsistencies, noise, and missing values-all of which can jeopardize subsequent analysis. Data cleaning thus serves to alleviate some of these issues while ensuring an accurate and usable dataset. Interpolation, for example, is frequently employed for estimating missing values based on nearby data points to maintain a continuous and complete dataset. Smoothing methods would ultimately reduce the random noise that impairs the otherwise observable patterns in the data, especially for time-series data. Erroneous or outlier values would then be imputed en masse using reasonably sound estimates to protect the validity of the original data. All of these would result in better quality data that is able to accurately depict the health of the patient, thereby making it reliable for predictive modeling or further analysis. With proper data cleaning, spacing allows in reducing the bias or chances of bringing up incorrect predictions, thus bettering the health care system.

Feature Selection Using Random Forest

Feature selection reduces the complexity of predictive model construction by selecting the pertinent features that greatly affect the accuracy of a model. Among the many available feature selection techniques, Random Forest (RF) is deemed effective as it ranks the features based on their importance in either predicting or classifying accurately.

The basic principle of RF is to look at each feature as to how much it improves the prediction of the accuracy score after the model is trained and assesses it by either Gini impurity or information gain. In doing so, it retains only the most important features for the next step of dimensionality reduction, thus discarding those redundant or irrelevant data points that rather introduce noise. Thus, it increases the efficiency of the model, requiring less computational power and memory. The other positive impact of decreased complexity is the speed of training and processing time, allowing the model to generalize better and thus attain accuracy and reliability in its predictions. Using this approach ensures that only the most informative feature names have made the model work efficiently. The Random Forest ranks the features according to their importance. Thus, the importance of a feature can be defined as follows in eq 1.

$$\text{Feature Importance } (f_i) = \sum_{t=1}^{T} \Delta\text{Gini}_t(f_i)\ldots(1)$$

Where, T is the number of trees in the Random Forest. $\Delta\text{Gini}_t(f_i)$ is the reduction in the Gini impurity due to feature f_i in tree t.

Feature Extraction Using Principal Component Analysis

Principal Component Analysis (PCA) is a key technologic phenomenon that is increasingly used to attain dimensionality reduction, especially in large datasets with many attributes. Initially, PCA converts original correlated features into a set of uncorrelated components, named principal components, which retain the maximum variance of the data. These components thus sketch the most important aspects of the data and consequently preserve essential information while discarding less-consequential variables.

PCA therefore gingerly brings down the number of variables, thus simplifying the dataset and speeding up the processing. Furthermore, it surely enhances computation given that redundancy is removed, many a times; features in high-dimensional data can be highly correlated.

With less features to analyze, the model thus enhances efficiency-a direct corollary of speedier predictions or classifications, albeit retaining the fundamental structure and patterns of the original data. PCA is a linear transformation having the ability to project data into a new set of axes to reduce dimensions. The transformation is stated as following in eq 2.

$$\mathrm{X}_{\text{new}} = \mathrm{X} \cdot \mathrm{W}\ldots(2)$$

Where, $\mathrm{X} \in \mathbb{R}^{n\times m}$ is the original dataset with n samples and m features.$W \in \mathbb{R}^{m\times k}$is the matrix of eigenvectors (principal components) that forms the new basis, where k is the reduced number of dimensions.$\mathrm{X}_{\text{new}} \in \mathbb{R}^{n\times k}$ is the transformed dataset in the lower-dimensional space.

Energy Management Model Using Energy-Based Models

Due to battery constraints, energy consumption of IoT devices is a vital issue in healthcare applications, and energy-based models are very crucial in this regard. It considers multiple factors, including data transmission frequency, sensor power consumption, and device processing workload. Based on these considerations, the model predicts energy requirements at various operational states. The device operations can be adjusted in real time by reducing sensor activity or optimizing data transmission intervals so that energy can be conserved. Besides, the models ensure that the system maintains a balance between energy efficiency and the need for pervasive monitoring and accurate data analysis. The focus is on allowing enough functionality and performance of the devices to maximize battery life so that healthcare service is not interrupted and the need to recharge is minimized. This ensures a more sustainable and cost-effective utilization of IoT healthcare devices in the long run. Energy consumption is modeled based on factors like data transmission frequency f_{trans} sensor power consumption P_{sensor} and the workload is given in eq (3).

$$E_{\text{total}} = P_{\text{sensor}} \cdot t_{\text{active}} + f_{\text{trans}} \cdot P_{\text{trans}} \cdot t_{\text{trans}} + W \cdot P_{\text{proc}} \cdot t_{\text{proc}} \ldots\ldots(3)$$

Where, P_{sensor} is the power consumed by the sensor.P_{trans} is the power consumed during data transmission.P_{proc} is the power consumed during data processing.t_{active}, P_{trans} and P_{proc} are the respective times the device is in each state. W represents the workload, impacting the processing power required.

Cloud Storage

Post-process for the data with feature selection and extraction, energy optimization after which the output is stored in the cloud. It is through cloud storage that scalability is offered to address the huge amount of health data storage that can easily be accessed and processed for future analysis. Since it is centralized, real-time data retrieval can be done to improve decision-making even among health professionals. Furthermore, cloud infrastructure supports the deployment of models over several nodes in the distributed network, allowing insight to be available whenever needed, thus improving system accessibility and efficiency. Requirements for storing S total in cloud storage can be computed as storage requirements of the size of the data being stored multiplied by the number of records is explained in eq (4).

$$S_{\text{total}} = N \cdot D \ldots (4)$$

Were, N is the number of data records. D is the size of each record.

Results and Discussion

The model for data processing and energy management for IoT healthcare systems proposed in the cloud was evaluated for performance in terms of metrics: response time, energy consumption, and accuracy of which the processes- Random Forest for Feature Selection, Principal Component Analysis (PCA) for Feature Extraction, and energy optimization models, which increased the efficiency of the system. Improvement realization of energy suppression and resources utilization was observed. Energy has been reduced from the system by a measure of not less than 32.5 watts in enhanced prediction accuracy. More so, scalability would be made possible by the cloud infrastructure for proper storage and processing of voluminous healthcare data. The performance metrics response time and accuracy also improved significantly, the proof of the combined advanced analytics and clouding for IoT healthcare applications. These make the model a possible solution for better patient care, efficiency in operations, and sustainability in healthcare IoT

Cloud storage efficiency is illustrated in Figure 2 during the interval of 1 to 6 hours. In the graph, the storage efficiency increases consistently with an increase in time interval. The x-axis denotes the time interval (hours), and the y-axis denotes storage efficiency (%). The plot, portrayed in the graph by connecting purple squares with a line, clearly demonstrates a positive correlation between time interval and storage efficiency: more time leads to improved storage management efficiency for the system. This trend suggests the possibility of enhanced performance for the cloud storage user on longer timescales.

In Figure 3, denote storage latency in milliseconds (ms) against the time interval varying from 1 to 6 hours. The x-axis shows the time interval (hours) on the other side, while the y-axis represents storage latency (ms). The red triangles connected by a line exhibit a clear positive trend, with latency increasing as the time interval progresses. Hence, it may be suggested that storage latency increases steadily with the passage of time and thus represents a gradual increase in processing delay. The same trend indicated here is significant in understanding how storage performance would possibly behave with long durations, particularly in real-time systems or cloud storage environments.

Figure.1 Optimized Data Processing and Energy Management for IoT Healthcare Systems

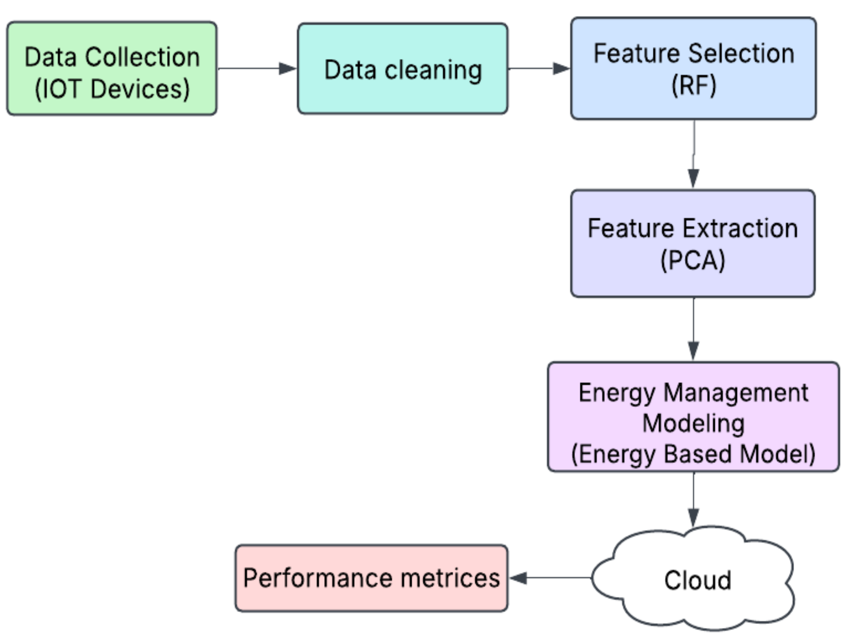


Figure.2 Cloud Storage Efficiency

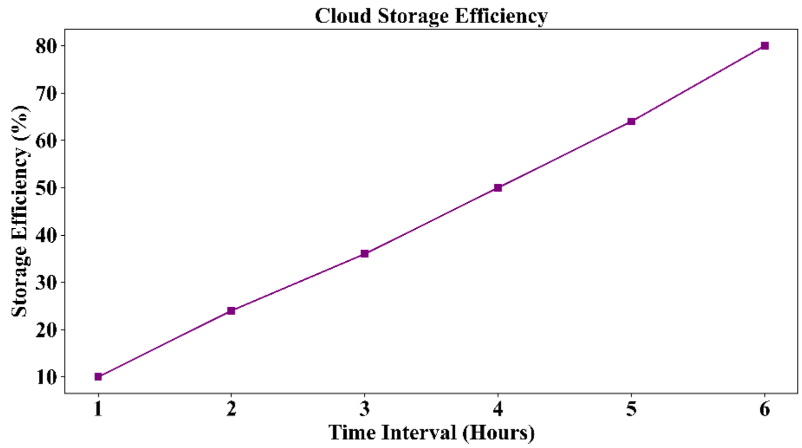
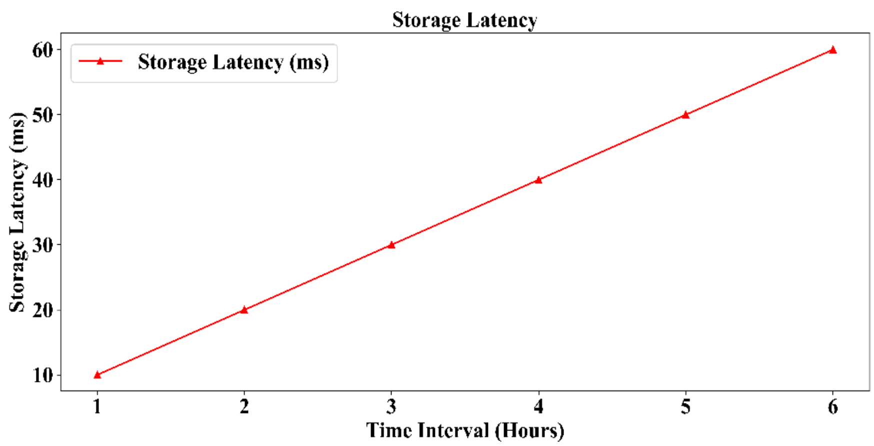


Figure.3 Storage Latency



Conclusions

This publish brings attention to cloud computing's prospective in optimizing and sustaining IoT healthcare systems. The incorporation of advanced energy management paradigms feature selection and principal component analysis for data reduction has effectively resolved major issues evidenced with the current healthcare data processing. This proposition ensures energy-efficient power use for IoT as well as increased scalability and accessibility for healthcare data. This model produces promising outcomes in resource usage optimization, data storage efficiency enhancement, and increased prediction accuracy to solve some problems affecting existing healthcare IoT systems. Future work is dedicated to fine-tuning these modalities and exploring their application across several healthcare environments for further progress related to patient care and system performance.

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