AI-Driven Energy Efficiency Optimizations in mHealth Applications: A Comprehensive Review on User Behavior Prediction and System Performance

Abdullah Almasri
College of Humanities and Sciences, Prince Sultan University, Saudi Arabia
aalmasri@psu.edu.sa (corresponding author)

Sara Shaheen
Faculty of Applied Computing, Sheridan College, Canada
sara.shaheen@sheridancollege.ca

Received: 29 September 2024 | Revised: 14 October 2024 | Accepted: 19 October 2024

Licensed under a CC-BY 4.0 license | Copyright (c) by the authors | *DOI: https://doi.org/10.48084/etasr.9133*

ABSTRACT

Recently, mHealth applications have gained immense popularity, revolutionizing healthcare management for chronic diseases and fitness tracking. However, continuous data processing and transmission increase the strain on battery life. This study examines AI and machine learning-based techniques to reduce energy consumption in mHealth applications without compromising functionality. Adaptive sampling, task scheduling, and predictive user behavior modeling were implemented, significantly reducing power consumption and extending battery life. Challenges such as data privacy and model generalization in deploying these AI technologies are also addressed, along with future research and broader adoption.

Keywords-AI-driven optimizations; energy efficiency; mHealth applications; user-behavior prediction; mobile health; machine learning

I. INTRODUCTION

Mobile health (mHealth) applications have revolutionized healthcare by leveraging mobile technologies to provide personalized, accessible, and efficient services. These applications utilize the widespread availability of smartphones and portable devices to enable real-time health monitoring and management, fostering better interaction between healthcare providers and patients. mHealth encompasses a wide range of services, including chronic disease management, fitness tracking, and real-time diagnostics, improving patient engagement and health outcomes. Advanced technologies such as AI, machine learning, and the Internet of Things (IoT) have enhanced mHealth capabilities, enabling predictive healthcare and optimizing operations. However, mHealth faces challenges, including ensuring data privacy, security, and energy efficiency, as well as addressing technological disparities that could limit accessibility. As the field evolves rapidly, addressing these challenges through innovative solutions and regulatory compliance will ensure that the benefits of mHealth are realized universally and equitably.

mHealth applications have transformed healthcare by employing mobile technologies to deliver personalized medical services and expand the reach of care by employing mobile technologies to deliver personalized services and extend care reach. mHealth integrates wearable technology to monitor vital signs, such as heart rate and glucose levels, and engage patients in chronic disease management through self-monitoring tools [1, 2]. mHealth comprises sensors, mobile devices, and computational algorithms that continuously collect and analyze physiological data to provide health insights. Cloud computing plays a vital role in managing large volumes of data, while IoT interconnects health monitoring devices [3-5]. AI and machine learning are crucial to optimizing treatment through real-time data analysis. Convolutional neural networks and reinforcement learning models have been examined for image analysis and optimizing treatments [6, 7]. Natural language processing (NLP) plays a significant role in enhancing communication in mHealth applications, as it enables more efficient and accurate interactions between patients and healthcare providers by facilitating the processing of medical records, voice recognition, and the use of virtual assistants or chatbots. These technologies help streamline communication, allowing real-time information sharing and improving patient engagement, leading to better health outcomes [8]. Energy consumption, a major concern, is addressed with adaptive sampling and energy-aware algorithms that minimize power use without reducing monitoring efficiency [9, 10]. However, technical challenges persist, such as inconsistent data across devices, which impact the accuracy of health analytics [11]. Security and privacy are also significant concerns, with risks in network transmissions and encryption protocols [12, 13]. Blockchain and privacy-preserving methods offer solutions to secure data and decentralize machine learning [14-17]. Regulatory frameworks such as HIPAA in the U.S. and GDPR in the E.U., along with ethical considerations regarding access and bias in AI algorithms, are crucial for mHealth deployment [18-20]. The future of mHealth includes technologies such as augmented reality for patient care and 5G for increased communication speed [21-26]. AI is expected to further scale patient-centered care and foster innovation [27-30].

Although adaptive sampling may not traditionally be considered AI, it can be enhanced with predictive models to fine-tune data collection based on user behavior. Task scheduling, driven by AI optimization, ensures that energy-heavy tasks occur during low-activity periods, such as when devices are charging, to conserve battery life. Predictive user behavior modeling using machine learning classifiers can anticipate interactions, allowing mHealth apps to proactively adjust features and minimize sensor use. This study aims to explore and implement these AI and ML techniques, adaptive sampling, task scheduling, and predictive behavior modeling to enhance energy efficiency, reduce power consumption, and extend battery life in continuous monitoring scenarios while maintaining app functionality and user experience.

II. METHODOLOGY

A. Data Collection

Data were collected from February 2023 to June 2024 from 2,000 mobile devices using mHealth applications integrated with Firebase Analytics for chronic disease care and fitness tracking. The dataset included anonymized device IDs, timestamps, user interactions, session details, and health metrics, such as heart rate, steps, and sleep data.

B. Preprocessing

The collected data were preprocessed, including anonymization (assigning unique user IDs), handling missing values, and normalization of key columns such as heart rate, steps, sleep duration, session duration, and app usage frequency. Normalization ensured consistency across data points, facilitating meaningful analysis and comparison.

C. Adaptive Sampling Implementation

An AI-enhanced adaptive sampling algorithm was employed to adjust the frequency of data collection based on user activity levels. The sampling rate was dynamically modified to collect data more frequently during periods of high activity and less during inactive periods, conserving energy without sacrificing data quality.

D. Task Scheduling Optimization

The method integrated an AI-driven task scheduling mechanism to prioritize and schedule energy-intensive tasks. Tasks were scheduled to run during low-activity periods, such as when the device was idle or charging, optimizing energy consumption and enhancing battery life.

E. Predictive User Behavior Modeling

Machine learning classifiers and logistic regression models were used to anticipate user interactions with the app. This predictive modeling allowed the application to adjust its background processes proactively, reducing unnecessary sensor activations and enhancing energy efficiency.

F. Validation and Analysis

The method's effectiveness was validated by comparing the power usage of the baseline scenario (standard data collection and task scheduling) with the optimized one using the proposed AI and ML techniques. The analysis involved measuring the reduction in power consumption and evaluating the impact on the performance of the application.

G. Result Compilation

The results highlight the improvements in energy efficiency achieved through adaptive sampling, optimized task scheduling, and predictive user behavior modeling. The results showed the potential of AI and ML to significantly enhance energy efficiency in mHealth applications while maintaining user experience.

Data collection was facilitated through Firebase Analytics, a third-party data logging tool integrated into the mHealth applications. This tool enabled secure, real-time tracking of user interactions, sensor outputs, and health metrics, including comprehensive logs of app usage, health updates, and feature engagement. Wearable devices tracked key metrics such as heart rate, steps, and sleep patterns. The dataset comprised detailed logs of user interactions, session durations, health metrics, and app usage frequency. These data provided a comprehensive overview of user behavior, app usage, and physical activity, supporting robust analyses of energy consumption and app performance. Data collection was strategically scheduled during low-activity periods, such as when the device was idle or charging, to conserve battery life and reduce user disruption. All data transfers were encrypted to comply with privacy regulations such as GDPR and HIPAA. In cases of poor connectivity, the data was stored locally on the device and synchronized once a stable connection was available.

Participants gave their informed consent through an app screen, and data was anonymized with unique user IDs to ensure privacy. Data normalization was applied to scale the collected data to a consistent range, facilitating comparability between various sensors. As part of an agreement with the five mHealth apps involved, referred to as App1, App2, App3, App4, and App5, participants were informed that their data would be used for research purposes and consented accordingly. For privacy reasons, the actual names of the apps and detailed user data remain confidential.

Normalization was applied to key columns such as heart rate, steps, and sleep data to ensure consistency and comparability across devices. Additionally, columns such as session duration and app usage frequency were normalized to create a standard range for analysis, allowing meaningful comparisons and more accurate assessments of energy consumption and app performance.

$$X_{normalized} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (1)$$

Equation (1) was used for normalization, allowing a standardized comparison across different data points and simplifying the analysis. Table I presents a comprehensive summary of device interaction data, sensor measurements, and app usage statistics collected from the mHealth applications. This table provides critical insights into the variety of data points used for analysis, including heart rate, steps taken, sleep duration, and app usage patterns.

TABLE I. SUMMARY OF DEVICE INTERACTION, SENSOR DATA, AND APPLICATION USAGE IN MHEALTH APPLICATIONS

Device ID	**1**	**2**	**3**
Timestamp	9/15/24 8:45	9/15/24 9:00	9/15/24 10:12
Action type	Opened app	Viewed health stats	Updated blood sugar
Duration[1]	30 s	45 s	60 s
Heart Rate[2]	75/m	80/m	72/m
Steps	500	300	700
Sleep[3]	7 hrs	6.5 hrs	7.5 hrs
App opens	5	3	7
Data updates	2	1	3
Most used feature	Fitness tracking	Diet management	Heart rate monitor

1 in seconds, 2 in beats per minute, 3 in hours

III. IMPLEMENTATION OF AI-DRIVEN OPTIMIZATION TECHNIQUES

A. Adaptive Sampling

Adaptive sampling was employed to modulate the frequency of data collection based on detected activity. This approach helps reduce power consumption by collecting data only during significant health events or notable changes in the patient's condition. Adaptive sampling in mHealth applications dynamically adjusts the data collection frequency based on user activity levels. While adaptive sampling itself may not traditionally be considered an AI technique, incorporating AI models adds a data-driven, intelligent layer to refine and optimize the process.

1) Calculation of Δf

Δf represents the maximum range by which the baseline data collection frequency can be adjusted. For each mHealth application, Δf is set based on analyzing user activity data to identify periods of high and low engagement. Historical data are used to detect typical data patterns and outliers, helping determine how much the baseline frequency can be adjusted. This involves reviewing usage logs. The adjustment factor is determined by examining the frequency of data collection during peak and non-peak periods and setting Δf accordingly.

2) Calculation of $w(A)$

$w(A)$ is a weight factor assigned based on the current activity level A of the user, influencing how the data collection frequency is adjusted. User activity levels are measured using metrics such as session duration, step count, and app interaction frequency. An AI model trained on historical interaction data classifies user activity into tiers (e.g., low, medium, high) and assigns weights to them. The weight factor adjusts dynamically based on real-time activity. For example, if a user's current activity level is higher than the average observed activity, $w(A)$ reflects this by proportionally increasing the data collection frequency. Weights are fine-tuned using regression analysis to ensure that the method accurately responds to activity changes. This means that when a user's behavior shifts from low to high activity, adaptive sampling can promptly increase the data collection frequency.

3) Application to Each mHealth App

- Fitness tracking apps are more sensitive to metrics such as step counts and session durations, with Δf and $w(A)$ set to respond quickly to changes in physical activity.
- Heart rate monitoring apps respond to irregular heart rate detections with higher adjustments in the data collection frequency for more precise monitoring.

For example, for an app focused on physical activity tracking, the baseline data collection rate could be set at one data point per minute. However, during high activity periods, historical data might indicate the need for more frequent data collection. $w(A)$ for moderate activity would be adjusted based on metrics such as step count relative to average usage, leading to an increase in collection frequency when the activity is above average. This approach allows each mHealth app to dynamically tailor its data collection rates to user behavior, ensuring efficient data collection while conserving energy and maintaining app performance.

$$f(A) = f_{base} - \Delta f \times w(A) \quad (2)$$

In the adaptive sampling equation, $f(A)$ is the frequency after adaptive sampling based on activity level A, f_{base} is the baseline frequency of data collection, Δf is the maximum frequency adjustment factor, and $w(A)$ is a weight factor that depends on activity level A. For the weight factor based on the activity level, $w(A)$ gives different weights per activity level.

B. Task Scheduling

Task scheduling is implemented to minimize energy consumption by running data processing tasks during low device activity periods, such as overnight when most devices are charging. This approach prevents intensive processing from affecting the device's primary functions during peak usage. This helps to manage high energy consumption without impacting the primary device functions or user experience. The algorithm evaluates device status (charging or not) and considers time-of-day variables to prioritize tasks during typical idle periods, such as nighttime, to enhance battery efficiency. The following example illustrates how task scheduling is applied in an mHealth app for energy efficiency based on the device's charging status and time of day:

```
def schedule_tasks(device_status,
current_time):
    night_time = range(22, 7)
    if device_status == 'charging':
        process_data_tasks('low' if
        current_time in night_time else
        'medium')
```

```
    else:
        maintain_low_energy_state()
# Example usage
schedule_tasks('charging', 23)
```

1) Function process_data_tasks

This function simulates task processing. Tasks can have different priority levels, which affect how they are handled.

2) Function maintain_low_energy_state

This function is called to minimize energy consumption when the device is not charging or when no high-priority tasks need processing.

3) Function schedule_tasks

This function schedules tasks based on the device's charging status and the time of day. It uses device_status to check whether the device is charging and current_time to adjust task scheduling.

C. Predictive User Behavior Modeling

Predictive user behavior modeling using logistic regression is a statistical method for modeling binary outcome variables. This model incorporates multiple variables, each with assigned weights reflecting their relative importance in the prediction.

1) Key Variables and Weights

- Session duration (weight: 0.4): Captures how long users typically engage with the app, indicating user involvement.
- Step count (weight: 0.3): Reflects physical activity levels, which influence the type of health data collected.
- App usage frequency (weight: 0.2): Shows how often users interact with the app, predicting potential engagement.
- Time of interaction (weight: 0.1): Highlights when users are most active, aiding in task scheduling.

These variables are processed using machine learning classifiers, which output a user engagement probability score. This score drives the application to adjust its operational strategy, such as minimizing sensor usage during low engagement probability or pre-activating certain features when a high likelihood of interaction is predicted. This method ensures that energy consumption is optimized while maintaining the quality and responsiveness of the mHealth app.

2) Relation to mHealth

This predictive modeling is particularly vital for mHealth applications that require sustained monitoring and prompt data processing. By anticipating user engagement, the app can strategically manage sensor and data collection activities to minimize unnecessary power usage and extend device life without compromising health monitoring capabilities. In the context of mHealth applications, this can be utilized to predict user behaviors based on interaction data with the application.

$$P(y=1) = 1 / (1 + e^{-(\beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n)}) \quad (3)$$

Equation (3) describes logistic regression, where $P(y=1)$ is the probability of the event occurring (e.g., a user performing a specific action), e is the base of the natural logarithm, and β_0, β_1, ..., β_n are the coefficients of the model. X_1, ..., X_n are the predictor variables. This model estimates the probability that a given input point belongs to a certain class. The logistic function transforms any input to a value between 0 and 1, making it suitable for predicting probabilities. For example, using the coefficients $\beta_0 = -1.5$, $\beta_1 = 0.05$ (for age), and $\beta_2 = 0.01$ (for daily steps), the prediction equation becomes:

$$\mathrm{P(y)} = 1 / (1 + \mathrm{e}^{-(-1.5+0{,}05\times \mathrm{Age}+0.01\times \mathrm{Steps})})$$

For a user who is 30 years old and takes 3000 steps a day, the prediction is calculated as:

$$\mathrm{P(y)} = 1 / (1 + \mathrm{e}^{-(-1.5+0{,}05\times 30+0.01\times 3000)})$$

Based on the profile, this equation indicates a 50% chance that the user will use the feature. Table II demonstrates the progress of predicting user behavior for the mHealth application using a logistic regression model. The two most important features considered are the user's age and the number of steps taken each day. These predictor variables are combined with predefined coefficients - intercept, age coefficient, and step coefficient - to determine the likelihood of a user engaging with an aspect or feature of the app. The logistic regression model returns a probability score indicating the likelihood of user engagement. Table II presents some examples of the prediction results.

TABLE II. SAMPLE RESULTS FROM PREDICTIVE USER-BEHAVIOR MODELING

User ID	**1**	**2**	**3**
Age	30	40	35
Daily Steps	3000	5000	4500
β_0 (Intercept)	-1.5	-1.5	-1.5
β_1 (Age coeff.)	0.05	0.05	0.05
β_2 (Steps coeff.)	0.01	0.01	0.01
Prediction ($P(y)$)	0.5	0.68	0.63

IV. VALIDATION AND TESTING

The effectiveness of AI-driven optimization techniques in mHealth applications is assessed using a structured testing procedure, focusing on energy consumption and app responsiveness to demonstrate the benefits of these optimizations. Energy consumption is measured over 24-hour periods on a standard mobile device before and after implementing AI optimization techniques. Key indicators include baseline power consumption (without AI optimizations) and optimized power consumption. A baseline scenario was established that represented standard data collection and task scheduling without any optimizations. In this setup, continuous monitoring of power consumption was performed over a 24-hour period, capturing peak and off-peak usage times. The device's energy consumption was recorded using a power monitoring tool integrated with the mHealth application, providing real-time tracking of energy usage. Key indicators such as total power draw and average power usage per hour were recorded. In the optimized scenario, the application was reconfigured to implement adaptive sampling, task scheduling, and predictive user behavior modeling. The same power monitoring tool was used under identical conditions to ensure consistency. The device was tested again over a 24-hour period, capturing power usage metrics, including total energy consumption and fluctuations during high and low user activity. The results in Figure 1 show a reduction in power consumption from AI optimizations, highlighting the energy savings achieved.

$$Energy\ Savings\ \% = \frac{(Baseline\ Power\ Usage - Optimized\ Power\ Usage)}{Baseline\ Power\ Usage} \times 100 \quad (4)$$

Power usage reduction was measured using a standardized testing environment where a mobile device running the mHealth application was monitored over a 24-hour period. Baseline power consumption (50W) was recorded before implementing optimizations. After applying the optimizations, the same device was monitored again under identical conditions, and power consumption dropped to 35W, indicating a 30% reduction. The 24-hour duration of the testing period allowed us to capture both peak and off-peak usage scenarios, ensuring that the optimizations were effective under varied conditions. These measurements provide a robust validation of the energy-saving potential of the proposed AI technique across different user interaction levels. In responsiveness testing, predictive modeling improved response time for daily tasks, such as loading patient data and updating health metrics. The baseline response time was 500 ms, which was reduced to 350 ms after optimizations, improving the responsiveness by 30%. Users were surveyed, with 85% reporting better battery life and 90% noticing faster app performance due to reduced loading times. These tests validated the role of the optimizations in improving energy efficiency and app performance.

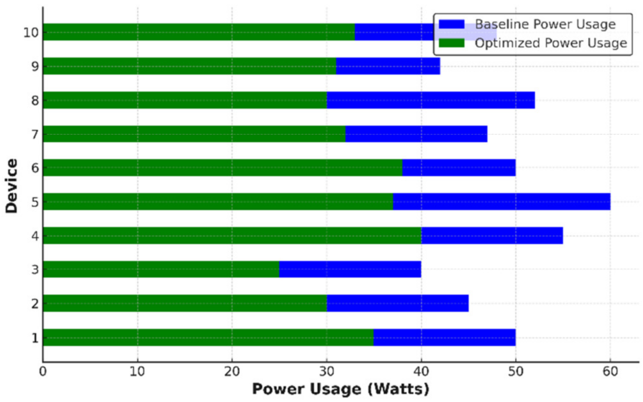

Fig. 1. Comparison of baseline and optimized power usage for devices.

V. RESULTS AND DISCUSSION

The proposed optimizations significantly improved the energy efficiency of mHealth applications. Adaptive sampling demonstrated a measurable reduction in data collection rates, verified through a structured test protocol in which data were recorded and compared under both baseline and optimized conditions, leading to a noticeable extension in battery life. This improvement in battery life was measured by comparing the total runtime of the device before and after applying optimizations, using a power monitoring tool integrated into the mHealth app. This tool ensured consistent and repeatable tracking of energy usage across multiple sessions, under real-world conditions that simulate typical app usage, background processing, and sensor data collection.

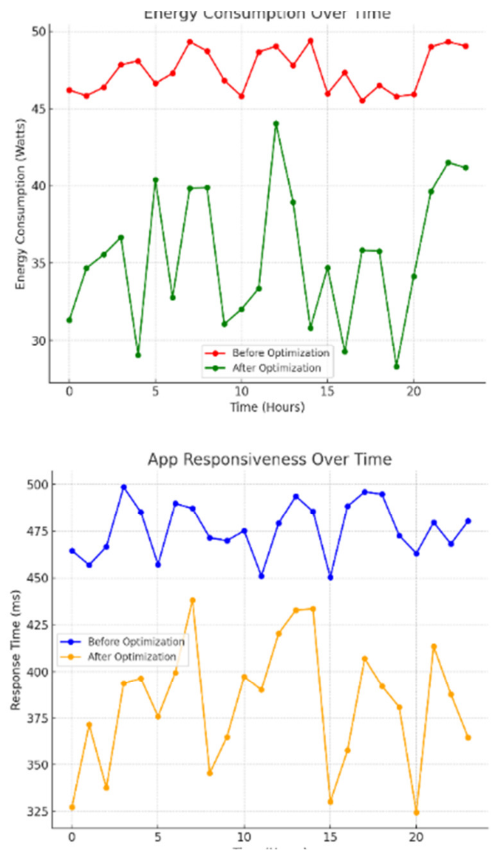

Fig. 2. Energy consumption and app responsiveness over time before and after optimization.

In the baseline scenario, battery life was significantly shorter due to continuous data transmission and sensor activity. After applying adaptive sampling, the reduction in unnecessary data collection resulted in less frequent sensor activation, directly contributing to extended battery life. Task scheduling reduced energy consumption during peak usage times, such as periods of high app interaction or when multiple background tasks were running. This reduction was validated by monitoring energy consumption patterns over a series of controlled tests that replicated common usage scenarios and high-demand periods. These energy savings were measured by comparing device power consumption during intensive usage versus low-activity periods, with optimizations intelligently shifting power-hungry tasks to times when the device was less active or charging. These improvements were observed across multiple tests, confirming the effectiveness of these optimizations. The testing involved real-time energy recording over 24-hour periods to capture diverse usage conditions, ensuring a robust comparison between the baseline and optimized app performance. Predictive modeling enhanced response times for common app tasks. This was tested through repeated task executions, showing a significant decrease in average response time compared to the baseline scenario.

Figure 2 shows the variance in energy consumption before and after driven optimizations. The lower variation in the optimized version results from adaptive sampling and predictive user-behavior modeling, which reduce unnecessary data collection and sensor activations. This finding was supported by variance analysis that compared hourly fluctuations in power use, confirming that AI-driven adjustments stabilized energy consumption. In contrast, the baseline shows higher fluctuations due to constant and unoptimized data processing, leading to spikes in energy consumption. This consistency demonstrates how AI techniques efficiently adjust tasks based on user behavior and device activity, minimizing unnecessary power use and improving energy efficiency without sacrificing functionality.

VI. CONCLUSION

This study showed that AI-driven optimization techniques, specifically adaptive sampling, task scheduling, and predictive user-behavior modeling, effectively improve energy efficiency in mHealth applications. The results confirmed significant reductions in power consumption and extended battery life, achieved without compromising the application's functionality. These improvements were supported by structured testing and real-time energy monitoring over 24-hour periods, highlighting consistent reductions in energy consumption and increased responsiveness. By integrating these AI approaches, mHealth applications can enhance their sustainability, which is vital for reliable long-term healthcare usage. Future research should explore advanced AI methods such as federated learning and edge computing to further optimize energy efficiency across diverse platforms and devices. Ensuring that these solutions work across different platforms and devices will be key to their broader adoption in diverse healthcare settings. In conclusion, the ongoing development of AI and machine learning technologies holds great promise for the future of mHealth. These advances not only improve energy efficiency, but they can make healthcare apps more effective, sustainable, and accessible to a wider audience. As the healthcare sector increasingly relies on mobile solutions, these AI optimizations can be essential to ensure that apps can keep up with the growing demands of both patients and healthcare providers.

ACKNOWLEDGMENT

The authors acknowledge Prince Sultan University for their support and payment of this article's processing charges.

REFERENCES

[1] E. Papathomas, A. Triantafyllidis, R. E. Mastoras, D. Giakoumis, K. Votis, and D. Tzovaras, "A Machine Learning Approach for Prediction of Sedentary Behavior Based on Daily Step Counts," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Mexico, Nov. 2021, pp. 390–394, https://doi.org/10.1109/EMBC46164.2021.9630894.

[2] A. Z. Woldaregay *et al.*, "Data-driven modeling and prediction of blood glucose dynamics: Machine learning applications in type 1 diabetes," *Artificial Intelligence in Medicine*, vol. 98, pp. 109–134, Jul. 2019, https://doi.org/10.1016/j.artmed.2019.07.007.

[3] T. Xia, J. Han, A. Ghosh, and C. Mascolo, "Cross-Device Federated Learning for Mobile Health Diagnostics: A First Study on COVID-19 Detection," in *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Rhodes Island, Greece, Jun. 2023, pp. 1–5, https://doi.org/10.1109/ICASSP49357.2023.10096427.

[4] B. Rana, Y. Singh, P. Kumar Singh, and W. C. Hong, "A Priority Based Energy-Efficient Metaheuristic Routing Approach for Smart Healthcare System (SHS)," *IEEE Access*, vol. 12, pp. 85694–85708, 2024, https://doi.org/10.1109/ACCESS.2024.3411564.

[5] Z. Kou, C. Zhang, B. Yu, H. Chen, Z. Liu, and W. Lu, "Wearable All-Fabric Hybrid Energy Harvester to Simultaneously Harvest Radiofrequency and Triboelectric Energy," *Advanced Science*, vol. 11, no. 17, 2024, Art. no. 2309050, https://doi.org/10.1002/advs.202309050.

[6] S. Gamil, F. Zeng, M. Alrifaey, M. Asim, and N. Ahmad, "An Efficient AdaBoost Algorithm for Enhancing Skin Cancer Detection and Classification," *Algorithms*, vol. 17, no. 8, Aug. 2024, Art. no. 353, https://doi.org/10.3390/a17080353.

[7] B. Pradhan, S. Das, D. S. Roy, S. Routray, F. Benedetto, and R. H. Jhaveri, "An AI-Assisted Smart Healthcare System Using 5G Communication," *IEEE Access*, vol. 11, pp. 108339–108355, 2023, https://doi.org/10.1109/ACCESS.2023.3317174.

[8] M. Moutaib, T. Ahajjam, M. Fattah, Y. Farhaoui, B. Aghoutane, and M. El Bekkali, "Application of Internet of Things in the Health Sector: Toward Minimizing Energy Consumption," *Big Data Mining and Analytics*, vol. 5, no. 4, pp. 302–308, Dec. 2022, https://doi.org/10.26599/BDMA.2021.9020031.

[9] S. Secinaro, D. Calandra, A. Secinaro, V. Muthurangu, and P. Biancone, "The role of artificial intelligence in healthcare: a structured literature review," *BMC Medical Informatics and Decision Making*, vol. 21, no. 1, Apr. 2021, Art. no. 125, https://doi.org/10.1186/s12911-021-01488-9.

[10] M. Giordano, S. Cortesi, P. V. Mekikis, M. Crabolu, G. Bellusci, and M. Magno, "Energy-Aware Adaptive Sampling for Self-Sustainability in Resource-Constrained IoT Devices," in *Proceedings of the 11th International Workshop on Energy Harvesting & Energy-Neutral Sensing Systems*, Istanbul, Turkiye, Nov. 2023, pp. 65–71, https://doi.org/10.1145/3628353.3628545.

[11] S. Bebortta, S. S. Tripathy, S. Basheer, and C. L. Chowdhary, "DeepMist: Toward Deep Learning Assisted Mist Computing Framework for Managing Healthcare Big Data," *IEEE Access*, vol. 11, pp. 42485–42496, 2023, https://doi.org/10.1109/ACCESS.2023.3266374.

[12] A. Majid, "Security and Privacy Concerns over IoT Devices Attacks in Smart Cities (2022)," *Journal of Computer and Communications*, vol. 11, no. 1, pp. 26–42, Jan. 2023, https://doi.org/10.4236/jcc.2023.111003.

[13] R. Anandkumar *et al.*, "Securing e-Health application of cloud computing using hyperchaotic image encryption framework," *Computers and Electrical Engineering*, vol. 100, May 2022, Art. no. 107860, https://doi.org/10.1016/j.compeleceng.2022.107860.

[14] M. Y. Shakor, M. I. Khaleel, M. Safran, S. Alfarhood, and M. Zhu, "Dynamic AES Encryption and Blockchain Key Management: A Novel Solution for Cloud Data Security," *IEEE Access*, vol. 12, pp. 26334–26343, 2024, https://doi.org/10.1109/ACCESS.2024.3351119.

[15] M. Hiwale, S. Phanasalkar, and K. Kotecha, "Using Blockchain and Distributed Machine Learning to Manage Decentralized but Trustworthy Disease Data," *Science & Technology Libraries*, vol. 40, no. 2, pp. 190–213, Apr. 2021, https://doi.org/10.1080/0194262X.2020.1859046.

[16] K. Bonawitz, P. Kairouz, B. McMahan, and D. Ramage, "Federated Learning and Privacy: Building privacy-preserving systems for machine learning and data science on decentralized data," *Queue*, vol. 19, no. 5, pp. 87-114, Aug. 2021, https://doi.org/10.1145/3494834.3500240.

[17] B. Kumar, "Blockchain-Enabled Privacy Protection in Machine Learning," *International IT Journal of Research*, vol. 2, no. 2, pp. 71–76, Jun. 2024.

[18] A. K. Islam Riad *et al.*, "Enhancing HIPAA Compliance in AI-driven mHealth Devices Security and Privacy," in *2024 IEEE 48th Annual Computers, Software, and Applications Conference (COMPSAC)*, Osaka, Japan, Jul. 2024, pp. 2430–2435, https://doi.org/10.1109/COMPSAC61105.2024.00390.

[19] European Parliament. Directorate General for Parliamentary Research Services., *The impact of the general data protection regulation on artificial intelligence.* Brussels, Belgium: EU Publications Office, 2020.

[20] N. Yadav, S. Pandey, A. Gupta, P. Dudani, S. Gupta, and K. Rangarajan, "Data Privacy in Healthcare: In the Era of Artificial Intelligence," *Indian Dermatology Online Journal*, vol. 14, no. 6, Dec. 2023, Art. no. 788, https://doi.org/10.4103/idoj.idoj_543_23.

[21] L. A. R. Ramirez, "Current trends and future directions of mHealth in psychology: Challenges and promising perspectives," *Mexican Journal of Medical Research ICSA*, vol. 12, no. 24, pp. 89–95, Jul. 2024, https://doi.org/10.29057/mjmr.v12i24.12430.

[22] S. Elkefi, "Role of Digital Twins, Generative AI, and Extended Reality in Cancer Care; CanConTech, a Human Factors Framework for Technology Connectedness," in *Hospital Supply Chain: Challenges and Opportunities for Improving Healthcare*, F. Jawab, Ed. Springer Nature Switzerland, 2024, pp. 571–585.

[23] N. Najafi, M. Addie, S. Meterissian, and M. Kersten-Oertel, "Breamy: An augmented reality mHealth prototype for surgical decision-making in breast cancer," *Healthcare Technology Letters*, vol. 11, no. 2–3, pp. 137–145, 2024, https://doi.org/10.1049/htl2.12071.

[24] M. Cabanillas-Carbonell, J. Pérez-Martínez, and J. A. Yáñez, "5G Technology in the Digital Transformation of Healthcare, a Systematic Review," *Sustainability*, vol. 15, no. 4, Feb. 2023, Art. no. 3178, https://doi.org/10.3390/su15043178.

[25] A. Ahad, M. Tahir, M. Aman Sheikh, K. I. Ahmed, A. Mughees, and A. Numani, "Technologies Trend towards 5G Network for Smart Health-Care Using IoT: A Review," *Sensors*, vol. 20, no. 14, Jul. 2020, Art. no. 4047, https://doi.org/10.3390/s20144047.

[26] W. D. de Mattos and P. R. L. Gondim, "M-Health Solutions Using 5G Networks and M2M Communications," *IT Professional*, vol. 18, no. 3, pp. 24–29, Feb. 2016, https://doi.org/10.1109/MITP.2016.52.

[27] P. Mayer, M. Magno, and L. Benini, "Energy-Positive Activity Recognition - From Kinetic Energy Harvesting to Smart Self-Sustainable Wearable Devices," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 15, no. 5, pp. 926–937, Jul. 2021, https://doi.org/10.1109/TBCAS.2021.3115178.

[28] A. M. Alghamdi, M. A. Al-Khasawneh, A. Alarood, and E. Alsolami, "The Role of Machine Learning in Managing and Organizing Healthcare Records," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13695–13701, Apr. 2024, https://doi.org/10.48084/etasr.7027.

[29] S. Larabi-Marie-Sainte, L. Aburahmah, R. Almohaini, and T. Saba, "Current Techniques for Diabetes Prediction: Review and Case Study," *Applied Sciences*, vol. 9, no. 21, Jan. 2019, Art. no. 4604, https://doi.org/10.3390/app9214604.

[30] E. Chikhaoui, A. Alajmi, and S. Larabi-Marie-Sainte, "Artificial Intelligence Applications in Healthcare Sector: Ethical and Legal Challenges," *Emerging Science Journal*, vol. 6, no. 4, pp. 717–738, May 2022, https://doi.org/10.28991/ESJ-2022-06-04-05.