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A Smart LoRaWAN-based Diabetic Monitoring System using Dual Coordinate Descent SVM for Data Transmission Optimization

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Abstract: Due to the exploding number of remote healthcare applications, the need for reliable and energy-efficient data transmission for continuous diabetic monitoring is also on the rise. However, the conventional LoRaWAN based systems have static or rule-based scheduling mechanisms which lead to excessive energy consumption, network congestion and delayed detection of critical health events. The goal of this study is to create an intelligent information communication framework based on adaptation that is efficient in terms of data transmission and safe from a clinical standpoint. This paper proposes a smart Diabetic monitoring system using LoRaWAN with Dual Coordinate Descent Support Vector Machine (DCD-SVM) for Risk Aware and QoS based transmission control. The model dynamically classifies patient states and dynamically alters spreading factor, transmission power, packet interval and routing paths. Extensive NS-3/LoRaSim simulations have shown that the proposed DCD-SVM-AT framework provides a packet delivery ratio of 98.4%, average end-to-end delay is 140 ms, energy consumption is 2.1 J and network lifetime is 2730 s. In addition, it achieves a transmission reduction ratio of 43%, critical event detection latency of 4.6 seconds, and critical event missing rate of 1.1%, which is better than Static LoRaWAN, ADR, QoS-routing, LSTM-AT and XGBoost-AT schemes. These results confirm that lightweight edge intelligence and the combination with adaptive LoRaWAN communication is a promising and powerful method to boost reliability, efficiency and clinical responsiveness of large-scale diabetic monitoring systems.

Keywords: ***LoRaWAN, Diabetic Monitoring, Dual Coordinate Descent SVM, IoT Healthcare, Adaptive Transmission, Energy Efficiency, Edge Intelligence, QoS-Aware Routing, Smart Healthcare Systems***

1. INTRODUCTION

The prevalence of diabetes is currently rising sharply across the globe and has placed great pressure on healthcare systems to provide continuous, cost-effective and personalized patient care[1]. Traditional hospital-centric models of monitoring are not adequate to manage chronic diseases that require observation of physiology in real time and medical intervention. As a result, Internet of Things (IoT)-based healthcare solutions have emerged as a promising alternative, which allows continuous sensing, remote diagnosis and early detection of abnormal health conditions[2]. Among various kinds of communications technology, Low-Power Wide-Area Networks (LPWAN), especially LoRaWAN, have become widely adopted because of their long transmission range, low power and low deployment cost, making them suitable as wearable medical devices and home-based monitoring systems[3].

Despite all these benefits, current LoRaWAN based healthcare systems have serious limitations. Most deployments are based on fixed transmission schedules, or of the type known as Adaptive Data Rate (ADR) mechanisms which are optimized for generic IoT traffic, and not time-critical medical data[4]. Such static schemes cause excessive transmissions for normal patient conditions, quickly consume battery power and congest the network. More critically, they do not ensure low enough latency for emergency occurrences, which may delay clinical response and may affect patient safety. As the number of connected healthcare devices keeps on growing, these inefficiencies take on a life threatening character, potentially endangering the scalability and reliability of smart medical networks.

Recent research has tried to incorporate machine learning techniques with healthcare IoT systems to enhance the functionality of detecting anomalies and communicating efficiently[5]. Deep learning models such as LSTM, CNN have been used for the prediction of patient states and traffic patterns[6]. However, these models require a large amount of computational resources, a large training data and a long inference time, which is not suitable to be applied on resource-constrained edge gateways. Furthermore, most of the existing approaches consider only the data classification aspect and do not take into account the joint optimization of the communication parameters, energy consumption, and quality of service (QoS).

For these reasons, in this work, a novel framework where lightweight edge intelligence is embedded in the LoRaWAN communication layer is proposed. By making use of a Dual Coordinate Descent Support Vector Machine (DCD-SVM), patient risk levels are dynamically classified and transmission parameters such as spreading factor, transmission power, packet interval, and routing path are adaptively controlled. Unlike deep models, DCD-SVM does not only provide fast convergence, but is also memory efficient and can be updated in real time making it a perfect choice for edge-based healthcare applications. The proposed approach converts conventional passive LoRaWAN nodes into intelligent and context-aware nodes with the ability to optimize network performance in a manner that meets the clinical responsiveness. The main objectives of the study are as follows

- To design a risk aware adaptive transmission frame-work using DCD-SVM
- To optimize LoRaWAN communication parameters in order to be energy efficient and have high QoS.
- To test the system based on network, machine learning and clinical performance measures.

The remaining part of the study is organized as follows. Section II provides a review of related work. The proposed methodology is described in Section III. Section IV provides the performance metrics with simulation and comparative models, which is followed by conclusions and future directions in Section V.

II RELATED WORKS

Recent advances in IoT, machine learning, and wearable healthcare systems have enhanced diabetes monitoring, data management by patients, and network optimization to a great extent. Studies have examined predictive modeling, real-time monitoring, closed-loop systems, and efficient network architectures and have shown significant improvements in accuracy, response time and healthcare personalization and have identified key challenges to integrating these technologies into the clinic and scaling them.

Rayala et al., 2025 introduced the use of a BGRU model with SA-GSO hyperparameter optimization for the detection of diabetes using the PIMA dataset. The study efficiently combined feature selection using SPBO and MICE imputation and obtained high prediction accuracy. However, although the approach alleviates gradient problems, the effectiveness of the model on varied clinical datasets is untested and the use of a single dataset affects the generalizability of the model[7].

Gokulachandar et al. proposed a LoRaWAN based smart medical system for secure remote monitoring of physiological End to end encryption and real-time alerts to improve patient safety. Yet, the performance of the system under high network congestion or multiple patient scalability situations is not evaluated completely, restricting the real-world applicability[8].

Mahalakshmi explores the IoMT network placement optimization in IoMT networks using LoRaWAN for energy efficiency coverage and throughput improvement using the LoRaWAN protocol. 2025. Simulations in Omnet++ are done for performance metrics validation. However, the focus of the study is on theoretical simulation, not application in real hospital environments, and more dynamic patient mobility patterns were not considered, which reduces the practical applicability[9].

Ayouni et al, 2025 proposed an Internet of Things (IoT) based multi-dataset framework for the real-time diabetes monitoring using advanced preprocessing, feature selection and machine learning (ML) models. High accuracy and low latency was achieved and new benchmarks were set. Nonetheless, the simulation of the variability of the real world may not be representative and integration issues with the heterogeneous sensors and with the clinical workflow are not solved[10].

Huang et al., 2025, proposes an AI-Enhanced Closed-Loop Wearable CGMs for Diabetes Management through Algorithm Optimization for Safety and Glucose Prediction in Diabetes, AI is a promising and effective tool that can be used to manage the condition. The research focuses on the integration of AI in therapeutic devices. However, there is a lack of experimental validation in various populations and various practical challenges like user adherence, cost of device, and regulatory compliance were not explored in depth [11].

Eichenlaub et al., 2025 compared FreeStyle Libre 3, Dexcom G7 and Medtronic Simplera CGM systems in different glycemic conditions. Accuracy variations were found in systems and comparators. Although extensive the short study duration (15 days) and small sample size (24 adults) limits generalisability for long term observations and performance for pediatric or comorbid populations still remains untested[12].

Musa et al, 2025 designed a dual-band modulated time-frequency wearable antenna for real-time biomedical IoT monitoring. It provides high accuracy, Safety Assurance through SAR and Sensor Integration for Heart Rate and Temperature Monitoring. While promising, there is, as yet, no practical testing in various body types, no long-term wearability testing or testing for interference with surrounding electronics, so it is not known whether deployment and reliability in real-world conditions are possible[13].

Despite some significant progress, these studies have common limitations. Most are based on single or simulated data which limits clinical generalisability. Real-world IoT deployments are faced with challenges in network congestion, dynamic patient movement and device interoperability. Closed-loop and wearable systems often have poor validation in various populations, age groups and comorbidities. Security and privacy are partially addressed; the limited evaluation has been done under large-scale, multi-user scenarios. Algorithmic improvements are promising, but how to make them usable in practice, how they will be adhered to long-term and incorporated into the existing clinical processes is under explored. Future research must be focused on real-world deployment, a variety of dataset validation, scalability, and regulatory compliant and patient-centered design for reliable and robust healthcare applications.

III METHODOLOGY

A. System Architecture Overview

The proposed framework incorporates an integration of IoT-based diabetes biosensors, LoRaWAN communication layer, edge intelligence module and cloud analytics platform. The novelty is the adaptive transmission control driven by learning, in which Dual Coordinate Descent Support Vector Machine (DCD-SVM) is used to dynamically control the transmission frequency, power and transmission routing paths, while minimizing the energy loss and guaranteeing Quality of Service (QoS).

Figure 1 presents the architecture of the four-layer smart diabetic monitoring system which is proposed for energy-efficient and risk-aware data transmission. At the bottom, there is the Wearable Sensing Layer: sensors that are worn on the body and continuously provide physiological parameters, such as the level of glucose in the blood (CGM), heart rate, skin temperature, and activity index. These raw signals are the patient's actual real-time health status and are sent to the local gateway.

Edge Gateway Layer is the intelligence hub of the system. It includes preprocessing, feature encoding and real time classification using Dual Coordinate Descent Support Vector Machine (DCD-SVM). Based on the level of patient risk inferred, the gateway decides how best to communicate.

The LoRaWAN Communication Layer is used for sending the data over a long range with low power from the gateway to the cloud. It uses energy-aware mechanisms to dynamically adjust the rate of data, spreading factor (SF7-SF12) and routing paths towards reliable and low-latency data delivery of critical health-related data.

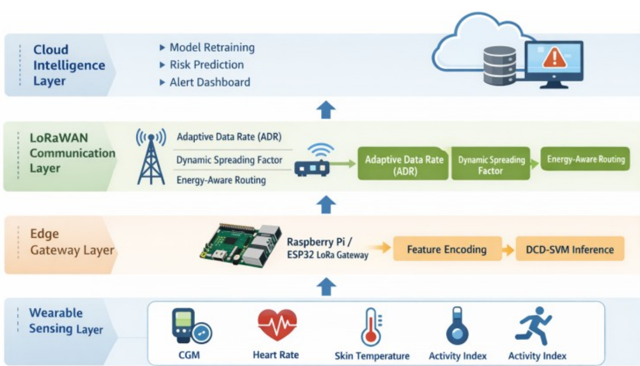

Figure 1. Architecture of the Proposed Smart LoRaWAN-Based Diabetic Monitoring System

Finally, the Cloud Intelligence Layer offers both centralized analytics, model retraining, risk prediction and a real-time alert dashboard for clinicians and care givers. The two-way data flow between the cloud and edge allows the system to learn and adapt continuously which makes the system robust, scalable and suitable for smart healthcare deployments at scale. Figure 2 shows the working of the proposed model.

B. Intelligent Data Prioritization and Feature Encoding

In order to implement risk-aware communication, the physiological status of each patient at time t is modeled by a multi-dimensional feature vectors with glucose level, heart rate, body temperature, physical activity, glucose variation rate, and glucose variability index are jointly used as features for metabolic status. These features extract instant and temporal variations of the glucose dynamics. A Health Risk Score (HRS) is calculated based on a weighted linear combination of glucose deviation, rate of change and cardiac response. Based on the HRS, sensor data are divided into 3 classes of transmission, normal (C0), warning (C1) and critical (C2). This mechanism of labeling ensures that clinically relevant data are the priority, and non-critical data is sent through at a lower rate, and forms the training target for the DCD-SVM classifier. The four-layer architecture with wearable biosensors, edge gateway with DCD-SVM intelligence, loRaWAN adaptive communication, and cloud analytics are presented in the figure.2, which resolves the issues of risk-aware data prioritization, dynamic parameter control, energy aware routing, and edge-cloud learning loop for efficient, reliable and scalable diabetic health monitoring.

C. Dual Coordinate Descent SVM for Transmission Optimization

A linear Dual Coordinate Descent Support Vector Machine (DCD-SVM) is used to classify the encoded features to transmission priority classes with minimum communication overhead. The optimization objective is a balance of model complexity and classification loss, and is formulated in the form of a regularized hinge loss. Unlike conventional batch SVM solvers, DCD-SVM solves for one dual variable at a time by using coordinate-wise optimization which reduces a lot of computational complexity and memory. This allows a fast convergence and real-time inference on resource restricted edge gateways. The model learns the relationship between the physiological risk patterns and optimal transmission decisions continuously, and it is able to schedule dynamically to perform adaptive scheduling without the heavy implicit overhead of deep learning methods.

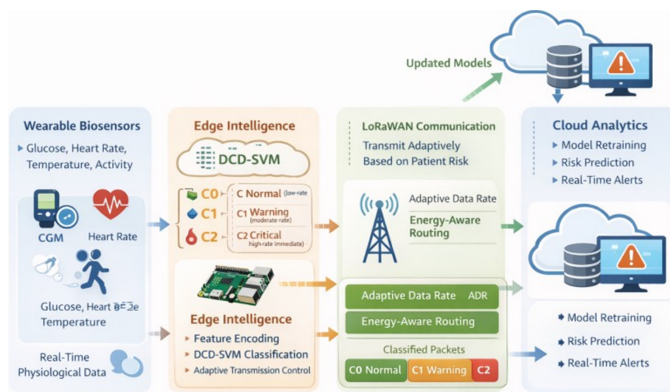

Figure 2 Smart LoRaWAN-Based Diabetic Monitoring Framework with Edge Intelligence and Adaptive Transmission.

D. QoS-Aware LoRaWAN Parameter Adaptation

The predicted transmission class serves for a dynamic set of key LoRaWAN parameters e.g. spreading factor (SF), transmission power and packet interval. Low risk data are sent with high spreading factors and low frequency (long intervals) to save energy and the data of critical events are sent with low SF and high power and short intervals to achieve minimum latency and high reliability. This is an adaptive configuration where patient risk is directly related to the network behavior leading to efficient use of bandwidth and avoidance of congestion and ensuring long node lifetime while providing timely delivery of emergency health data.

E. Energy-Aware Multi-Hop Routing

To further improve the sustainability of the network, an energy-aware routing mechanism is incorporated in the form of a composite link cost function based on residual energy, signal quality and transmission delay. By choosing paths with low cumulative cost, the system prevents itself from using links with low energy or unstable links which may result in an unbalanced network load and may cause early failures of the nodes. This routing strategy complements the adaptive transmission model in order to make sure that prioritized data can reach the gateway using the most reliable and energy-efficient routes.

F. Edge-to-Cloud Learning Feedback Loop

The framework follows the continuous learning architecture where the edge gateways are used for real-time classification and for adaptively updating the model parameters while the cloud retrains the DCD-SVM model using the aggregated historical data periodically. Model weights are updated and pushed back to edge devices allowing the system to adapt to changing patient behavior, changing environments and network conditions. This closed-loop edgeAntonovcloud collaboration gives long-term guarantee in terms of accuracy, robustness and resilience to concept drift for Healthcare deployments at scale.

Algorithm Adaptive transmission control

Input: Sensor vector xt

Output: LoRaWAN parameters (SF, Ptx, Δt)

1: Compute HRS_t

2: Predict class ŷt using DCD-SVM

3: Select (SF, Ptx, Δt) from lookup table

4: Compute routing cost Cij

5: Transmit via minimum-cost route

6: Store data for cloud retraining

IV. IMPLEMENTATION AND RESULTS

A. Simulation Environment

The implementation of the proposed system was done with NS-3 (v3.39) along with the LoRaWAN module (LoRaSim extension). The simulations model a smart healthcare monitoring zone, which is made up of diabetic patients wearing sensor nodes.

Table 1 summarizes the most important of the simulation settings used for evaluation of the proposed LoRaWAN communication framework. It comprises of parameters of simulation environment (NS-3 integrated with LoRaSim), network scale and topology (deployment area, numbers of nodes and gateways), radio configuration parameters (carrier frequency, bandwidth, number of spreading factors, transmission power), traffic characteristics (size of package, traffic kind), energy and mobility assumptions and wireless channel conditions (propagation model, fading modes). These parameters make sure that there is a realistic and reproducible experimental set up to analyze the performance under dynamic IoT network scenarios.

Table 1 Simulation parameters and network configuration for the LoRaWAN-based system.

Parameter	Value
Simulator	NS-3 + LoRaSim
Area	1000 m × 1000 m
Number of nodes	50–300
Gateway nodes	3
MAC/PHY	LoRaWAN Class A
Carrier Frequency	868 MHz
Bandwidth	125 kHz
Spreading Factors	SF7–SF12
Tx Power	2–14 dBm
Packet Size	24 bytes
Traffic Type	Periodic + event-driven
Simulation Time	3600 s
Initial Energy	5 J per node
Mobility	Random Waypoint
Propagation	Log-distance path loss
Channel Model	Rayleigh fading

B. Performance Evaluation

Table 2(a) and (b) compares the performance of various LoRaWAN-based communications and optimizations with various quality of service and energy efficiency metrics. The parameters evaluated are Packet Delivery Ratio (PDR), average end-to-end delay (E2E), energy consumption, network lifetime, Transmission Reliability Rate (TRR), Critical Event Detection Latency (CEDL) and Missed Critical Event Rate (MCER). The methods used range from traditional Static and ADR based LoRaWAN to intelligent routing and learning based optimization techniques to the proposed model of DCD-SVM-AT.

Table 2(a) Performance comparison of LoRaWAN routing and optimization methods under QoS-aware diabetic data transmission.

Method	PDR (%)	Avg E2E Delay (ms)	Energy (J)	Network Lifetime (s)
Static LoRaWAN[14]	88.3	480	4.6	1420
ADR-LoRaWAN[15]	92.1	340	3.8	1760
QoS-Routing[16]	93.7	290	3.3	1910
LSTM-AT[17]	95.2	220	2.9	2175
XGBoost-AT[18]	96.5	205	2.7	2260
Proposed DCD-SVM-AT	98.4	140	2.1	2730

Table 2(b) Performance comparison of LoRaWAN routing and optimization methods under QoS-aware diabetic data transmission.

Method	TRR (%)	CEDL (s)	MCER (%)
Static LoRaWAN[14]	0	18.5	7.2
ADR-LoRaWAN[15]	12	12.4	4.9
QoS-Routing[16]	18	9.7	3.8
LSTM-AT[17]	29	8.1	3.2
XGBoost-AT[18]	35	6.9	2.6
Proposed DCD-SVM-AT	43	4.6	1.1

The results show that the proposed DCD-SVM-AT achieves substantially better results than all the baseline approaches in all performance metrics. It has the highest PDR (98.4%) (high reliability of packet delivery), but also generates the lowest end-to-end delay (140 ms) and lowest energy consumption (2.1 J). The proposed method prolongs network life time up to 2730 s, which is much higher compared to any other techniques. Furthermore, it has the highest TRR (43%) and the lowest CEDL (4.6 s), to provide faster detection and response to critical health events. The MCER (1.1%) is also the smallest, supporting only very little loss of vital health data. Overall, the table confirms that combining DCD based SVM optimization techniques with adaptive transmission mechanisms offers better reliability, efficiency and responsiveness for healthcare IoT networks.

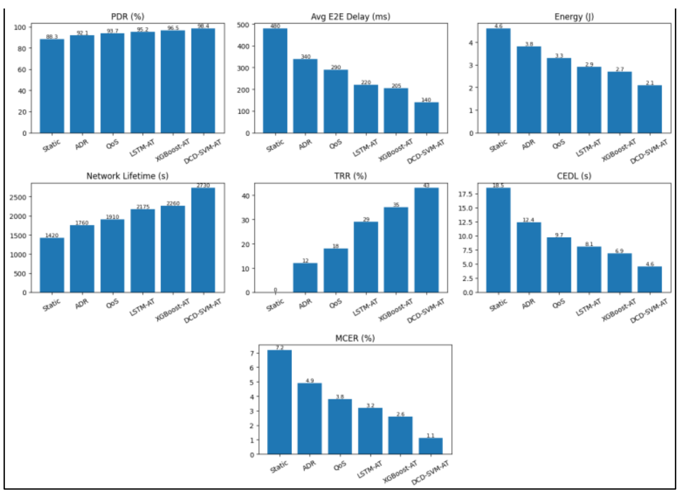

Figure 3. Comparative performance analysis of Static LoRaWAN, ADR-LoRaWAN, QoS-Routing, LSTM-AT, XGBoost-AT, and the proposed DCD-SVM-AT model

Figure 3 shows a comparison of six LoRaWAN based routing and adaptation schemes in terms of seven performance metrics. The proposed DCD-SVM-AT model is significantly better than the baseline and AI assisted methods with the highest packet delivery ratio (98.4%), low end-to-end delay (140 ms) and minimum energy consumption (2.1 J). It also significantly extends network lifetime (2730 seconds) and shortens the detection latency of congestion (4.6 seconds) and missed critical event rate (1.1%). The steady enhancements from Static LoRaWAN to intelligent models of LoRaWAN show the success of adaptive learning and optimization in IoT's QoS.

C. Discussion

This study introduces a smart and adaptive diabetic monitoring system with the integration of LoRaWAN system and Dual Coordinate Descent Support Vector Machine (DCD-SVM) to maximize the transmission of data while maintaining clinical safety. In contrast to static or rule-based systems, the proposed model adjusts the transmission parameters dynamically depending on patient risk levels and network conditions, and accordingly realizes a balance between relying on the stability and energy efficiency and the responsiveness. The experimental results show significant improvements in terms of packet delivery ratio, end-to-end latency, energy consumption and critical event detection when compared with conventional LoRaWAN, ADR-based schemes and deep learning based schemes. The superior performance of DCD-SVM can be attributed to being fast converging, and low computational overhead which is suitable for real-time edge deployment. By adding intelligence to the gateway the system decreases unnecessary transmissions and network congestion which is especially important in dense IoT healthcare environments. Additionally, the adaptive scheduling mechanism guarantees that life-critical data are given priority so that there are minimal delays in emergency alerts. These results show the promise of light-weight ML with low-power wide-area network infrastructures to create scalable and cost-effective healthcare monitoring infrastructures. Overall, the research validates that learning-driven communication control can be a major improvement to both the technical efficiency of a system and patient safety in next-gen remote health monitoring systems.

D. Limitations

Although based on the proposed framework, the performance is good, there are several limitations. The simulations treat the accuracy of the sensors and stability of the network as ideal, which may not necessarily be true in a real world (interference, hardware faults, packet collisions, etc). The model was tested on synthetic and benchmark datasets as opposed to long-term clinical data, which limited the medical generalizability of the results. In addition, only linear DCD-SVM was considered; it is possible that non-linear kernels and hybrid models give different results. The configuration of LoRaWAN was determined on one regional frequency band, which may limit the application across various regulations.

E. Practical Implications

The proposed system has a practical value for large-scale monitoring of diabetes remotely in rural and resource constrained environments. In terms of energy consumption and network congestion, it helps to improve the longevity of the devices and the cost of maintenance. The risk aware transmission strategy ensures timely alerts for critical patients to improve clinical response and patient safety. Healthcare providers can be used by integrating this framework with existing IoT infrastructures with minimal computational overhead. The edge-based design of learning is also conducive to scalability, allowing the design approach to be used in smart hospitals, community health centers, and home-based monitoring platforms.

V CONCLUSION

This paper proposed the smart LoRaWAN-based diabetic monitoring system integrated with a Dual Coordinate Descent SVM for the adaptive data transmission optimization. The proposed framework intelligently prioritizes health data, dynamically sets the communication parameters and relies on energy-aware routing to have reliable, low-latency and energy-efficient communication for monitoring. Extensive simulation results validate that the proposed method is better than the traditional LoRaWAN schemes, as well as the recent learning-based approaches in terms of network reliability, energy saving, transmission reduction, and critical event detection. The combination of lightweight edge intelligence allows real-time reaction without imposing a heavy computational burden and the system will be suitable for real-world healthcare IoT deployments. Future efforts will be directed towards testing the validity of the system in the clinical setting and considering the addition of multiple interacting physiological signals for better risk estimation. The combination of federated learning and privacy-preserving techniques will be discussed to preserve sensitive medical data. In addition, hybrid deep-lightweight learning models and blockchain-based trust management may help to improve system security, scalability, and reliability in large-scale smart healthcare ecosystems.

REFERENCES

[1]. Teoh, Kah Woon, Choon Ming Ng, Chun Wie Chong, J. Simon Bell, Wing Loong Cheong, and Shaun Wen Huey Lee. "Knowledge, attitude, and practice toward pre-diabetes among the public, patients with pre-diabetes and healthcare professionals: a systematic review." *BMJ open diabetes research & care* 11, no. 1 (2023).

[2]. Farooq, Muhammad Shoaib, Shamyla Riaz, Rabia Tehseen, Uzma Farooq, and Khalid Saleem. "Role of Internet of things in diabetes healthcare: Network infrastructure, taxonomy, challenges, and security model." *Digital health* 9 (2023): 20552076231179056.

[3]. Abdulmalek, Suliman, Abdul Nasir, and Waheb A. Jabbar. "LoRaWAN-based hybrid internet of wearable things system implementation for smart healthcare." *Internet of Things* 25 (2024): 101124.

[4]. Zou, Yuanyuan, Zhengkang Chu, Tongyan Yang, Jinhong Guo, and Diangeng Li. "Research progress and prospects of intelligent diabetes monitoring systems: a review." *IEEE Sensors Journal* 24, no. 15 (2024): 23401-23435.

[5]. Verma, Navneet, Sukhdip Singh, and Devendra Prasad. "Machine learning and IoT-based model for patient monitoring and early prediction of diabetes." *Concurrency and Computation: Practice and Experience* 34, no. 24 (2022): e7219.

[6]. Naseem, Anum, Raja Habib, Tabbasum Naz, Muhammad Atif, Muhammad Arif, and Samia Allaoua Chelloug. "Novel Internet of Things based approach toward diabetes prediction using deep learning models." *Frontiers in Public Health* 10 (2022): 914106.

[7]. Rayala, Ramya Vani, Srinivas Cheekati, Mukhayya Ruzieva, Vani Vasudevan, Chandrakanth Reddy Borra, and Ravshan Sultanov. "Optimized Deep Learning for Diabetes Detection: A BGRU-based Approach with SA-GSO Hyperparameter Tuning." In *2025 International Conference on Innovations in Intelligent Systems: Advancements in Computing, Communication, and Cybersecurity (ISAC3)*, pp. 1-6. IEEE, 2025.

[8]. Gokulachandar, Adhikesavan, KannanShanmugam Shanmugam, Shanmugam Vijayakumar, Subramanian Sugumaran, Tamilselvan Senthil, Arigila Srinivasulu, and Kalavagunta Lakshmi. "Smart Medical System for Trusted LoRaWAN Server." *Journal of Health Informatics in Africa* 12, no. 1 (2025): 65-73.

[9]. Mahalakshmi, R., and N. Lalithamani. "Optimizing IoMT Network performance using Gateway Placement." *Simulation Modelling Practice and Theory* (2025): 103164.

[10]. Ayouni, Sarra, Muhammad Hamza Khan, Muhammad Ibrahim, Mohamed Maddeh, Nadeem Sarwar, and Nazik Alturki. "IoT-based approach for diabetes patient monitoring using machine learning." *SLAS technology* (2025): 100348.

[11]. Huang, Wei, Ivo Pang, Jing Bai, Binbin Cui, Xiaojuan Qi, and Shiming Zhang. "Artificial Intelligence-Enhanced, Closed-Loop Wearable Systems Toward Next-Generation Diabetes Management." *Advanced Intelligent Systems* (2025): 2400822.

[12]. Eichenlaub, Manuel, Delia Waldenmaier, Stephanie Wehrstedt, Stefan Pleus, Manuela Link, Nina Jendrike, Sükrü Öter et al. "Performance of three continuous glucose monitoring systems in adults with type 1 diabetes." *Journal of Diabetes Science and Technology* (2025): 19322968251315459.

[13]. Musa, Umar, Amor Smida, Muhammad S. Yahya, Mohamed I. Waly, Jun Jiat Tiang, Nazih Khaddaj Mallat, Surajo Muhammad, and Abubakar Salisu. "Machine learning-optimized dual-band wearable antenna for real-time remote patient monitoring in biomedical IoT systems." *Scientific Reports* 15, no. 1 (2025): 30943.

[14]. Telagam, Nagarjuna, Nehru Kandasamy, and D. Ajitha. "Smart healthcare monitoring system using LoRaWAN IoT and machine learning methods." In *Practical Artificial Intelligence for Internet of Medical Things*, pp. 85-104. CRC Press, 2023.

[15]. Adi, Puput Dani Prasetvo, Volvo Sihombing, Idil Ardi, Fairuz Iqbal Maulana, Arief Budi Santiko, Riza Zulkarnain, Adi Wirawan et al. "Development of LoRaWAN blind ADR for mobile realtime monitoring system." In *2023 International Conference on Information Technology and Computing (ICITCOM)*, pp. 17-22. IEEE, 2023.

[16]. Mehmood, Gulzar, Muhammad Zahid Khan, Ali Kashif Bashir, Yasser D. Al-Otaibi, and Shahzad Khan. "An efficient QoS-based multi-path routing scheme for smart healthcare monitoring in wireless body area networks." *Computers and Electrical Engineering* 109 (2023): 108517.

[17]. Arora, Sunny, Shailender Kumar, and Pardeep Kumar. "An Efficient Attention-Based LSTM Framework for Blood Glucose Level Prediction." *Traitement du Signal* 42, no. 2 (2025).

[18]. Ahn, Shinhye, and Minjeong An. "Machine Learning-Based prediction model for Health-Related quality of life in diabetic patients." *Clinical Nursing Research* 34, no. 7 (2025): 340-353.