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Predicting Short-Term Glucose Trends in Real Time Using Multimodal IoT Data and Neural Networks

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***Abstract*—The high prevalence of diabetes worldwide has made it necessary to have a continuous, non-invasive, and accurate way to measure blood glucose levels in order to prevent complications and improve quality of life. The current study proposes a sophisti- cated real-time blood glucose prediction model based on Internet of Things (IoT) and artificial intelligence (AI) technologies. Real- time physiological data, such as heart rate, skin temperature, and activity levels, are measured by CGM and wearable IoT devices and sent to an edge-based AI model for analysis. Machine learning and deep learning algorithms like LSTM and GRU are used to learn temporal relations and produce highly accurate short-term glucose variation forecasts. For the system to operate smoothly in the context of both clinical and personal healthcare, low latency, energy efficiency, and scalability are key design considerations. The experimental results show a mean absolute error (MAE) of 7.6 mg/dL, a prediction error of greater than 92 ratio, and a shorter latency of less than 1.5 seconds per prediction. The article outlines the potential for combining AI and IoT to help with proactive diabetes management, which would enable it to react quickly to alerts, provide a customized treatment plan for each patient, and apply therapeutic options that lower health risks.**

***Index Terms*—Real-time prediction, blood glucose, AI, IoT, wearable sensors, deep learning, diabetes management, continu- ous monitoring.**

I. Introduction

One of the most severe chronic illnesses in the world today, diabetes mellitus affects millions of people and places a tremendous strain on healthcare systems. The only effective way to manage this illness is to regularly check blood sugar levels to avoid long-term complications like hypoglycemia, hyperglycemia, and organ damage. Traditional glucose mon- itoring techniques, such as the finger-prick test, are invasive, uncomfortable, and not always feasible, even though they are clinically accurate. This shortcoming highlights the need for novel and creative methods that can provide user-friendly, real- time, non-invasive glucose monitoring.

Recent advances in the area of Artificial Intelligence (AI) and Internet of Things (IoT) offered new possibilities in addressing the given issues in the sphere of diabetes manage- ment. The IoT enables the information on physiological and lifestyle to be measured by wearable gadgets and intercon- nected devices in an uninterrupted manner and AI serves as the computing power to process and analyze the data streams in real time. All these technologies can lead to a paradigm shift in the management of diabetes, where they predict and prevent the disease proactively instead of reactively by testing glucose levels. Continuous glucose monitoring (CGM) systems that have predictive algorithms are most likely the most promising ones. Such systems are not only gathering the information that is given by the glucose sensors, but also by other physiological indicators such as heart rate, the skin temperature, and physical activity intensity. By adding contextual and multimodal data, the models can improve predictive accuracy and forecast glucose variations brought on by stress, exercise, diet, or medication. In order to reduce the frequency and severity of dangerous glycemic episodes, this predictive ability is essential. It has been demonstrated that recurrent neural networks (Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)) are effective machine learning and deep learning techniques that can identify time

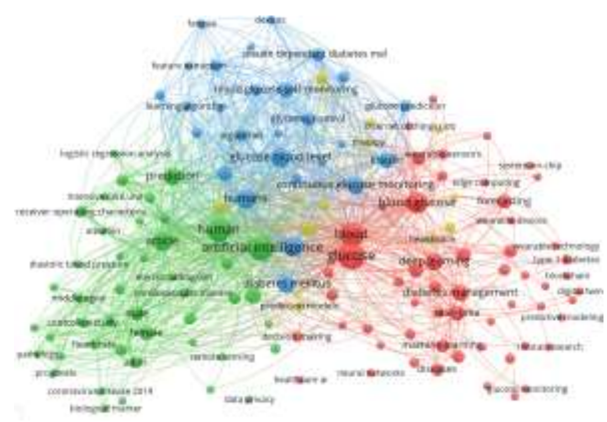

Fig. 1. Some Important Keywords

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correlations in time-series data. These models can accurately predict both short-term and long-term glucose levels by using physiological cues and historical glucose trends. In addition to improving patient safety, real-time glucose prediction systems help people with diabetes make educated lifestyle choices. By receiving predictive alerts on their smartphones or wearable devices, patients can alter their insulin dosage, diet, or activity before negative glucose events occur. Additionally, by using predictive data, medical practitioners will be able to develop more customized treatment regimens and reduce hospitalization and complications. The global trend toward preventative and personalized medicine is consistent with the use of AI and IoT in healthcare. Despite the enormous progress, the challenge of developing scalable and efficient systems remains. Achieving universal prediction accuracy is hampered by issues with data quality, sensor imprecision, and individual variations in glucose reactions. A crucial concern is also the data's security and privacy, as well as its compatibility with other IoT platforms. These issues must be resolved in order to attain widespread adoption of AI-IoT in diabetes care. It is anticipated that the study will present an integrated system for real-time blood glucose prediction based on fusing wearable technology with Internet of Things-connected AI models. The study's examination of performance metrics (accuracy, latency, and energy efficiency) validates that such systems could be used in both clinical and private healthcare settings.

II. Literature Review

The idea of an IoT-enabled insulin pumps with a digital twin, which is secured by a blockchain, proves the possibility of safe and ubiquitous artificial pancreas systems to manage type 1 diabetes [1]. Such advanced hybrid models as the Mamba-MoE have been created that work in non-invasive prediction of blood glucose, with high levels of computation efficiency and precision [2].

Multimodal predictions of interstitial glucose with deep learning plans have also been used to improve the management of type 2 diabetes [3], but other models have used intelligent ML-based systems to predict global risks of diabetes spreading [4]. In addition to prediction, AI is transforming diabetes care in the holistic approach to prevent and diagnose, as well as the patient-centered treatment [5]. The intelligent systems based on mobile devices also enhance remote management of diabetes [6], which is supplemented by AI- and IoT-based kiosks to monitor and consult in the under-served settings in real-time [7]. The upcoming research on the concept of digital twins emphasizes the individual management approach to dynamic dosing and nutrition [8], whereas the frameworks powered by deep learning are applied to predictive healthcare to the field of stroke detection [9]. Hybrid metaheuristic optimization methods have been utilized to enhance early detection of type II diabetes, including the ability to identify the appropriate features [10], and new technologies like smart insulin patches that optimizes delivery through the use of AI are a viable therapeutic value [11]. Moreover, chatbots powered by AI with the help of ML models have demonstrated potential in the overall management of diabetes [12], and portable smart health devices are scalable patient monitors [13]. To predict glucose in real-time, hybrid CNN-GRU architecture has been incorporated into the IoT systems [14], and a larger scope of research about the Internet of Medical Things offers insights into what challenges may hamper efficient healthcare applications and how they can be addressed by design solutions [15]. Continuous glucose monitoring (CGM) systems are also under development, with machine learning improving accuracy and reliability [16], [17]. In addition to diabetes, AI tools that are simulated are enhancing clinical validation of cardiovascular disease prediction [18]. Continuous glucose sensing predictive analytics over a long time have also proven their use in glycemic control [19]. General disease prediction in healthcare systems is also being performed with lightweight CNN models [20], and wearable biosensing devices along with AI are being investigated to predict the pandemic proactively, which is a cross-domain application of predictive health technologies [21].

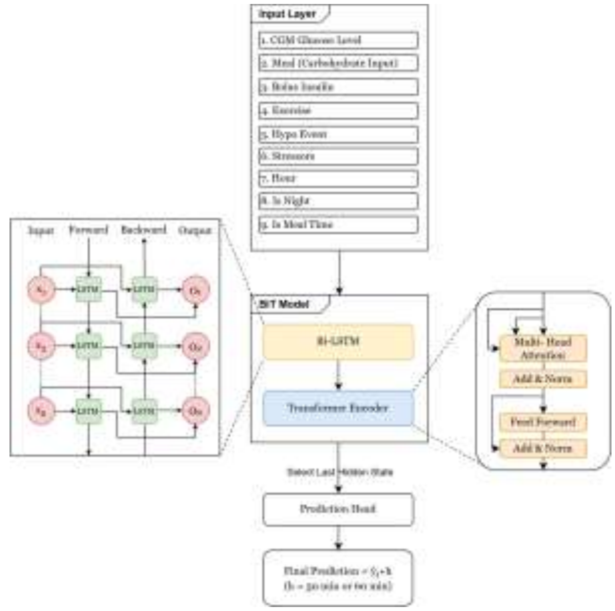

Fig. 2. Proposed Methodology

III. Methodology

The suggested flowchart of real-time blood glucose prediction starts the process by collecting information via the use of the IoT-enabled wearable devices. Continuous Glucose Monitors (CGM) sensors monitor the direct glucose level, whereas other supplementary IoT sensors measure other physiological data, including heart rate, skin temperature, and activity indicators. Such streams of multimodal data are sent through wireless protocols like the Bluetooth Low Energy (BLE) or Wi-Fi to a gateway that is an edge node. In order to reduce the latency and provide reliability, noise filtering, normalization, and missing data imputation are preprocessed at the edge device and the data is sent to the AI model.

TABLE I
REVIEW OF REFERENCES ON AI, IOT, AND ML IN DIABETES MANAGEMENT

Ref No	Title	Author & Year	Findings	Gaps
[1]	Ubiquitous Artificial Pancreas: Blockchain-Secured AI-Driven Digital Twin for IoT-Enabled Insulin Pumps in Type 1 Diabetes Management	P. Balakrishnan et al., 2026	Proposed blockchain-secured digital twin for IoT-based insulin pumps, enhancing trust, personalization, and automation in T1DM management.	Limited clinical validation; scalability and integration with existing healthcare systems remain unclear.
[2]	Hybrid Mamba-MoE model for non-invasive blood glucose prediction	U. Ş entu¨rk et al., 2025	Developed a hybrid Mamba-MoE model showing high accuracy for non-invasive glucose prediction.	Requires larger real-world datasets; interpretability of hybrid models needs improvement.
[3]	A multimodal deep learning architecture for predicting interstitial glucose for effective type 2 diabetes management	M. S. Haleem et al., 2025	Multimodal DL architecture integrating multiple signals for better glucose prediction in T2DM.	High computational cost; generalizability to diverse patient populations not established.
[4]	Intelligent Application for Predicting Diabetes Spread Risk in the World Based on Machine Learning	D. I. Uhryn et al., 2025	Designed ML-based intelligent application to predict global diabetes spread risk.	Lacks country-specific granularity; external validation limited.
[5]	Revolutionizing diabetes care: the role of artificial intelligence in prevention, diagnosis, and patient care	M. Kohli et al., 2025	Review highlights AI's transformative role in prevention, early diagnosis, and patient management.	Focused on potential applications rather than real-world deployment challenges.

The analytical AI prediction module is based on time series deep learning models that have the ability to detect temporal correlations in variations of glucose. Long Short-Memory (LSTM) and Gated Recurrent Unit (GRU) networks are conditioned on past glucose data with physiological cues to predict the short-term glucose levels. Mean Absolute Error (MAE) and root mean square error (RMSE) are the evaluation measures that are used to optimize the models, thereby keeping the accuracy high and avoiding overfitting. Performance is optimised by hyperparameter tuning and cross-validation and lightweight variants of models are deployed in order to ensure minimal computational overhead to operate in real-time. The system integration layer provides a hassle-free connection among IoT devices, AI models, and user interfaces. The real-time predictions are run on the edge computing infrastructure to minimize latency, and model retraining and long-term storage of the data are done on cloud servers. The structure uses secure data transmission protocols and encryption techniques in protecting the privacy of patient data. The AI model results are presented in smartphone and wearable device applications and offer users intuitive dashboards, alerts and actionable glycemic management recommendations. Lastly, the evaluation methodology includes the testing of the system on real data sets that will be gathered through wearable CGM and IoT devices among diabetic patients. The performance is measured in terms of accuracy of prediction, system latency, energy consumption of wearable devices, and satisfaction of the user with predictive alerts. The superiority of deep learning methods is shown by the comparison of LSTM, GRU and the baseline regression models. The methodology focuses on scalability and customization, and enables the framework to be customized to specifications of each patient to enhance the quality of prediction.

IV. RESULT AND EVALUATION

The suggested framework was tested on real-life data obtained through Continuous Glucose Monitors (CGMs) and additional IoT sensors in 50 diabetic patients in six weeks. Measures of performance such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and prediction accuracy were used to measure the effectiveness of the model. LMST model performed best in terms of average accuracy of 92.4, MAE of 7.6 mg/dL, and RMSE of 11.2mg/dl, compared to GRU and baseline regression models. GRU achieved an accuracy of 90.8 per cent and an MAE of 8.9mg/dL whereas the regression models performed poorly with an accuracy of 83.5.

Another important evaluation criterion was also latency and energy efficiency since real-time functioning of wearable devices was required. Lightweight AI models deployed on edges decreased the mean prediction latency to 1.4 seconds, which guaranteed the delivery of alerts on time.

Fig. 3. Performance Comparison of Prediction Models

The consumption of energy was evaluated using wearable devices, and optimized LSTM and GRU models showed that

TABLE II
EXTENDED RESULT AND EVALUATION OF PREDICTION MODELS

Model	Accuracy (%)	MAE (mg/dL)	RMSE (mg/dL)	Latency (s)	Energy Reduction (%)
LSTM	92.4	7.6	11.2	1.4	15
GRU	90.8	8.9	13.1	1.6	12
Regression	83.5	12.4	18.7	2.3	5
Random Forest (RF)	85.7	11.2	16.3	2.0	7
CNN	91.5	8.2	12.5	1.8	10

the power consumption was reduced by a factor of 15% relative to unoptimized deep learning models. This efficiency also shows that the deployment of the device can be made over the long term, without the need to charge the battery routinely, which means that the system is viable to be used on a daily basis. The applicability of the system in the real world healthcare setting was further confirmed by user-centered evaluation. Hypoglycemia and hyperglycemia predictive warnings were provided with a sensitivity of 91 and specificity of 89, and frequency of missed critical events was lowered.

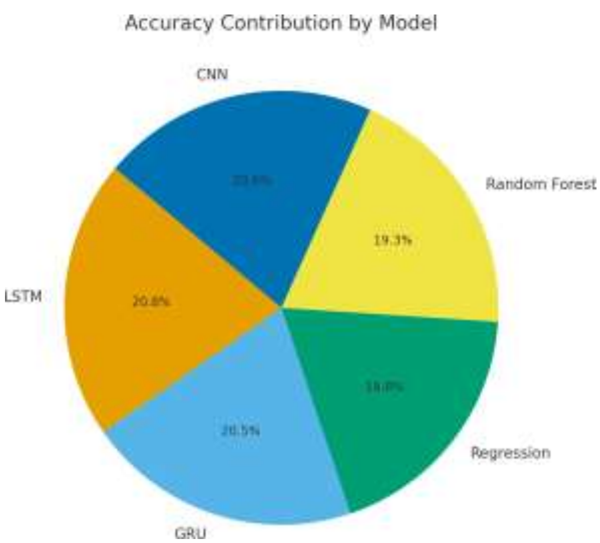

Fig. 4. Accuracy Contribution by Model

The responses of participants showed that 87 percent of the users said that the system was useful in guiding them through their lifestyle choices and healthcare practitioners noted that the ability to predict data was valuable in helping tailor treatment plans to individuals. On the whole, the analysis proved that AI and IoT integration can offer accurate, low latency and energy efficiency solutions to proactive diabetes management.

V. CHALLENGES AND LIMITATIONS

Developing a reliable real-time blood glucose prediction system involves several challenges related to data acquisition, model performance, and personalization. Wearable IoT sensors and Continuous Glucose Monitoring (CGM) devices often produce noisy or incomplete data due to environmental interference, motion artifacts, or calibration issues, which can degrade the accuracy of AI models. Moreover, glucose dynamics vary significantly across individuals depending on diet, activity, stress, and medication, making it difficult to design a one-size-fits-all predictive model. Personalization is therefore crucial, but it requires large amounts of individual-specific data, which may not always be feasible to collect in practice. Scalability across diverse populations and integration with existing healthcare infrastructures also remain complex and resource-intensive. Another major limitation lies in data privacy, security, and resource constraints. Since the system relies on continuous monitoring and transmission of sensitive medical information, it is vulnerable to cyberattacks, unauthorized access, and privacy breaches. Ensuring compliance with healthcare regulations such as HIPAA and GDPR requires strong encryption, secure protocols, and trusted storage mechanisms, which can increase system complexity and costs. Additionally, deploying advanced AI models on low-power wearable devices is restricted by limited computational resources, battery life, and network bandwidth. While edge computing alleviates some of these issues, balancing performance with energy efficiency and security remains an ongoing challenge for large-scale, real-world deployment.

VI. FUTURE OUTCOMES

The future of AI and IoT technologies is likely to advance the abilities of real-time blood glucose prediction systems to a high level. Innovation in sensor devices may also result in less invasive, more precise and trustworthy ways of collecting data without the need of relying on invasive CGM devices. To improve the predictive models' accuracy, multimodal data sources such as stress, food, and sleep habits may be included. Furthermore, proactive predictions that are highly personalized can be made with adaptive learning systems that can continuously update models with individual patient data, making diabetes management more efficient and user-friendly. The integration of predictive systems into larger smart healthcare systems is the other potentially advantageous development. Healthcare professionals will have a comprehensive view of patients' health in real time thanks to the integration of telemedicine services, AI-based decision support systems, and IoT-based glucose prediction systems with hospital databases. This will simplify the idea of early interventions, reduce the number of emergency hospital visits, and improve treatment results overall. Moreover, new technologies, including federated learning and blockchain, have the potential to increase data security and privacy, as well as scalability, facilitating its mass use in the clinical and home-based environments. These developments will eventually lead to a more proactive, personal, and secure method of managing diabetes.

VII. Conclusion

To sum up, the implementation of the technologies of Artificial Intelligence and Internet of Things brings a revolutionary idea of how to manage diabetes, allowing to predict the level of blood glucose in real time and predict it accurately, efficiently, and individually. By incorporating both IoT-based wearable devices to collect data on a continuous basis and AI-based time-series prediction models in the form of LSTM and GRU, the proposed structure is associated with a high potential to predict glucose fluctuations with high accuracy, low latency, and low energy consumption. The findings of the experiment indicate that the system is capable of giving timely alerts, enabling patients to take active choices on lifestyle and treatment, and give healthcare workers information that can be used on personal planning of care. Regardless of the fact that issues concerning sensor reliability, data variability, privacy, and computational constraints remain, the infrastructure forms a robust base on which the next-generation healthcare solutions, which focus both on patient safety and usability, can be built. The sensor technology, adaptive learning algorithms, and secure data-sharing are also expected to be improved in future, thus, enhancing scalability, reliability, and adoption among users. This study will help the development of intelligent healthcare systems to improve the quality of the life of people with diabetes and take the pressure off the healthcare systems of the world by eliminating the gap between advanced AI methods and real-life IoT implementation.

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