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A Non-Invasive Measuring and Monitoring Blood Glucose System Based on Deep Learning Algorithm

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A B S T R A C T

The persistent challenge of achieving accurate, painless, and continuous blood glucose monitoring in diabetes management has driven intensive research toward non-invasive technological solutions that balance precision, accessibility, and patient comfort. This work examines recent advancements in sensor-based glucose estimation and emphasizes the strong synergy between modern sensing technologies and deep learning methodologies. Emerging techniques such as bioimpedance analysis, near-infrared (NIR), and mid-infrared (Mid-IR) spectroscopy have demonstrated promising potential for glucose monitoring without the need for invasive blood sampling. In parallel, hybrid sensor architectures combined with artificial intelligence–driven predictive models have shown the ability to mitigate traditional limitations and enhance real-time monitoring performance. Despite these advances, significant challenges remain, including environmental sensitivity, inter-individual physiological variability, and calibration stability. To address these issues, adaptive machine learning frameworks are being developed to improve system robustness and reliability. This review critically evaluates current progress, identifies existing limitations, and outlines future research directions toward clinically viable, FDA-compliant non-invasive glucose monitoring systems.

1. Introduction

The blood glucose concentration level is kept under observation using a blood glucose monitoring device [1], Usually, diabetic people use such device to track their blood glucose level all day to enable them to comprehend the behavior of the blood concentration depending on food consumption and exercise as figure (1).

Fig. 1. The glucose meter [1].

Usually, as can be seen, blood glucose readings are taken with a glucose meter, to perform this test, the user must draw their blood and apply it to the test-strip. The glucose meter must be inserted with this test strip to obtain the reading. Basically, many different manufacturers create this standard glucose meter using a similar technique whereby most systems measure the electrical characteristic of the voltage output from the biosensor or test-strip passing a filter mechanism to enhance the signal for a better voltage to blood glucose concentration conversion.

Diabetes mellitus is a heterogeneous group of metabolic diseases involving impaired glucose homeostasis caused by insulin secretion or insulin action dysfunction. This implies that the human body either produces low levels of insulin or the body's cells use insulin poorly, leading to chronic high blood sugar levels. Diabetes mellitus is primarily classified into three main types: T1D, T2D, and GDM or PDG. [2] Type 1 Diabetes (T1D), [3] Type 2 Diabetes (T2D), and Gestational Diabetes Mellitus [4] (GDM), as figure 2.

Fig. 2. Different types of diabetes [39].

T1D is an autoimmune disease in which the body's immune system destroys the insulin-producing beta cells in the pancreas and eliminates or virtually eliminates insulin production. [5,6].

The lack of insulin, which has a social role in maintaining proper levels of blood glucose, requires insulin administration throughout her life to maintain blood glucose levels and avoid serious consequences such as the development of diabetic ketoacidosis [7,8]. T1D is known to develop in childhood and adolescence, but it can develop at any age as well. [9-11]. Nevertheless, T2D stands for more than 85% of diabetes cases and develops due to insulin resistance. However, the insulin sensitivity of the cells decreases in this condition; therefore, the pancreas secretes more insulin for the glucose to be retained at normal concentrations. However, if one's body constantly requires more insulin, the pancreas eventually may not be able to produce enough to meet this need, and blood sugar levels rise. It is well associated with obesity, with physically inactive and unhealthy diets that result in insulin intolerance [12]. GDM is diagnosed during pregnancy in women who did not have diabetes before pregnancy, presenting high blood sugar levels, usually in the second or third trimester. GDM typically manages at the birth of a child, but it exposes the woman to developing T2D in the future and pregnancy complications, including high birth weight and preterm labor. In addition, the children, who have been born to those mothers with GDM, they too are likely to develop diabetes in their lifetime [13].

Essential health assessments include general health check-ups and guided diabetic health screenings because diabetes mellitus is fast becoming an epidemic. Globally attributed to bad lifestyles, poor diets, and high populations of obesity. Screenings are necessary because about 70% of people with diabetes still go undiagnosed for years, and, in most cases, their T2D is ignored in its initial stages. There is evidence that a large number of people can have preclinical or latent diabetes for a few years, and by the time they developed symptoms of the diseases, they may have complications in the form of cardiovascular diseases, neuropathy, or kidney damage, among others [14]. Screening tests include fasting blood glucose tests, which test glucose levels in the blood once the patient has abstained from eating for at least 8 hours. Waist circumference measurements are another important one because these values reflect the distribution of the fat in the bodies, which is known to be a significant threat for occurring insulin resistance and Type 2 Diabetes [15-17], Store accurate information and non-invasive methods of blood glucose monitoring [1] [18], have come out as major footnotes in diabetes treatment since they pose discomfort, inconvenience, and potential complications with invasive methods such as finger-prick tests. These non-invasive systems are hoped for to offer simpler and easier methods as well as a more comfortable experience to those being diabetic and enable more effective compliance of the disease management. As highlighted in the literature, different innovative practices have been proposed in this area. An example of a well-developed technology is spectroscopy-based systems that determine glucose levels by studying the reaction of tissue to light, figure (3).

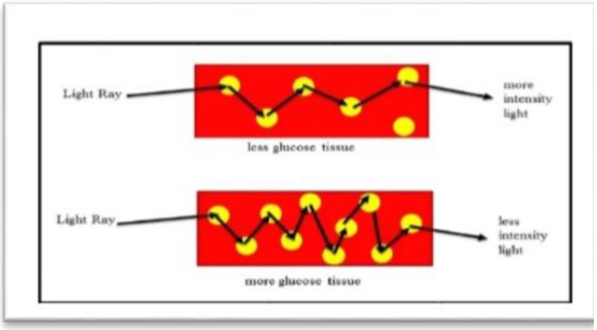

Fig. 3. Effect of glucose on the light path and intensity [39].

such systems have high benefits since they do not often need calibration as the usual glucose meters' do and meet the glucose measurements' MARD of 14.5%, indicating a favorable direction in increasing use convenience without hindering importance and reliability. Another promising concept is the devices that are based on near-infrared (NIR) technology and enhanced by complex linear regression models [19].

The ability to use near-infrared light to penetrate the skin to obtain glucose readings improves the usability factor in the device because while the light is deeply penetrating, it is not painful to the user, and the readings that are taken are highly accurate [20]. Moreover, other photonic systems, which involve the use of novel sensor technologies, are also being considered. These systems make use of the principles of optical functioning to deliver constant glucose readings without the use of the needles, thereby enhancing the ease with which the systems can be used by the users, especially those who are unable to withstand the discomfort of constant blood glucose testing [21, 22]. Moreover, the recent innovation that has the potential to sense glucose in the deeper skin layers, where tissue blood content is higher, is the depth-gated mid-infrared optoacoustic sensor (DIROS). The operation principle of this technology is to reduce interference from the upper layers of the skin, which may distort the measurement results in other non-contact techniques, which allows obtaining more accurate readings [23].

Altogether, these innovations describe a revolution in the approach to glucose availability, giving an individual lots of painless, easy, and efficient ways of checking glucose levels, which can bring long-term change and enhanced adherence to the glucose-checking routines and an improved quality of life to those with diabetes [24], A non-invasive blood glucose measurement and monitoring system utilizing deep learning substantially advances sustainable growth in multiple aspects.

The integration of artificial intelligence and machine learning advances the creation of accurate and efficient medical technology, hence enhancing healthcare quality. The suggested system enhances the quality of life for diabetes patients by offering a secure and convenient means of monitoring blood glucose levels without traditional intrusive methods, thus alleviating everyday discomfort. Secondly, the implementation of a non-invasive technology diminishes medical waste produced by traditional equipment such as needles and lancets, so promoting environmental sustainability.

This corresponds with the third Sustainable Development Goal (SDG) of achieving optimal health and well-being through the promotion of illness prevention and enhancement of public health. Moreover, these advances enhance economic sustainability by reducing healthcare expenses related to diabetes management and its complications. This can improve access to healthcare services in underprivileged and resource-constrained populations, so advancing the tenth Sustainable Development Goal of mitigating economic and social inequalities.

The research integrates technical advancement with sustainable development by improving public health, reducing environmental impact, and fostering social and economic fairness

1.1 Research contributions and novelty

Though there have been many advances in the domain of 'non-invasive blood glucose monitoring' a systematic and comparative assessment of the most recent discoveries in spectral analysis bioimpedance and AI-driven approaches is yet absent,

In this study differs from earlier research in that is:

- Offering a thorough evaluation approach methodically classifying and assessing several non-invasive glucose monitoring systems
- Emphasizing the way artificial intelligence and deep learning combine to increase precision of sensors and glucose prediction, therefore overcoming important constraints in previous research
- Talking about frequently disregarded clinical and regulatory issues influencing the implementation of non-invasive blood sugar monitoring devices affects their deployment
- Providing a road map for further studies involving adaptive artificial intelligence models multimodal sensor integration and

real-time glucose monitoring with using internet of things (IoT)

For bridging gaps in the literature and delineating unambiguous research directions for enhancing non-invasive glucose monitoring technology, this work acts as a reference for researchers and industry experts.

2. Methodology

This study guarantees a reliable as well as in-depth examination of new technologies by means of a strict and comprehensive approach to investigate developments in non-invasive watching for blood sugar levels. (Fig 4). Emphasizing spectroscopy-based investigation, biological items impedance-based indicators, and artificial based on intelligence approaches, the research procedure consisted of the recognition of research papers submitted to reviewed by expert's publications, proceedings from seminars, and brand names given between 2014 and 2024. To ensure a broad spectrum of works, literature was gathered from credible professional and academic records including IEEE Xplore, PubMed, Science Direct, Springer Publishers, and the Google Scholars.

Leading the search process were defined keyword combinations like non-invasive blood sugar evaluation, spectroscopy-based sugar sensing, bio capacitance glucose estimation, machine learning algorithms for monitoring of glucose, and detectors used on the human body for diabetes management. Articles were carefully filtered and selected based on their relevance, impact factor, citation frequency, and compliance with experimental validation standards.

The studies included in this review were selected based on several essential criteria Table (2), research that introduced or evaluated non-invasive glucose monitoring techniques Table (3), incorporated artificial intelligence, spectroscopy, or bio impedance methodologies, and provided validated experimental results was prioritized.

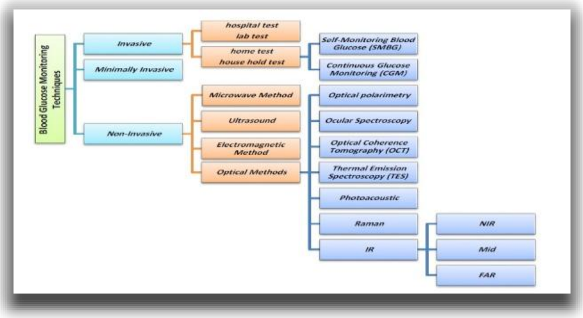

Fig. 4. Blood glucose monitoring techniques: A classification graph [37].

Studies published in peer-reviewed journals and reputable conference proceedings during the designated period were included to ensure scientific rigor. Conversely, research focusing solely on invasive glucose measurement techniques, lacking experimental validation, or relying entirely on theoretical modelling without practical implementation was excluded. Additionally, non-English publications and studies without full-text availability were not considered to maintain consistency in the evaluation process. To systematically compare and assess the selected studies, several performance indicators were analysed.

These included the accuracy and sensitivity of glucose estimation relative to traditional invasive methods, the technological feasibility of the proposed solutions for clinical deployment, and the level of user convenience in terms of device portability and invasiveness To ascertain the possibility for actual use, the evaluation also took regulatory standard compliance—that of the FDA and ISO—into account Research employing artificial intelligence employed the root mean square error, mean definitive error in percentage, and value of tenacity among other evaluation metrics to evaluate machine learning algorithms for glucose level prediction Studies were assessed according to their data pre-processing techniques, choice of characteristics methods, and model training approaches, thereby assuring an in-depth understanding of how artificial intelligence aids non-invasive glucose monitoring improvements,

The methodologies, key findings, and limitations of each inquiry were methodically compiled using a consistent data collection process Comprehensive statistical analysis was conducted to discern trends, correlations, and patterns among several non-invasive glucose monitoring systems, the systematic and methodical methodology guarantees an unbiased and thorough assessment of modern glucose monitoring devices, therefore offering a crucial insight into their viability and relevance, this work seeks to provide insightful analysis of these data, therefore guiding the future trajectory of non-invasive glucose monitoring and promoting ongoing advancements in diabetes management and medical technology.

3. Related Studies

A non-invasive measuring and monitoring blood glucose system has witnessed significant advancements, as numerous studies confirmed that discussed inventions with diverse techniques in this field can help to improve the type of test and the monitoring accuracy. From the figure (4), can understand the types of Blood Glucose Monitoring Techniques,

In 2014, Dantu et al. developed a non-invasive blood glucose monitoring system using a smartphone, their contributions include an enhancement to the Beer-Lambert law through the integration of multiple wavelengths thereby improving the applicability of optical spectroscopy additionally, they introduced a cost-effective solution for glucose monitoring using a smartphone biosensor system facilitating real-time glucose measurement without the need for conventional glucose meters [25]

In 2015, J. Yadava et al. reviewed the prospects and challenges of NIRS-based glucose monitoring their study emphasized the necessity of a non-invasive affordable and reliable device for frequent glucose monitoring the authors examined various glucose measurement techniques and elaborated on the potential of NIRS while also discussing the limitations and technical challenges in developing accurate non-invasive system [26].

In 2016, S.H. Ling et al. proposed a hypoglycemia monitoring system for Type 1 Diabetes Mellitus (T1DM) patients using an extreme Learning Machine (ELM) algorithm their system utilized physiological parameters extracted from ECG signals demonstrating promising results in detecting hypoglycemia, clinical trials with pediatric T1DM patients showed that the ELM-based algorithm effectively identified hypoglycemia highlighting its potential for real-time non-invasive monitoring [27].

In 2017, S-G. Oh et al. introduced a non-invasive approach for visualizing mast cell recruitment and evaluating its impact on lung cancer growth using optical imaging and glucose metabolism analysis , their methodology combined in vivo optical imaging with 18F-FDG PET scans revealing a correlation between mast cell recruitment and increased glucose up take which may have implications for glucose monitoring technologies[28].

In 2018, C. Trondstad et al. investigated a multi-sensor case-based reasoning (CBR) system integrating NIR spectroscopy bioimpedance and skin temperature analysis to predict glucose trends in T1DM patients , their findings suggested that bioimpedance provided the most predictive value among the tested methods supporting the idea that sensor fusion can improve non-invasive glucose monitoring [29].

In 2019, J.Y. Chen et al. demonstrated that incorporating button contact pressure into Mid-Infrared (Mid-IR) spectroscopy significantly improved glucose measurement accuracy, so their system achieved more than 95% accuracy meeting FDA requirements and presenting a viable alternative to traditional glucose meters [30].

In 2020, M. Gusev et al. explored the integration of machine learning (ML) with neural networks (NN) with heart rate variability (HRV) analysis for glucose monitoring, their research highlighted the potential of wearable ECG sensors to track autonomic dysfunction in diabetes patients though challenges such as high implementation costs remain [31].

In 2021, S.S. Gupta et al. developed a miniaturized PPG-based system to contactless glucose monitoring, integrating red, green, and infrared LEDs, which their machine learning approach using the XGBoost regressor, showed strong statistical and clinical accuracy, However, challenges in signal consistency and portability require further improvements [32].

In 2021, Y. Yao et al. introduced a flexible wearable glucose sensor utilizing interstitial fluid sampling and a G/CNTs/GOx composite electrode tested on porcine and human skin which the sensor demonstrated high sensitivity and accuracy comparable to invasive methods offering a promising solution for continuous glucose monitoring [33].

In 2021, H.V. Dudukcu et al. employed a fusion of deep learning Networks-Long Short-Term Memory (LSTM) wavenet which gated recurrent unit (GRU)—for blood glucose prediction, their approach outperformed baseline models demonstrating the potential of deep learning in diabetes management [34].

In 2022, M. Valero et al. designed a non-invasive prototype using near-infrared laser technology and a Raspberry Pi-based imaging system despite limitations in accuracy (79% for finger-based and 62% for ear-based measurements), their work underscored the feasibility of affordable, non-invasive glucose monitoring solutions [35].

In 2022, C.-T. Yen et al. combined dual-wavelength PPG with bio-electrical impedance for glucose monitoring, the system achieved high clinical accuracy (R^2 = 0.997) demonstrating the efficacy of multimodal sensing with machine learning integration [36].

In 2023, H. Zheng et al. compared five glucose screening devices and identified Mid-IR and NIR spectroscopy as the most viable for non-invasive applications validating their effectiveness through case studies [37].

In 2023, A. Ahmed et al. explored AI-driven predictions of blood glucose levels using wearable devices (WDs), their machine learning models achieved RMSE values between 0.099 and 0.197, showing potential for real-time, non-invasive glucose monitoring [38].

In 2023, Bader et al. developed an IoT-enabled glucose monitoring system using near-infrared sensors which their regression models trained on data from 54 diabetic patients achieved 85% accuracy with 55% of readings classified as clinically accurate (Region A of the Clarke Error Grid) [39].

In 2023, Huda et al. developed a non-invasive blood glucose monitoring system using near-infrared (NIR) spectroscopy, based on light scattering and absorption concepts, the system measured glucose levels using a photodetector (FDS100) and a 940 nm LED. With 55% of values categorized as clinically correct (Section A of the

Clarke Errors Grid), a model of regression trained on information collected from 55 diabetes patients—21 females, 34 men—achieves 85% accuracy. The system includes IoT features to track glucose real-time via WiFi and Thing Speak, therefore enhancing remote monitoring and diabetes control [40]

In 2024, A. Kandwal et al. reviewed microwave radiation for continuous glucose monitoring discussing sensor power consumption, accuracy, and user safety concerns, they proposed a multidisciplinary approach to further develop this technology [41].

In 2024, X . Huang et al. compared CNN, LTF, LSTM-A , and BiLSTM for glucose level prediction using physiological signals finding BiLSTM to be the most effective in extracting meaningful features for accurate monitoring [42].

In 2024 , L. Z. Chee et al . employed a CNN-LSTM model to analyze gait patterns for diabetes diagnosis, their system achieved 91.25% accuracy, suggesting a novel application of gait analysis in diabetic screening.[43].

In 2024 , N. Uluç et al. introduced a depth-gated mid-infrared optoacoustic sensor (DIROS) for direct blood glucose measurement improving accuracy by minimizing interference from upper skin layers [44].

In 2024, K . Putra et al. developed an advanced cnn-based model for non-invasive glucose, which that tracking integrating random oversampling to address data imbalance issues in the deep learning applications [45].

In 2024, Goktas et al. designed a capacitive glucose monitoring system using sliding window-based on the algorithm offering a fast cost-effective and scalable alternative to traditional methods [46].

In 2024 , Martins et al. conducted a review on non-invasive optical and microwave sensors for glucose monitoring, discussing hybrid sensor systems as a pathway to future improvements in-accuracy[47].

In 2024, Naresh et al. introduced a dual wavelength short NIR technique with machine learning for non-invasive glucose estimation achieving clinically acceptable - error margins with 99% accuracy in classification [48].

In 2024, Sameera et al. validated a dual-wavelength NIR system for diabetes diagnosis achieving a mean absolute percentage error (MAPE) of 5.99%, supporting its potential for clinical-adoption[49].

In 2024, zhang et al. introduced a nickel oxide-decorated biochar sensor for detecting glucose in saliva samples ,their sensor demonstrated high sensitivity (228.17 μA/mM/cm²) and selectivity presenting a potential alternative to blood-based monitoring.[50].

In 2024, Feng and Ling implemented a quaternion-valued LSTM neural network for glucose estimation using multi-channel PPG signals achieving high accuracy through biologically interpretable feature extraction [51],

for Comparative analysis of different non-invasive blood glucose monitoring technologies See Table 1 and table 2.

Table 1. Performance metrics and accuracy comparison for various deep learning models used in glucose monitoring, based on literature review.

	Year	Method	Technology	Result	Notes
[25]	2014	Non-invasive blood glucose monitoring using smartphone	Smartphone-based optical spectroscopy	Improved Beer-Lambert law by adding multiple wavelengths; developed smartphone non-invasive biosensor system for glucose monitoring	Inexpensive and noninvasive method, benefiting diabetic patients
[26]	2015	Review of glucose monitoring techniques	NIRS-based noninvasive glucose monitoring system	Highlighted potential and challenges of non-invasive glucose measurement using NIRS	Need for cheap, small, and painless devices for frequent blood testing
[27]	2016	Creation of non-invasive hypoglycemia monitoring system for Type 1 diabetes	Extreme learning machine (ELM) based on ECG signals	Showed good performance in detecting hypoglycemia in children with Type 1 diabetes	Improved real-time monitoring of hypoglycemia
[28]	2017	Visualization of mast cell recruitment and lung cancer growth	Optical reporter gene imaging and glucose metabolism analysis	Enhanced tumor growth and glucose uptake due to mast cell attraction	Demonstrated the relationship between mast cells and tumor microenvironment
[29]	2018	Prediction of blood glucose fluctuation during hypoglycemia	Multisensor CBR system with NIR spectroscopy, bio impedance, and skin temperature	Bio impedance was most predictive of NIR spectroscopy; challenging to predict glucose levels during hypoglycemia	Proposed integration of sensor modalities for effective non-invasive glucose trend prediction

[30]	2019	High accuracy non-invasive glucose monitoring	Mid-IR spectroscopy	Achieved 95% accuracy with the inclusion of button contact pressure	First FDA-compliant portable non-invasive glucose meter
[31]	2020	Non-invasive glucose measurement using machine learning and heart rate variability (HRV)	Wearable ECG sensors and neural networks	Correlated heart rate data with glucose levels; identified challenges like cost and patient adoption	Potential for real-time glucose monitoring with AI and nanotechnology advancements
[32]	2021	Miniaturized PPG system for contactless blood glucose (BG) measurements	PPG with reflective and transmissive configurations (Red, Green, IR LEDs)	Machine learning (XGBoost) showed excellent BGL estimation, tracking heart rate (HR), oxygen saturation (SpO_2)	Potential for future wearable systems; signal consistency and portability need improvement
[33]	2021	Flexible, wearable non-invasive glucose sensor	Interstitial fluid sampling using reverse iontophoresis with G/CNTs/GOx composite	Accurate glucose readings comparable to invasive meters; portable and non-intrusive	Tested on porcine, mouse, and human skin; potential for public use with further enhancements in usability
[34]	2021	Blood glucose prediction using deep learning	Long short-term memory (LSTM), WaveNet, and GRU networks	Demonstrated robust performance in predicting blood glucose levels	Highlighted future potential for deep learning in healthcare
[35]	2022	Non-invasive blood sugar monitoring prototype	Near-infrared laser, Raspberry Pi, and neural network	79% accuracy for finger measurements, 62% for ear measurements	Prototype improvement needed with a larger dataset and refined design
[36]	2022	Dual-wavelength PPG combined with bioelectrical impedance	PPG and bioelectrical impedance with machine learning (BPNN)	R^2 of 0.997 and results in clinically accurate Region A of Clarke error grid	Combines PPG, bioelectrical impedance, and PCA with BPNN; proven highly accurate for non-invasive glucose monitoring
[37]	2023	Non-invasive glucose monitor methods	Comparison of CGM with AGP, mid-infrared, and near-infrared spectroscopy	Identified two non-invasive technologies as best for glucose screening	Case study emphasized importance of intelligent health monitoring and dynamic glucose inspection
[38]	2023	AI-assisted glucose prediction using wearable devices (WDs)	Off-the-shelf wearable devices (WDs) with AI prediction	RMSE ranging from 0.099 to 0.197; AI-based solution for BG level estimation with acceptable accuracy	Research highlighted potential of WDs for continuous non-invasive glucose monitoring
[39]	2023	Infrared-based Non-invasive Blood Glucose Measurement and Monitoring System	Near-infrared light	development of a non-invasive, portable device that uses an infrared sensor to measure glucose levels in the blood	development of a non-invasive, portable device that uses an infrared sensor to measure glucose levels in the blood
[40]	2023	Non-invasive blood glucose monitoring system using IoT	Near-infrared light and IoT	85% of predicted glucose levels acceptable; real-time monitoring possible via ThingShow app	Significant improvement for non-invasive glucose monitoring
[41]	2024	Review of microwave radiation for continuous glucose monitoring	Microwave radiation-based sensor technology	Identified major challenges in power consumption, sensor accuracy, and user comfort/safety	Collaborative multidisciplinary approach suggested for further development
[42]	2024	Pilot study comparing DL methods for interstitial glucose (IG) prediction	Wearable device (Empatica E4 wristband) with CNN, LTF, LSTM-A, BiLSTM	BiLSTM model exhibited the best performance with RMSE of 13.42 mg/dL and MAPE of 0.12	Correlation between physiological signals and IG level changes demonstrated potential for accurate predictions
[43]	2024	Gait analysis for diabetes diagnosis	CNN-LSTM deep learning algorithm	CNN-LSTM accuracy of 91.25% for diabetes diagnosis	Recommended wavelet activation functions for feature extraction; potential for early diagnosis

[44]	2024	Mid-infrared optoacoustic technology for blood glucose monitoring	Depth-gated infrared optoacoustic sensor (DIROS)	New method for non-invasive blood glucose measurement with improved accuracy and reduced time lag	DIROS aims for better accuracy in accessing blood glucose levels without direct access to blood, overcoming limitations
[45]	2024	Deep learning framework (CNN architecture)	Non-invasive PPG systems for continuous glucose monitoring	Improved predictive capabilities for glucose fluctuations in diabetic and non-diabetic populations	Used random oversampling to handle data imbalance; further research suggested to explore the potential of non-invasive systems
[46]	2024	Sliding window-based algorithm	Non-invasive capacitive glucose and nitrogen monitoring with Vector Network Analyzer (VNA) measurements	Fast, real-time, and inexpensive monitoring of glucose and nitrogen concentrations	Mica glass produced better results than urine containers; future work includes antenna optimization and enhanced deep learning techniques
[47]	2024	Non-invasive optical and microwave sensors	Raman, NIR, Microwave	Reviewed non-invasive glucose sensors using Raman and NIR spectroscopy, and microwave sensing. Optical and microwave techniques face issues like signal interference and tissue intimacy.	Hybrid sensor systems and AI may help improve the accuracy of glucose sensing for diabetes management.
[48]	2024	Non-invasive glucose prediction and classification	NIR with Machine Learning	Developed a dual-wavelength NIR system with a regression model using machine learning (feed-forward neural network). Achieved R^2 of 0.99 and MSE of 2.49 mg/dL, with 99% classification accuracy.	High accuracy in predicting glucose levels with machine classifiers (MLP and KNN).
[49]	2024	NIR-based optical methods	Dual-wavelength NIR system	Achieved 95.6% accuracy in predicting glucose levels with a MAPE of 5.99%. Demonstrated potential for clinical applications.	Focused on the clinical accuracy of NIR-based methods for non-invasive glucose monitoring.
[50]	2024	Electrochemical sensor for saliva analysis	NiO-decorated popcorn-derived biochar	Developed a NiO/PPC-A/GCE sensor with high sensitivity (228.17 $\mu A/mM/cm^2$), a broad linear range, and low detection limit.	Establishes a strong linear relationship between salivary and blood glucose, enabling non-invasive monitoring.
[51]	2024	Non-invasive glucose estimation using quaternion-valued features	Quaternion-valued LSTM Neural Network	Achieved MARD of 14.31%–14.41% and 81.43%-83.09% classification accuracy in Zone A of the Clark error grid.	Introduces quaternion-valued operations for improved accuracy in glucose estimation without needle use.

Table 2. Summary of key findings from reviewed studies on non-invasive glucose monitoring, including trends in accuracy and adoption.

Technology/Method	Studies	Count
AI (Artificial Intelligence)	[31], [34], [38], [41], [42], [44], [47], [50]	8
NIR (Near-Infrared Spectroscopy)	[26], [30], [35], [36], [37], [39], [46], [47], [48]	9
Machine Learning/Deep Learning	[27], [31], [34], [41], [42], [47], [51]	7
Mid-IR (Mid-Infrared Spectroscopy)	[30], [43], [48]	3
PPG (Photoplethysmography)	[32], [36], [44]	3
ECG (Electrocardiogram)	[27], [31]	2
Wearable Devices	[31], [32], [38], [41], [43]	5
IoT (Internet of Things)	[39]	1
Optical Technology (Optoacoustic, Optical)	[28], [43], [46]	3
Bioelectrical Impedance	[29], [36]	2
Electrochemical Sensors	[49]	1
Microwave Technology	[40], [46]	2
Raman Spectroscopy	[46]	1
Reverse Iontophoresis	[33]	1

4. Results and Discussion

The results of this review highlight the significant progress made in non - invasive blood glucose monitoring particularly in spectroscopy -based methods bioimpedance analysis and artificial intelligence-driven models, each of these approaches has shown potential in reducing patient discomfort while maintaining accuracy yet several challenges remain in achieving clinical viability, spectroscopy-based methods particularly those utilizing near-infrared and mid -infrared technologies have demonstrated promising capabilities in glucose estimation , some studies incorporating pressure-based enhancements have achieved accuracy levels nearing regulatory standards , however, these techniques are still limited by factors such as environmental interference variations in skin properties and frequent calibration requirements which can reduce their practicality in real- world settings Bio impedance analysis has emerged as an alternative approach leveraging the electrical properties of human tissue to estimate blood glucose levels research has shown that integrating additional physiological parameters such as skin hydration and temperature which can improve accuracy, however variations in individual tissue composition and the need for standardization present ongoing obstacles while bio impedance based techniques offer a less intrusive alternative further development is required to refine their precision and ensure consistent performance across diverse user, artificial intelligence and deep learning have played a crucial role in optimizing non-invasive glucose monitoring systems which that integration of AI with spectroscopy and bio impedance methodologies has yielded improved predictive performance with deep learning models such as Deep neural networks (DNNs) and long short-term memory (LSTM) networks demonstrating substantial enhancements in accuracy, (Table 3). Despite these advancements challenges persist in terms of data availability generalizability across different populations and the need for large-scale clinical validation before these systems can be widely adopted, ensuring the transparency and interpretability of AI-based predictions remains a priority to facilitate their acceptance in clinical practice , so, the integration of artificial intelligence, particularly deep learning algorithms, has significantly enhanced the accuracy and reliability of non-invasive glucose monitoring,

Table 3. Comparative analysis of non-invasive glucose monitoring technologies

Technique	Accuracy	Advantages	Limitations
Near-Infrared Spectroscopy (NIR)	80-90%	Non-invasive, widely studied, moderate cost	Affected by skin properties and hydration, requires frequent calibration
Mid-Infrared Spectroscopy (Mid-IR)	85-95%	Higher accuracy than NIR, deeper tissue penetration	High cost, sensitive to environmental conditions
Bio impedance Analysis	70-85%	portable, cost-effective, does not require optical calibration	Limited accuracy due to variations in tissue composition
Artificial Intelligence -Based Models (AI)	90-96%	highly adaptive, improves over time with more data	Requires large datasets, generalization across populations remains a challenge
Hybrid Multi-Sensor Approaches	+95%	combines several modalities for highest accuracy.	Complex implementation , higher computational requirements

Models such as Deep neural networks (DNNs) and recurrent neural networks (RNNs) enable more precise glucose estimation by reducing signal noise and adapting to physiological variations, additionally, multi-modal AI frameworks combining spectroscopy and bio impedance data improve accuracy through sensor fusion techniques mitigating environmental and biological variability and making AI-powered non-invasive monitoring a viable alternative to traditional methods, while significant progress has been made standardization remains a key challenge, the lack of uniform calibration methods and variations in device design across studies hinder the reproducibility of the results , additionally regulatory approval remains a considerable barrier as non-invasive glucose monitors must undergo rigorous clinical trials to validate their safety and effectiveness, future research should focus on the integration of multi-modal approaches that combine spectroscopy bio impedance and AI-driven analytics to maximize accuracy while minimizing external influences looking ahead the advancement of wearable sensor technology coupled with real-time data processing through IoT-enabled platforms , is expected to drive the next generation of non-invasive glucose monitoring systems so, development of adaptive AI algorithms capable of adjusting to individual variations in physiological responses will further enhance the reliability and usability of these technologies.

5. Conclusion

The advancements in non-invasive blood glucose monitoring, especially the merging of deep learning techniques with sensor-based approaches, reflect a major revolution in diabetes control, so, in this paper emphasizes how spectroscopy, bioimpedance, and AI-driven models could improve glucose estimate accuracy and lower patient pain, for those great advances, problems including environmental fluctuation, calibration difficulty, and finally, but not least regulatory approval still exist for increase dependability and clinical relevance, future studies should concentrate on multimodal sensor combination, adaptive artificial intelligence algorithms, and continuous evaluation through (IoT) integration, this translation of these breakthroughs into FDA-compliant, widely available, non-invasive glucose monitoring technologies that potentially transform diabetes treatment depends on multidisciplinary cooperation among engineers, healthcare practitioners, and regulatory authorities.

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