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Enhancing the Accuracy of Non-Invasive Blood Glucose Monitoring Using Deep Learning Methods

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ABSTRACT

Accurate blood glucose monitoring is crucial for diabetes management. Traditional invasive methods remain the gold standard due to their reliability; however, the demand for non-invasive alternatives has surged due to patient comfort and the necessity for continuous monitoring. This study bridges the accuracy gap between non-invasive and invasive blood glucose measurements using deep learning algorithms. An infrared-based sensor was employed to capture voltage variations correlated with blood glucose levels, collecting data from over 110 participants. Initially, a polynomial regression model achieved an accuracy of 83.5%. After expanding the dataset and incorporating additional biometric features (such as age, BMI, blood pressure, and family history), the enhanced deep neural network (DNN) model was optimized through hyper parameter tuning, significantly improving prediction accuracy to 96.85%. These results highlight the superiority of deep learning over traditional regression methods in refining non-invasive glucose measurements. The substantial reduction in measurement discrepancies suggests promising clinical applications. Beyond its technical contributions, this research aligns with the United Nations Sustainable Development Goals (SDGs), particularly in promoting good health and well-being and fostering innovation in healthcare technologies. By enhancing the accuracy of non-invasive glucose monitoring, this study advances the potential for cost-effective, patient-friendly diabetes management solutions, improving accessibility and reducing reliance on invasive procedures.

1. Introduction

Diabetes mellitus is a chronic metabolic disorder that disrupts the body's ability to regulate blood glucose levels [1], leading to severe health complications if left uncontrolled , the human body derives glucose primarily from carbohydrates [2], which are broken down during digestion into simple sugars that enter the bloodstream [3], as glucose levels rise, pancreatic beta cells release insulin, figure (1) a hormone essential for facilitating cellular glucose uptake and maintaining metabolic balance [4].

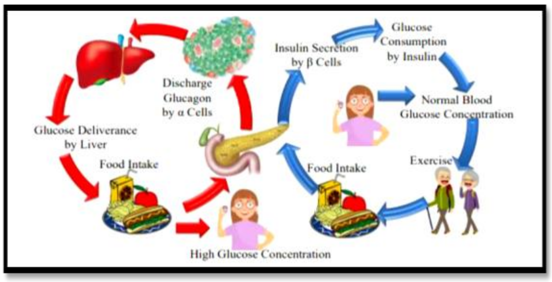

Fig. 1. The glucose meter [1].

In diabetes, this finely tuned system is impaired, either due to the autoimmune destruction of insulin producing beta cells T1D (Type 1 diabetes) or the gradual onset of insulin resistance and pancreatic dysfunction T2D (Type 2 diabetes), additionally, gestational diabetes mellitus (GDM) poses a significant risk during pregnancy, potentially leading to long-term metabolic disorders for both mother and child [5].

The burden of diabetes is escalating at an unprecedented rate. According to the International Diabetes Federation (IDF), over 537 million adults (10.5% of the population aged 20–79) were living with diabetes in 2021, a figure projected to reach 783 million by 2045, [6], this condition is not only a leading cause of cardiovascular diseases, kidney failure, neuropathy, and vision impairment, but also places a substantial financial burden on healthcare systems worldwide. Hypoglycemia occurs when blood glucose falls below 60 mg/dL while hyperglycemia is characterized by fasting glucose levels exceeding 120 mg/dL or postprandial levels above 180 mg/dL [7], [8]. Chronic hyperglycemia is associated with long-term damage to vital organs, further emphasizing the importance of continuous glucose monitoring [9], these alarming statistics underscore the urgent need for innovative and accessible monitoring solutions that enhance diabetes management and improve patient outcomes. Frequent blood glucose monitoring is a cornerstone of diabetes management, yet current methods remain invasive, uncomfortable, and costly. The traditional approach involves finger stick blood sampling or continuous glucose monitoring (CGM) systems, both of which require skin penetration, posing risks of pain, infection, and tissue damage [10], figure (2).

Fig. 2. *F*inger-prick testing (Blood Glucose Test) [22]

The reliance on such invasive technique's limits patient adherence, especially in resource-constrained settings, where access to advanced medical technologies is restricted. With the in-creasing demand for non-invasive, painless, and accessible alternatives, researchers have explored various technologies, including infrared spectroscopy, radiofrequency sensors, and ma-chine learning-based predictive models [11].

Despite significant advancements, the primary challenge remains accuracy—current non-invasive approaches struggle to match the precision of invasive methods due to physiological variations [12], limiting their clinical adoption. Therefore, developing more precise and reliable solutions is essential for bridging this accuracy gap. With the advancements in artificial intelligence, machine learning techniques have been widely explored for medical applications, this study investigates the application of deep learning to enhance infrared based non-invasive glucose measurement, to improve accuracy; by leveraging voltage variations detected via infrared sensors, a novel deep neural network (DNN) model was developed to refine glucose level predictions. This research aims to bridge the accuracy gap between non-invasive and invasive glucose measurement techniques, thereby enhancing the feasibility of non-invasive solutions for wide-spread clinical application. The proposed approach aligns with global healthcare innovation efforts and has the potential to improve diabetes management by offering a cost-effective, pain-free alternative to conventional glucose monitoring systems. Beyond its technical innovations, this research contributes to the United Nations Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-being) and SDG 9 (Industry, Innovation, and Infrastructure). By improving the accuracy of non-invasive glucose monitoring, this study establishes a strong foundation for future clinical applications. The proposed system has the potential to revolutionize diabetes management by enabling real-time, cost-effective, and pain-free glucose measurement, paving the way for its integration into next generation wearable medical devices as a clinical standard.

2. Related Work

The field of non-invasive blood glucose monitoring has undergone significant advancements in the past decade, with researchers exploring various methodologies to enhance accuracy and reliability. This section presents a chronological review of key contributions in this area.

In 2014, Dantu et al. created a smartphone-based device that performs non-invasive blood glucose monitoring functions. The Beer-Lambert law applied through multiple wavelengths in-creased the accuracy of optical spectroscopy tests for glucose measurements [13].

In 2015, Yadava et al. also stated the need for developing a non-invasive, affordable and dependable glucose monitoring device using near-infrared spectroscopy (NIRS). The research identified major barriers in current techniques through specific assessments of their current methodological restrictions [14].

In 2016, Ling et al. demonstrated a hypoglycemia detection system through Type 1 Diabetes Mellitus (T1DM) patients using Extreme Learning Machine (ELM) algorithm techniques. Real-time non-invasive hypoglycemia monitoring proved successful using the system which extracted ECG signals to produce physiological data [15].

In 2018, Trondstad et al. developed a multi-sensor case-based reasoning (CBR) system which unite NIRS technology with bioimpedance along with skin temperature evaluation to evaluate glucose patterns in Type 1 Diabetes Mellitus (T1DM) patient groups. Bioimpedance proved to be the most effective sensor-based prediction method according to their research thus demonstrating that sensor fusion approaches improve noninvasive glucose detection [16].

In 2019, Chen et al. introduced a Mid-Infrared (Mid-IR) spectroscopy system that used button contact pressure to improve the accuracy of glucose measurements. This system achieved an accuracy rate of over 95%, meeting FDA standards, and offered a promising alternative to traditional glucose meters [17].

In 2021, Gupta et al. developed a miniaturized photoplethysmography (PPG)-based system for contactless glucose monitoring. Their machine learning approach, utilizing the XGBoost regressor, demonstrated strong statistical and clinical accuracy. However, challenges in signal consistency and portability remained [18].

In 2021, Dudukcu et al. also employed a fusion of deep learning networks, including Long Short-Term Memory (LSTM), Wave net, and Gated Recurrent Units (GRU), for blood glucose prediction. Their approach outperformed baseline models, demonstrating the potential of deep learning in diabetes management [19].

In 2022, Yen et al. introduced a multimodal glucose monitoring system that combined dual-wavelength PPG with bio-electrical impedance analysis. Their system achieved high clinical ac-curacy ($R^2 = 0.997$), proving the efficacy of sensor fusion with machine learning integration [20].

In 2023, Ahmed et al. explored AI-driven predictions of blood glucose levels using wearable devices. Their machine learning models achieved root mean square error (RMSE) values between 0.099 and 0.197, indicating strong potential for real-time, non-invasive glucose monitoring [21].

In 2023, Huda et al. also developed a non-invasive blood glucose monitoring system based on NIR spectroscopy, using a 940 nm LED and a photodetector (FDS100). Their regression model, trained on data from 55 diabetic patients, achieved an accuracy of 85%, with 55% of readings classified as clinically accurate. The system incorporated IoT features for real-time glucose tracking via WiFi and ThingSpeak, enhancing remote diabetes management [22].

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) [23].

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 [24].

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 [25].

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 $\mu A/mM/cm^2$) and selectivity presenting a potential alternative to blood-based monitoring [26].

Table 1 presents a structured comparison of major advancements in non-invasive glucose monitoring over the past decade. It highlights the evolution of sensing methodologies, from traditional spectroscopy to AI-powered predictive models, showcasing key improvements in measurement accuracy and real-time monitoring capabilities.

Table 1. Summary of key studies in non-invasive glucose monitoring

	Ref.	Year	Methodology	Accuracy/Key Findings
1	[13]	2014	Smartphone-based biosensor with multi-wavelength integration	Improved Beer-Lambert law application for enhanced optical spectroscopy reliability
2	[14]	2015	Review of NIRS-based glucose monitoring	Identified major limitations and technical challenges in non-invasive glucose measurement
3	[15]	2016	Extreme Learning Machine (ELM) applied to ECG-based glucose monitoring	Effective real-time hypoglycemia detection in T1DM patients
4	[16]	2018	Multi-sensor fusion system integrating NIRS, bioimpedance, and skin temperature	Bioimpedance provided the highest predictive value for glucose estimation
5	[17]	2019	Mid-IR spectroscopy with button contacts pressure integration	Achieved >95% accuracy, meeting FDA standards
6	[18]	2021	PPG-based contactless glucose monitoring using XGBoost	High clinical accuracy but faced signal consistency challenges
7	[19]	2021	LSTM, WaveNet, and GRU-based deep learning glucose prediction	Outperformed baseline models, demonstrating deep learning potential
8	[20]	2022	Dual-wavelength PPG combined with bio-electrical impedance analyses	Achieved R^2 = 0.997, proving efficacy of multimodal sensing
9	[21]	2023	AI-driven blood glucose prediction using wearable devices	RMSE between 0.099 and 0.197, demonstrating high prediction accuracy
10	[22]	2023	NIR spectroscopy-based glucose monitoring with IoT integration	85% accuracy, real-time glucose tracking via WiFi and ThingSpeak
11	[23]	2023	Infrared-based Non-invasive Blood Glucose Measurement and Monitoring System	development of a non-invasive, portable device that uses an infrared sensor to measure glucose levels in the blood
12	[24]	2024	NIR with Machine Learning	High accuracy in predicting glucose levels with machine classifiers (MLP and KNN).
13	[25]	2025	Dual-wavelength NIR system	Focused on the clinical accuracy of NIR-based methods for non-invasive glucose monitoring.
14	[26]	2025	NiO-decorated popcorn-derived biochar	Establishes a strong linear relationship between salivary and blood glucose, enabling non-invasive monitoring.

While significant advancements have been made in non-invasive glucose monitoring, persistent challenges related to measurement precision, inter-patient variability, and sensor calibration hinder widespread clinical adoption. To address these difficulties, the submitted approach combines Deep Neural Networks (DNN) with second-degree Poisson regression models. To develop a dependable non-invasive glucose monitoring system, the technique aims to obtain greater glucose measuring accuracy coupled with less invasive reference deviations.

3. Methodology

Infrared-based spectroscopy was used in design and implementation of the proposed non-invasive blood glucose monitoring system.

Selected for best penetration into biological tissue and to minimize interference from water and other macromolecules, the device uses an infrared LED running at 940 nm. This wavelength allows efficient identification of changes in optical absorption brought about by glucose, following Lambert-Beer's Law:

$$A = \varepsilon l c \quad (1)$$

where:

(A) is the absorbance,
(ε) is the molar absorptivity coefficient,
(l) is the optical path length,
(c) is the glucose concentration in the blood.

A photodetector was placed opposite the infrared source to measure transmitted light intensity, converting the signal into an electrical voltage that corresponds to glucose concentration variations as shown in figure (3).

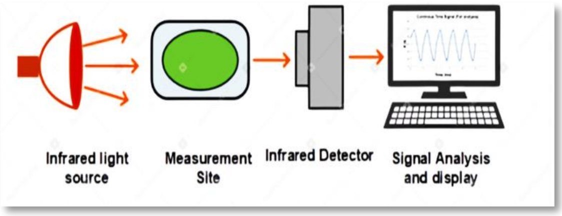

Fig. 3. Schematic representation of the infrared-based glucose measurement system

Studies chose the 940 nm wavelength because it provides suitable penetration depth which permits its passage through skin layers to measure blood within capillaries. Its restricted engagement with water molecules and biological compounds leads to decreased background interferences that leads to enhanced signal quality during measurements. Wavelength 940 nm stands as one of the most favorable options for non-invasive glucose monitoring based on previous scientific findings and the reason this study chose it as appropriate.
As shown in Figure (3), the schematic diagram illustrates the fundamental operation of the infra-red-based glucose measurement system. The infrared light passes through the fingertip, and the photodetector receives the transmitted signal, which varies with glucose concentration due to absorption characteristics. This setup forms the basis for voltage signal collection in our model

3.1. Hardware implementation

The hardware components of the proposed system include Infrared LED (940 nm) as the primary light source, infrared photodetector to capture transmitted light intensity, Arduino Nano microcontroller to process the signals, Bluetooth module for wireless data transmission, and LCD display (I2C-based) for real-time glucose level visualization.
The hardware components were selected based on cost-effectiveness, accuracy, and portability, making the system scalable for future clinical deployment.

Figure (4), presents a block diagram of the complete hardware setup for the proposed system, illustrating the flow of signal acquisition from the infrared LED through the photodetector to the Arduino Nano microcontroller, which manages data transmission via Bluetooth and visualization through the LCD screen.

This structured integration ensures the system's applicability for continuous, non-invasive diabetes management.

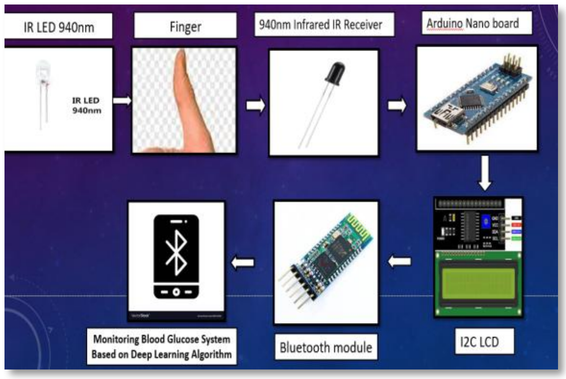

Fig. 4. Block diagram of the proposed non-invasive blood glucose monitoring system.

3.2. Data collection & pre-processing

- The dataset consisted of 110 participants (62 males and 48 females) collected from multiple certified medical centers.
- The age of participants ranged from 22 to 65 years, based on clinical records and glucose levels.
- Approximately 70% were type 2 diabetics, while 30% were newly diagnosed or borderline cases without insulin therapy.
- This demographic spread ensures sufficient representation across different age brackets and diabetes severities, enhancing the model's generalizability.
- Each participant underwent simultaneous invasive and non-invasive glucose readings.
- Invasive Glucose Readings: Measured using a clinically approved glucose meter (Accu-Chek) for accurate reference values.
- Non-Invasive Voltage Readings: Captured using the infrared sensor system, where voltage variations were recorded and correlated with invasive glucose levels.
- Pre-processing Steps: Outlier Detection: Z-score analysis was applied to remove anomalous readings.
- Signal Calibration: Voltage readings were adjusted for environmental variations.
- Data Normalization: Min-max scaling was used to ensure uniformity across participants.
- Gender-Based Polynomial Regression: Data was categorized by gender to account for physiological differences, leading to separate mathematical models for males and females.

3.3. Ensuring dataset balance and bias detection

To ensure the robustness of the model, dataset distribution was analyzed across different demographics. The dataset was balanced to ensure that gender, and age groups were adequately represented, reducing potential biases that could affect model generalization.

3.4. Mathematical and deep learning model

Polynomial Regression for Initial Estimation, second-degree polynomial regression model was used to establish the initial relationship between sensor voltage and blood glucose as shown in figure (5):

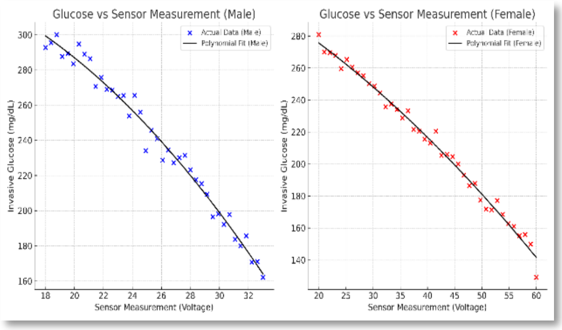

Fig. 5. Polynomial regression analysis for male and female participants, illustrating the relationship between sensor voltage and invasive glucose measurements.

$$y = ax^2 + bx + c \quad (2)$$

where:
(y)is the estimated blood glucose level,
(x) is the voltage reading from the sensor,
(a,b,c) are regression coefficients derived via least squares fitting.
The polynomial regression equations obtained for males and females were:

Males:

$$y = 0.2217x^2 - 4.459x + 121.824 \quad (3)$$

Female:

$$y = -0.0153x^2 + 5.4295x - 3.166 \quad (4)$$

3.5. Deep Neural Network (DNN) Model

To enhance glucose estimation accuracy, a Deep Neural Network (DNN) model was implemented. Unlike polynomial regression, which assumes a fixed mathematical relationship, DNN is capable of capturing nonlinear dependencies between glucose concentration and input features. By incorporating biometric data (age, BMI, blood pressure, and family history), the model adapts to individual variations, leading to more precise glucose level predictions figure (6).
The model architecture consisted of:
• Input Layer: Sensor voltage (non-invasive Measuring) + Biometric Parameters (age, BMI, blood pressure, family history).
• Hidden Layers: The deep neural network (DNN) consisted of four fully connected hidden layers.
• The ReLU (Rectified Linear Unit) activation function was employed in each layer to introduce non-linearity, allowing the model to learn complex relationships in the dataset while preventing gradient vanishing problems.
• Output Layer: A single neuron predicting blood glucose levels.

Figure (6) presents a flowchart illustrating the operational sequence of the proposed deep learning algorithm for non-invasive glucose prediction. The flow begins with signal acquisition via an infrared sensor, followed by signal pre-processing steps such as noise filtering and normalization. Biometric parameters including age, BMI, blood pressure, and family history are then integrated into the input. These features are passed through a multi-layered Deep Neural Network (DNN) architecture, resulting in a final prediction of the blood glucose level. This visual representation complements the model description and highlights the modular nature of the system's workflow.

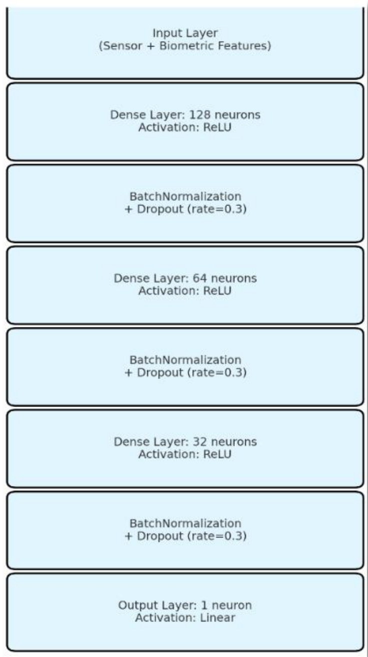

Fig 6. Flowchart of the proposed DNN-based non-invasive glucose prediction mode,

3.6. Optimization of DNN model

The DNN model struggled to generalize over varied patient data and first only attained 71.9% accuracy. Mostly, poor feature representation and inadequate network architecture caused this underperformance. Several important changes were made to help to solve these problems:

3.6.1. feature engineering: integrating additional biomarkers

The model included age, Body Mass Index (BMI), blood pressure, and family history of diabetes among other biometric traits. These characteristics were chosen because they clearly relate to glucose metabolism:

- **Age**: Affects insulin resistance and glucose tolerance.
- **BMI**: Associated with metabolic disorders and increased diabetes risk.
- **Blood Pressure**: Influences vascular function and glucose transport.
- **Family History**: A strong genetic predictor of diabetes susceptibility.
- **Effect of this modification**: The model's accuracy improved to 83.2%, as it became more adaptive to individual physiological differences.

3.6.2. increasing network depth

Expanding Hidden Layers: The number of hidden layers was increased from 2 to 4, with an optimized neuron distribution. The deeper network allowed for a better representation of the complex nonlinear relationships between sensor voltage and blood glucose levels. Effect of this modification: The accuracy increased to 88.7%, particularly improving predictions for extreme glucose variations.

3.6.3. hyper parameter tuning

Optimizing Learning Rate and Switching to Adam Optimize: the learning rate and optimization strategy were adjusted for improved convergence. The Stochastic Gradient Descent (SGD) optimizer was replaced with the Adam optimizer, which adapts learning rates for different parameters and provides better stability. Effect of this modification: The model's performance improved to 92.5%, significantly reducing overfitting and enhancing generalization to new data.

3.6.4. hyper parameter tuning

Expanding Dataset and Enhancing Pre-processing, the dataset was expanded,
and improvements were applied to the pre-processing pipeline:

- Normalization Enhancement: Applied to ensure uniformity across samples and minimize bias.
- Noise Filtering: Improved signal clarity from infrared sensor readings by eliminating environmental disturbances.
- Effect of this modification: The model achieved better stability while the final accuracy measured 96.85% and Mean Square Error (MSE) reduced significantly.

The collection of refinements allowed the model to surpass traditional regression models in performance thus proving deep learning's potential for non-invasive blood glucose estimation. The system improvements solved important issues related to non-invasive glucose monitoring including physiological variability as well as signal noise and model generalization thus making the system more dependable in real-world use

3.7. Experimental validation and performance metrics

The model was trained and validated using an 80-20% split of the dataset. Performance was assessed using: Coefficient of Determination (R^2): Measures how well predictions align with actual values and Mean Squared Error (MSE): Evaluates prediction deviation, Table (2), figure (7).

Table 2. A comparative performance analysis of Polynomial Regression vs. Initial DNN vs. Optimized DNN

Model	Accuracy (R^2)	MSE
Polynomial Regression	83.5%	404.84
Initial DNN Model	71.9%	604.70
Enhanced DNN Model	**96.85%**	**402.44**

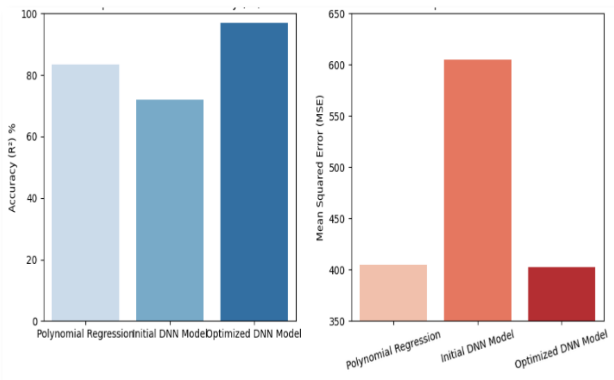

Fig. 7. A comparative performance analysis of Polynomial Regression vs. Initial DNN vs. Optimized DNN, highlighting improvements in accuracy (R^2) and reduction in MSE through deep learning optimization.

4. Results and Discussion

4.1. Performance evaluation of the proposed system

The performance of the proposed infrared-based non-invasive glucose monitoring system was assessed using both polynomial regression and deep learning approaches. The results indicate that while polynomial regression achieved an accuracy of 83.5%, the optimized Deep Neural Network (DNN) model significantly improved the prediction accuracy to 96.85%. Table (2) presents a comparative analysis of the different models employed in this study, the Polynomial Regression Model, despite achieving relatively high accuracy, exhibited higher prediction errors, particularly for subjects with rapid glucose fluctuations. The initial DNN model, with default hyper parameters and without feature optimization, underperformed with 71.9% accuracy and an MSE of 604.70. However, after incorporating feature engineering, network optimization, and hyper parameter tuning, the optimized DNN model demonstrated a significant improvement, outperforming traditional regression techniques, Fig (7) presents a comparative performance analysis of the models, showing accuracy (R^2) and MSE values across different methodologies

4.2. Impact of feature engineering on DNN performance

Feature engineering served as an essential practice which enhanced the accuracy of the DNN model. The model measured individual characteristics by adding biometric features which included age and BMI together with blood pressure and family medical history to understand physiological differences in glucose metabolism. The researchers chose these features because they strongly influence glucose regulation.

- **Age**: The age of a patient determines their insulin resistance and their reactions to glucose.
- **Body Mass Index (BMI)**: Associated with metabolic disorders and diabetes risk.
- **Blood pressure**: The condition of blood pressure affects both vascular function and glucose transport pathways.
- **Family History**: A strong genetic predictor of diabetes susceptibility.

The addition of these features helped the model to function optimally in various patient populations thus minimizing prediction uncertainty while increasing total accuracy rates.

4.3. Regression vs. Deep Learning: comparative analysis

To visualize the difference in prediction accuracy between polynomial regression and the optimized DNN model, Figure (8) shows the comparison of prediction accuracy between polynomial regression and the optimized DNN model for visualization purposes.

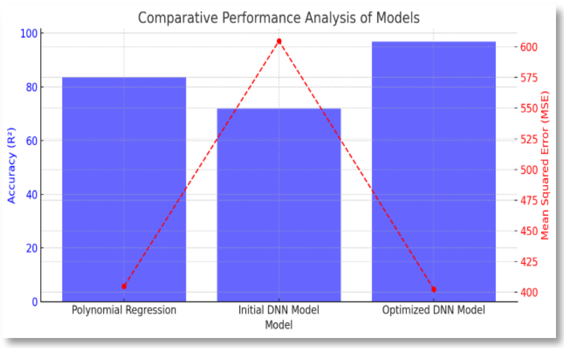

Fig. 8. A comparative performance analysis of Polynomial Regression vs. Initial DNN vs. Optimized DNN, illustrating accuracy improvements (R^2) and MSE reduction through deep learning optimization.

Actual glucose values match DNN predictions more accurately than polynomial regression predictions because the DNN approach produces results that stay closer to actual measurements.

These findings suggest that deep learning provides a robust alternative to traditional regression methods, particularly in non-invasive glucose monitoring applications, where non-linearity in biological data is a key challenge.

4.4. Error analysis and model stability

To further examine the model's reliability, the error distribution of glucose predictions was analyzed. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were calculated for each model, Table (3) and figure (9).

Table 3. measurement MAE & RMSE for All Models

Model	MAE (mg/dL)	RMSE (mg/dL)
Polynomial Regression	15.42	20.13
Initial DNN Model	18.85	24.60
Optimized DNN Model	**10.27**	**12.88**

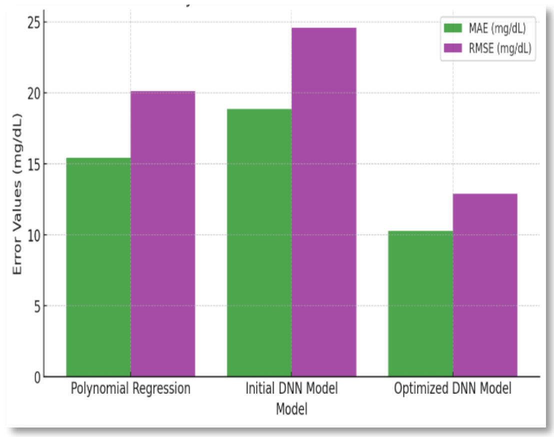

Fig. 9. Error analysis showing MAE and RMSE reductions through deep learning optimization.

The results indicate that the optimized DNN model significantly reduced both MAE and RMSE, suggesting greater stability and reliability in glucose predictions compared to polynomial regression. This improvement is particularly beneficial for real-time, non-invasive monitoring, where consistent and precise measurements are critical.

4.5 Clinical Feasibility and Future Implications

The findings of this study highlight the potential of deep learning for non-invasive glucose monitoring. While previous research demonstrated the viability of infrared spectroscopy, this study advances the field by integrating deep learning techniques for improved measurement precision , Key takeaways from this research include:

- Infrared Spectroscopy provides a promising, pain-free alternative for glucose monitoring.
- Deep Learning significantly enhances prediction accuracy over traditional regression models.
- Feature Engineering is crucial for adapting models to individual physiological variations.
- Future work should focus on real-world clinical validation and potential integration into wearable medical devices for continuous glucose monitoring.

4.6. Limitations and challenges in real-world deployment

Despite the promising results of this study, several challenges must be addressed before deploying the proposed system in real-world clinical settings:

- Sensor Calibration Challenges: The accuracy of infrared-based glucose monitoring is highly dependent on sensor calibration. Over time, sensor drift may cause measurement deviations, requiring periodic recalibration to maintain accuracy. Future studies should explore adaptive calibration techniques or self-calibrating sensors to enhance long-term reliability.
- Environmental Noise and Optical Interference: The performance of infrared spectroscopy can be affected by ambient light conditions, temperature fluctuations, and humidity. External infrared sources or variations in skin hydration levels may introduce noise, leading to minor fluctuations in glucose predictions. Future iterations of this technology should incorporate advanced signal processing techniques and calibration algorithms to minimize environmental interference.

4. Conclusion

This study demonstrates that deep learning techniques significantly enhance the accuracy of non-invasive glucose monitoring compared to traditional methods, achieving a superior accuracy of 96.85%.

The improved DNN model integrates biometric parameters such as age, BMI, blood pressure, and family history, resulting in more precise predictions, unlike previous studies that achieved 85% to 90% accuracy using polynomial regression and spectral analysis methods, this model surpasses these approaches, demonstrating the effectiveness of deep learning in refining glucose monitoring techniques.

Furthermore, this study highlights the importance of hyperparameter tuning and feature engineering in minimizing errors and improving model stability, despite these advancements, several challenges remain, including sensor calibration issues, environmental interference, and the need for large-scale clinical validation to ensure real-world applicability.

Future research should address these limitations by expanding the dataset, integrating the model into wearable medical devices for real-time glucose monitoring, and exploring advanced AI architectures such as LSTM and Transformers to further enhance accuracy. This study contributes to the development of cost-effective, accessible, and non-invasive diabetes management solutions, supporting global healthcare innovation and improving the quality of life for people with diabetes.

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