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DIETARY-GDM: AI-powered dual-source framework for personalized dietary recommendation in gestational diabetes management

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ABSTRACT

Gestational diabetes mellitus (GDM) is a condition of glucose intolerance that occurs during pregnancy, characterized by elevated blood glucose levels. However, the existing approach was validated on limited datasets, which may affect its generalizability to diverse real-world clinical settings, and its real-time deployment feasibility has not been thoroughly examined. In this research, a novel DIETARY-GDM (DIETARY food recommendation for GDM) has been proposed for managing diabetes in pregnant women through personalized diet food recommendations. Wavelet denoising and text cleaning are employed to remove noise in the signal and user input to enhance the quality. The enhanced signals and text are then extracted using the convolutional neural network-long short-term memory (CNN-LSTM) and universal sentence encoding (USE) to effectively analyze the body condition of the pregnant women. A deep neural network (DNN) integrated with a Bayesian optimization algorithm (BOA) is utilized to predict personalized dietary food recommendations. Finally, an artificial intelligence (AI)-bot generates food suggestions for pregnant women to improve maternal health. From the experimental results, the DIETARY-GDM achieves an accuracy of 99.21%. The accuracy of the DIETARY-GDM was higher than that of the convolutional neural network (CNN), artificial neural network (ANN), gated recurrent unit (GRU), and long short-term memory (LSTM) by 7.98%, 5.65%, 3.35%, and 1.97%, respectively.

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1. INTRODUCTION

Gestational diabetes mellitus (GDM) is prevalent endocrine disorder in up to 9-26% of pregnancies, based on criteria established by the International Association of Diabetes and Pregnancy Study Groups (IADPSG) consensus panel [1], [2]. The elevated blood glucose crosses the placenta, resulting in elevated blood glucose fatally that the baby's pancreas produces more insulin to help remove the excess blood glucose levels [3]. The metabolism of a pregnant human body acts upon established pathophysiologic conditions, which also allow maximal maternal glucose to enter the system postprandially [4], [5]. Risk factors for GDM are a family history of diabetes, age, low activity Level, growth pre-pregnancy BMI, and dietary patterns [6], [7]. Food suggestions for pregnant women (PW) [8] to lower the diabetes level must consider the healthier diet to sustain [9], [10]. Assigning a unique postprandial glucose response (PPGR) to a food indicates that the response is only due to the food itself [11]. When monitoring nutrient intake using the artificial intelligence (AI) Chabot [12], it is often best to have a meeting with nutrition and dietetics professional for personal insight and recommendation [13], [14].

Alqushaibi *et al.* [15] developed a convolutional neural network (CNN) that offers impressive outcomes in several medical fields where the Bayesian optimization algorithm (BOA) is used for parameter optimization and hyperparameter selection. In terms of total accuracy, it attains 89.36%. Cheltha *et al.* [16] developed a human motion detection with hybrid red deer algorithm and whale optimization algorithm (RDA-WOA) based recurrent neural network (RNN) and multiple hypothesis tracking for occlusion handling. It achieved an accuracy of 98%, respectively. Naseem *et al.* [17] proposed a merging of deep learning (DL) and machine learning (ML) approaches with an Internet of Things (IoT)-based monitoring system to develop an intelligent patient health monitoring system that helps identify a patient's chronic sickness early and accurately. It achieves 81% accuracy overall. Malibari [18] proposed an equilibrium optimizer (EO) optimized automatic modulation classification that is lightweight to enable accurate prediction of a patient's chronic health, a network called EO-LWAMCNet model is proposed. This model has a 93.5% accuracy rate in predicting whether kidney or heart disease will be present.

Aung *et al.* [19] introduced an enhanced u-net with attention mechanisms for improved feature representation in lung nodule segmentation. The proposed model achieved a Dice similarity coefficient of 84.30%, significantly outperforming the baseline U-Net model. Verma *et al.* [20] suggested a model that collects patient data in real time using IoT HEADR algorithm for LoRa protocol. It attains 96.48 percent total accuracy. Kaneho *et al.* [21] suggested that GyBot, a BiGRU-based chatbot, greatly improves response accuracy in obstetric care. In their tests, the suggested system's prediction accuracy was 98.5%. Khan *et al.* [22] developed a system-based mobile phone rating classification approach using federated learning and term frequency-inverse document frequency (TF-IDF) features. The federated deep neural network (FDNN) approach achieved 96.68% accuracy at the aggregated server level while preserving customer data privacy on local devices. Alkanhel *et al.* [23] proposed a unique hybrid convolutional neural network and gated recurrent unit (CNN-GRU) that may be included into diabetes management systems provided by the IoT, enhancing prediction timeliness and accuracy by enabling real-time data processing on edge devices. Accordingly, it attains an overall accuracy of 99.02%.

Kujur *et al.* [24] presented a dependence of brain magnetic resonance imaging (MRI) on various predictive models of CNN based on the complexity of the data for brain tumor and Alzheimer’s disease. The results illustrate that the highest accuracy for Alzheimer’s dataset is 98.02%. Alnowaiser [25] suggested an automated approach to diabetes prediction that focuses on increasing accuracy and handling missing data in a suitable manner. The provided model exhibits remarkable performance measures, such as an accuracy of 97.49%. From the literature review above, a number of previous models still encounter roadblocks such as handling complex patient data, scalability, and domain solutions for PW with GDM. To overcome these issues, the DIETARY-GDM model will use multi-source health data and advanced AI models to generate accurate and individualized dietary suggestion for satisfactory GDM management. The main contributions of this work are as follows:

a. The wavelet denoising and text-cleaning methods are combined to improve diet text assessment and reduce noise from physiological signals.
b. CNN-LSTM were used for the spatial and temporal dependency capture from physiological signals, and universal sentence encoding (USE) was used to produce numerical values from the text sentences.
c. DNN with BOA were used to improve prediction performance, allowing dietary recommendations to be made with high levels of accuracy with computational efficiency.
d. Finally, the AI-bot generated dietary recommendations and made personalized food recommendations to PW diagnosed with gestational diabetes.

The remainder of this research was arranged as follows. Section 2 explains the proposed methodology. The outcomes of the proposed model are displayed in Section 3. The conclusion and future work are enclosed in Section 4.

2. PROPOSED METHODOLOGY

In this research, a novel DIETARY-GDM has been proposed for GDM in PW through personalized dietary food recommendations. The input signal is preprocessed using the wavelet to remove the noise and natural language processing techniques to clean the text inputs. The CNN-LSTM approach captures both spatial and temporal dependencies. The USE extracts meaningful representations from dietary text inputs, while the extracted signal and text features are combined to effectively assess the body condition of the PW. The integration of DNN with BOA is utilized to improve performance and effective dietary food suggestion for PW. Finally, an AI-powered chatbot generates personalized dietary food suggestions based on the identified body condition to support diabetes management during pregnancy. Figure 1 display the overall workflow of the DIETARY-GDM.

The DIETARY-GDM framework in the form of an end-to-end automated decision-support system is capable of combining signal acquisition, preprocessing, feature extraction, refined prediction and AI-informed generation of recommendations with a minimum intervention of a human operator. The system facilitates the real-time monitoring of health and automatic dietary advice, which is in line with the concepts of intelligent healthcare automation.

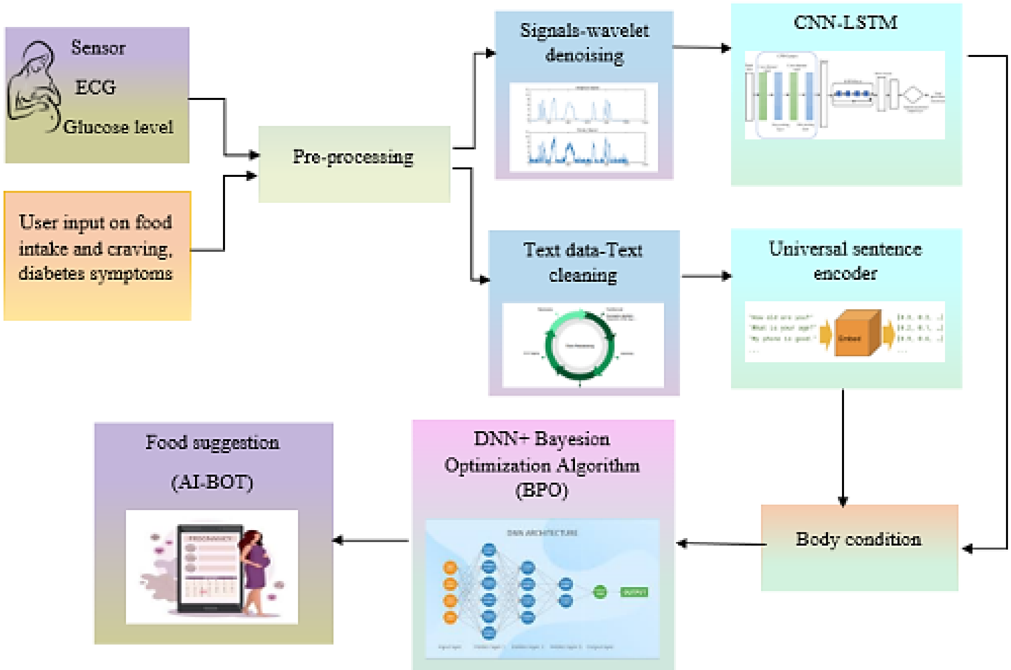

Figure 1. Architecture of proposed methodology

2.1. Dataset description

The gravid diabetes (GD) dataset employed in this exploration was obtained from experimental data sourced from State Government Hospitals in Ondo State, Nigeria. The GD data has 12,582 clinical records of patients in the State Government Hospitals of Ondo State, Nigeria. The dataset is not public because of the privacy of hospital data and ethical limitations. It has 12 clinical attributes and binary GDM label, which is involved in training the risk prediction module. The recommendation module produces individualized dietary recommendations based on the risk level of GDM that was predicted. A "0" illustrates that the case does not have GDM, while "1" represents that they do have GDM.

Preprocessing of data, such as wavelet denoising and text cleaning, were done individually on the training and testing sets to avoid data leakage. Moreover, to reduce overfitting, dropout regularization and early stopping were also used. The fact that the training and validation accuracy curves are exactly at the same level also suggests that the process is indeed being generalized correctly and there are no major instances of overfitting. Physiological signals are collected from PW using wearable sensors and glucose monitoring devices, with each reading automatically timestamped. Dietary text inputs are entered through a mobile app and also timestamped. Temporal synchronization is achieved by aligning signal segments with corresponding meal timestamps using sliding windows. After wavelet denoising, ECG features and glucose features are extracted using CNN-LSTM. Text inputs are converted into embeddings using universal sentence encoder. Both feature sets are fused using feature-level concatenation and fed into a DNN optimized with Bayesian optimization to generate personalized dietary recommendations.

DIETARY-GDM is a predictive, instead of a full-fledged clinical management system. It is concerned with the classification of early GDM risks and analysis of dietary patterns based on structured clinical data. One area, which is outside the focus of continuous glucose monitoring, modulation of medicine and direct clinical supervision, which can be incorporated in future extensions with the help of professional medical supervision.

2.2. Wavelet-based signal denoising and text preprocessing

The wavelet denoising reduces the noise in the signals to identify the health condition of the PW. The noise removes the noise while preserving and not distorting the beauty of the processed signal. The noise corrupted ECG signals from the PW are passed through the wavelet transformer it decomposes the signals into different frequency.

$$b(n) = a(n) + \sigma\varepsilon(n) \tag{1}$$

$$k(a) = \sum_{q=1}^{q} \alpha_q \emptyset_q(a) \tag{2}$$

where $b(n)$ denotes the sensor data and ECG signals collected from the PW. $\varepsilon(n)$ represents the random noise in the ECG signal. $a(n)$ refers to the original ECG signal of the PW. $k(a)$ represents the selected wavelet function, a denotes the input ECG signal of the PW or sensor data. $\emptyset_q$ represents the wavelet bias function which is time frequency records of the ECG signal.

$$G = \text{TRIM}(\text{CLEAN}(\text{text})) \tag{3}$$

$$T = text.lower() \tag{4}$$

This ensures the noise free texts for the effective dietary analysis in the gestational diabetes prediction. The $lower$ () method convert all the text into one common lower format. Once the data preprocessing is completed, the next step represents the feature extraction techniques of the DIETARY-GDM model, which is utilized to predict the body condition of the pregnant women.

2.3. Feature extraction using CNN-LSTM and universal sentence encoder

In feature extraction, the CNN-LSTM techniques extract both spatial and temporal features of the ECG signal and glucose level of the PW. The USE captures the dietary inputs of the PW to suggest foods,

$$(k * l)(o) = \int_{-\infty}^{\infty} k(\tau)l(k-\tau)d\tau \tag{5}$$

$$O_n = \delta(S_n[d^{(n-1)}, a^o] + y_n \tag{6}$$

where $k(\tau)$ denotes the smoothing filter, $l(k-\tau)$ refers to the input signal of the PW and $(k * l)(o)$ represents the filtered signal at time 0. The USE converts the normal text into meaning full numerical vectors,

$$A(u) = USE(u)\epsilon N^{512} \tag{7}$$

where u denotes the input text from the pregnant women like cravings, food log, and sentence. The USE transforms the unstructured text into numerical embeddings. By combining the local patterns, long-term memory and text embedding enhances the accuracy of personalized dietary food suggestion for PW.

2.4. DNN with Bayesian optimization algorithm for classification

The DNN system recommends a list of foods for pregnant women to control their diabetes by using the profile from the preference categorization model. Using the information provided by the expectant mothers, it determines a recommendation score for each dish in the database.

$$(k_o) = (\frac{\frac{k_m+k_a+k_e}{T_{otal}}}{T_{otal}}) \times (1 + \frac{c_{te}}{5}) \tag{8}$$

where c_{te} number of dishes that has been eaten by the pregnant women for the lunch, breakfast and dinner. k_m denotes the number of foods eaten by pregnant women in the morning. k_a number of dishes eaten by the pregnant women in the afternoon for lunch. The DIETARY-GDM approach described (1)-(10) that indicate signal processing, feature extraction, and optimization, as well as recommendation. Every equation is linked to a computational step within the system, and does not have to be in a generic form. Specifically, equation (5) is a recommendation scoring system that combines foreseen GDM risk level, dietary intake characteristics, and DNN-optimized solutions in order to offer physiologically and nutritionally suitable food recommendations. The architecture of DNN with BOA is illustrated in Figure 2. DNN uses the amplitude of gradients during backpropagation to assist in finding and highlighting important aspects in meal recommendations.

$$q\big(k(a)\big) = K, b = I(\mu(a*), \sigma^2(a^*)) \tag{9}$$

$$q(k_o(a)|a,\theta) = I(\hat{k}\big(a, o{:}\,\theta_\mu\big), \theta_{\sigma^2}) \tag{10}$$

$\mu(a*)$ denotes the mean predictive it expected health improvement for the food suggestion. $\sigma^2(a^*)$ represents the predictive variance risk of the PW in diabetes. In (15), $q(k_o(a)|a,\theta)$ represents the probability outcome of the recommended foods. $\hat{k}\big(a, o{:}\,\theta_\mu\big)$ denoted the predictive mean effect under the parameter θ_μ. The DIETARY-GDM approach is the binary classification task, according to which the model predicts the presence (1) or absence (0) of GDM based on multimodal inputs. The dietary recommendation module is an application that becomes active after being classified as a decision-support layer. Therefore, supervised GDM prediction task is not substituted or altered by the generative component.

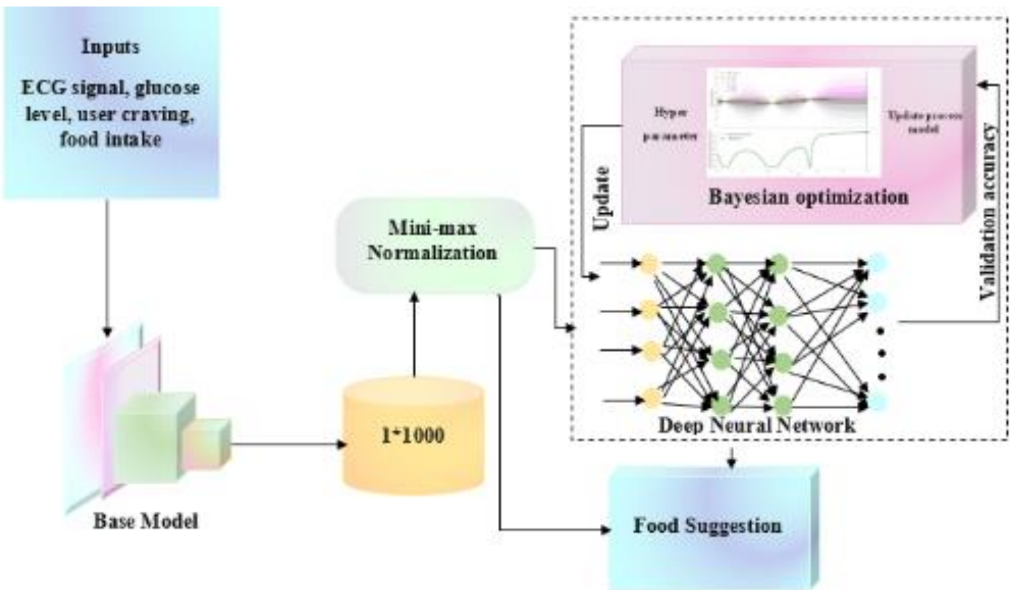

Figure 2. Architecture of DNN with Bayesian optimization algorithm

The hyperparameter settings of the DIETARY-GDM approach are illustrated in Table 1. The model was trained with Adam optimizer, learning rate of 0.001 and a batch size of 64. In all hidden layers, ReLU activation was used. The DNN model has four hidden layers with 128 neurons each, which has adequate capacity to learn intricate patterns with combined physiological and textual features without experiencing reduction in convergence and generalization test.

Table 1. Hyperparameter of the DIETARY-GDM approach

Component	Value
Optimizer	Adam
Learning rate	0.001
Number of epochs	100
Batch size	64
Activation function	ReLU
Neurons per layer	128
Number of hidden layers	4

3. RESULT AND DISCUSSION

In this section, the experimental setup for the investigation, conducted on an Intel i3 2.10 GHz processor PC with 8 GB RAM running Windows 10 OS. A novel DIETARY-GDM has been proposed for providing AI-bot personalized dietary food suggestion to pregnant women in controlling the diabetes.

Figure 3 illustrates experimental analysis of the proposed DIETARY-GDM model here, the mobile app is developed to support the pregnant women. The first screen shows the correlation between the meals and the blood glucose levels to identify which food keep their sugar level stable. The second screen shows settings page which allows user to share data about healthcare in SMS, notifications, daily remainders like glucose checking, breakfast, and prenatal vitamins. The third screen represents the weekly progress displaying meals and blood glucose where green icons indicate the healthy food suggestions and red color denote the unhealthy foods. These features together maintain the diets and glucose level to avoid diabetes during pregnancy.

Figure 3. Experimental analysis of the proposed DIETARY-GDM framework

3.1. Performance analysis

In order to evaluate the DIETARY-GDM model, several metrics were examined, such as network metrics from the data we obtained. The evaluation metrics used to evaluate the performance of the DIETARY-GDM model are accuracy (ACC), precision (PRE), specificity (SPE), recall (REC), and F1-Score (F1),

$$SPE = \frac{N_{true}}{N_{true}+P_{false}} \tag{16}$$

$$PRE = \frac{P_{true}}{P_{true}+P_{false}} \tag{17}$$

$$ACC = \frac{P_{true}+N_{true}}{Total\ no.of\ samples} \tag{18}$$

$$F1 = 2\left(\frac{PRE*REC}{PRE+REC}\right) \tag{19}$$

$$REC = \frac{P_{true}}{P_{true}+N_{false}} \tag{20}$$

where P_{true} and P_{false} represents the true-positive and false-positive, N_{true} and N_{false} represents true-negative and false-negative.

The accuracy curve of the proposed DIETARY-GDM model is shown in Figure 4, where epochs and accuracy are positioned on the opposing axes. The precision rises in tandem with the number of epochs. The loss curve of the proposed DIETARY-GDM model is shown in Figure 5, where the number of epochs grows as the loss framework lowers. The best accuracy, 99.21%, is attained by the proposed DIETARY-GDM model. The AI-bot is integrated with the trained CNN-LSTM, USE, and DNN-BOA models through a backend server to generate personalized dietary recommendations based on glucose readings, physiological signals, and user-input food logs. A prototype mobile application was developed for glucose tracking, meal logging, weekly progress monitoring, and chatbot-based dietary guidance.

Table 2 presented a BOA compared to manual and grid search tuning approaches. It also demonstrated improved convergence stability by efficiently exploring the hyperparameter space. This confirms that BOA provides better performance than conventional hyperparameter tuning approaches. The DIETARY-GDM approach achieves 99.21% accuracy, 92.34% F1-Score, respectively.

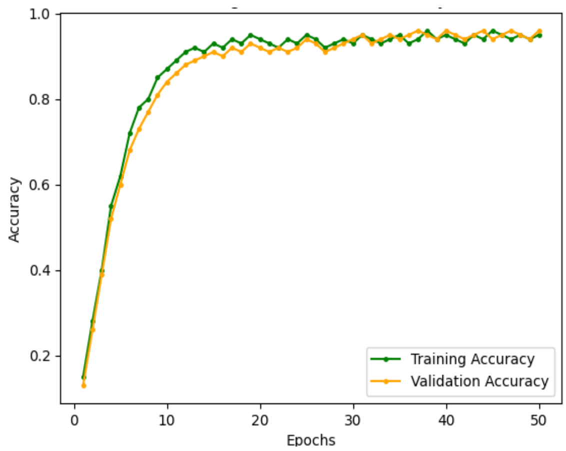

Figure 4. The accuracy curves of the DIETARY-GDM

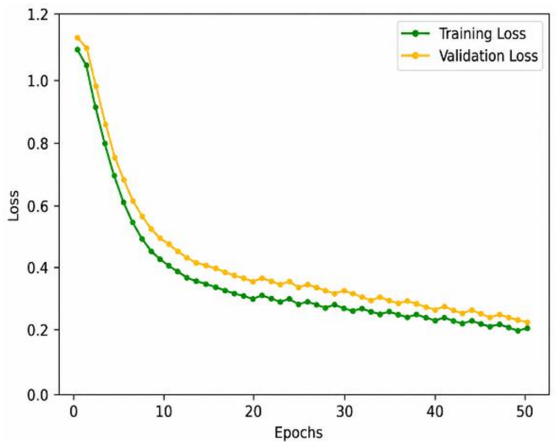

Figure 5. The loss curve of the DIETARY-GDM

Table 2. Hyperparameter tuning comparison with manual tuning, grid search, and BOA

Tuning Method	Best Learning Rate	Batch Size	Hidden Layers	Accuracy	F1-Score
Manual Tuning	0.001	32	3	97.84%	89.76%
Grid Search	0.0005	64	4	98.63%	90.85%
BOA	0.001	64	4	99.21%	92.34%

3.2. Comparative analysis

In comparative analysis, the DIETARY-GDM model patent application is jointly compared with various other existing approaches and methods qualitatively based on different performance and accuracy metrics. The CNN, ANN, GRU, and LSTM approaches were trained on the same data, the same input of features, and a fixed 70% for training 10% for validation and 20% for testing split to be able to assess them equally. All the baseline mechanisms were developed only to classify GDM as binary. They were optimized using the traditional grid search on their hyperparameters, whereas the DIETARY-GDM approach used BOA to optimize their parameters.

Table 3 compares the traditional networks to identify the effectiveness of the DIETARY-GDM. The accuracy of the DIETARY-GDM was higher than that of CNN, ANN, GRU, and LSTM by 7.98%, 5.65%, 3.35%, and 1.97%, respectively. The reported p-values from paired t-tests are all below 0.05, indicating that the performance improvements of DIETARY-GDM are statistically significant compared to traditional approaches. The DIETARY-GDM technique outperforms the current methods with an accuracy of 99.21%.

Table 3. Comparison evaluation between various traditional networks

Networks	Accuracy	Specificity	Precision	Recall	F1-Score	P-value
ANN	91.23	89.54	88.56	86.98	83.23	0.043
GRU	93.56	90.78	90.34	88.43	84.77	0.039
CNN	95.88	93.90	92.89	91.87	86.90	0.036
LSTM	97.24	95.67	92.99	92.45	90.67	0.033
CNN-LSTM	99.21	96.89	94.98	93.45	92.34	0.027

Table 4 represents the contrast of different existing methods with the DIETARY-GDM framework based on the gathered dataset. The DIETARY-GDM model improves the overall accuracy of 11.02%, 2.82%, 0.72% and 0.19% better than CNN, HEADR, GyBot and CNN-GRU respectively. From the above comparison table, the proposed model achieves the highest accuracy of 99.21% respectively.

Table 4. Comparison of DIETARY-GDM model with existing models

Authors	Methods	Accuracy
Alqushaibi *et al*. [15]	CNN	89.36%
Verma *et al*. [20]	HEADR	96.48%
Kaneho *et al*. [21]	GyBot	98.5%
Alkanhel *et al*. [23]	CNN-GRU	99.02%
Proposed	DIETARY-GDM	99.21%

3.3. Ablation study

Table 5 presents a comparison of the DIETARY-GDM with and without wavelet, CNN-LSTM, and DNN with BOA. without wavelet accuracy is 95.21%, performance is still lost because the images are not properly denoised. The DIETARY-GDM approach, which includes both wavelet, text cleaning, CNN-LSTM, and DNN with BOA, achieves 99.21% accuracy. These wavelet, text cleaning, CNN-LSTM, and DNN with BOA components work together to improve the DIETARY-GDM approach's accuracy and reliability over the reduced versions.

The DIETARY-GDM system does not produce food prescriptions exclusively on the ECG indications or textual cravings. ECG data is considered as auxiliary physiological features, and structured clinical features and the recorded glucose are the main predictors. The system is not a substitute of medical supervision because it is a data-driven decision support tool. In order to minimize black-box behavior, the suggestions are based on observed patterns between clinical characteristics and dietary behaviors in the data and the predictions make it possible to suggest the suggestions, based on the predicted GDM status and patient profile characteristics, rather than arbitrary model results.

Table 5. Comparison of the DIETARY-GDM with and without wavelet, CNN-LSTM, and DNN with BOA

Parameter	Without wavelet	Without CNN-LSTM	Without USE	Without DNN and BOA	With wavelet	With CNN-LSTM	With USE	With DNN and BOA
Accuracy	95.21%	95.36%	96.38%	97.45%	96.42%	96.65%	97.15%	98.51%
Precision	91.56%	90.62%	91.67%	92.02%	91.05%	91.41%	92.55%	93.24%
Recall	88.35%	89.07%	89.53%	90.63%	89.26%	89.59%	90.34%	91.86%
F1-Score	88.13%	89.23%	89.69%	90.56%	89.41%	89.68%	90.21%	91.63%
Specificity	92.43%	92.97%	93.34%	93.68%	93.19%	93.48%	94.03%	95.42%

4. CONCLUSION

This research introduced a novel DIETARY-GDM model for managing gestational diabetes in pregnant women through personalized dietary food recommendations. An AI enabled bot was developed to enhance the usability of the model, creating personalized dietary recommendations for adequate diabetes management during pregnancy. From the experimental results, the DIETARY-GDM achieves the highest accuracy of 99.21%, respectively. The DIETARY-GDM increases the overall accuracy of 11.02%, 2.82%, 0.72% and 0.19% better than CNN, HEADR, GyBot and CNN-GRU respectively. The DIETARY-GDM approach is created as a decision-support system to help in supplementing the usual care of GDM. The eating guidelines are created considering the methodical clinical information and predefined nutritional approaches. To achieve actual clinical implementation, interoperability with medical supervision and additional clinical assessment would be performed to make sure that it adheres to the healthcare standards. In future work, the system can be extended with additional multimodal clinical data, deployed as a real-time mobile monitoring application, and enhanced with explainable artificial intelligence for improved clinical interpretability and large-scale validation.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

The authors certify that the nature and purpose of this study have been explained to the above-named individual, and the authors have been discussing the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

ETHICAL APPROVAL

This manuscript was reviewed and ethically approved this manuscript for publishing in this journal.

DATA AVAILABILITY

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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