DIA-CHAT: Diabetes Classification and Diet Guidance in Pregnant Women using an Intelligent Chatbot

ANANTHI A., KIRUBAGARI B
Department of Computer Science and Engineering,
Annamalai University,
Annamalainagar, Tamil Nadu 608002,
INDIA

Abstract: - Gestational diabetes mellitus (GDM), which frequently endangers both the mother and her unborn child, is often detected between weeks 22 and 26 of pregnancy. However, the chatbot limitations include its dependency on static information and the absence of real-time data integration. It is also unable to adjust to varied demographics and does not offer personalized health feedback and continuous monitoring. In this paper, a novel DL-based DIA-CHAT approach has been proposed for diabetes classification using the Convolutional Neural Network-Bidirectional Gated Recurrent Unit (CNN-BiGRU). The input signals are preprocessed using the discrete wavelet transform (DWT) to remove the powerline interference and baseline wander from the ECG signal. The CNN-BiGRU integrates with a CNN to extract the shape and slope of the features and BiGRU is used to classify the diabetes and improve the performance. The CNN-BiGRU model classifies the ECG signals of pregnant women as diabetic and non-diabetic, and if diabetes is detected, the result is sent to a chatbot that provides personalized diet guidelines for pregnant women. The performance of the DIA-CHAT approaches was assessed using metrics such as recall, F1 score, accuracy, specificity, and precision. The DIA-CHAT maintains high accuracy levels of 99.67%. The DIA-CHAT approach enhances the total accuracy by 3.63%, 12.13%, and 1.52% better than OD-DSAE, En-RfRsK, and DiabChatbot, respectively.

Key-Words: - Diabetes, Convolutional Neural Network, Bidirectional Gated Recurrent Unit, pregnant women, ECG signal, discrete wavelet transform.

Received: April 26, 2025. Revised: September 23, 2025. Accepted: October 21, 2025. Published: July 6, 2026.

1 Introduction

Diabetes is a chronic illness that affects millions of people worldwide, [1]. It calls for regular treatment and individualized recommendations for nutrition, diet, and medication. Pregnant women with pre-existing diabetes mellitus (DM) have a much greater prevalence of perinatal problems than the general population, [2]. Pregnancy issues such as abnormal fetal weight and length, neonatal hypoglycemia and other metabolic diseases, and an elevated risk of obesity and type 2 diabetes in adulthood are all linked to high glycemia levels, [3]. Premature delivery, cesarean delivery, obstetric trauma, and hypertensive pregnancy syndromes are all more likely to occur in pregnant women with diabetes mellitus, [4]. Furthermore, because women typically gain weight during pregnancy, if this gain is excessive, it may raise the risk of obesity by increasing postpartum weight retention, [5].

Consuming a healthy diet is one of the most important components of effective glycemic management because it helps to meet the mother's increased nutritional needs while also supporting healthy fetal growth and development, [6]. Carbohydrate counting, linked to lower glycated hemoglobin (HbA1c) and improved quality of life, has been characterized as a crucial meal planning technique for diabetics since the Diabetes Control and Complications Trial, [7]. Greater freedom and flexibility in food choices are hallmarks of this approach, and consistent nutritional education policies and initiatives are necessary to ensure the diet's quality, [8].

The Convolutional Gated Recurrent Unit (CGRU), a deep learning (DL), [9] technique, combines temporal and spatial information extraction to increase classification efficiency. The incorporation of machine learning with Artificial Intelligence (AI) in healthcare provides potential solutions to these challenges, enables real-time support, gives personalized guidance, and improves patient engagement, [10]. The SVM and KNN algorithms in the system help in analyzing the inputs from the user, classifying the health metrics, and producing personalized, actionable advice, [11]. The public's interest in chatbots increases as their conversational skills rapidly advance. Patients are able to explain their problems, and chatbots will respond with information and suggestions, [12]. Chatbots, for instance, are frequently used by patients to track their mental health and assess their symptoms. The efficacy and adherence of a smartphone app that offers positive psychology techniques to enhance happiness and decrease side effects, [13].

However, the DiabChatBot performance is limited by the use of static datasets (PIMA and a regional Diabetes dataset) rather than real-time patient data. It is insufficiently adaptable to various environmental conditions, habits, and demography outside of the Indian context. Additionally, the system only focuses on diabetes prediction without integrating continuous physiological monitoring or personalized feedback, which limits its effectiveness for real-time healthcare and early intervention. To overcome this problem, the DIA-CHAT approach is proposed for diabetes classification. The research's primary contributions are below:

- The input signals are preprocessed using the DWT to remove powerline interference and baseline wander from the ECG signal.
- The hybrid CNN-BiGRU model is used to extract the shape and slope of the features, while the BiGRU enhances the performance and classifies diabetes as diabetic or non-diabetic. Finally, the chatbot gives personalized nutritional guidance to pregnant women.
- The DIA-CHAT approach performance was assessed using metrics like precision, F1 score, specificity, recall, and accuracy.

The remaining portions of this work are structured as follows: The literature survey is summarized in Section 2. In section 3, the diabetes classification is explained, and in section 4, the results and discussion of the DIA-CHAT approach are explained. The conclusion and future work for further investigation are given in Section 5.

2 Literature Survey

In this paper, researchers have proposed several advanced ML and DL designs for diabetes classification. lightGBM, CNN, and GAN have been used with various techniques and designs for diabetes classification in the research studies that have been proposed. Some of the research is examined in the following section.

In 2021[14] developed an OD-DSAE approach to diagnosing and classifying GDM. The OD-DSAE model provides a reliable and automated approach for early prediction of GDM, enabling timely intervention for high-risk pregnancies. According to the experimental results, the OD-DSAE approach performed better than the approaches that were examined and attained a high precision of 96.17%.

In 2022 [15] presented the first 19-week risk prediction approach that included indicators of renal and coagulation function as well as multiple possible GDM predictions. The approach to forecasting was constructed using SVM and light gradient boosting machine (lightGBM) to estimate possible connections with GDM. Early prediction of GDM was achieved, with PAT-APTT showing an AUC of 94.2%.

In 2023 [16] introduced a diabetes categorization framework optimized with ML GAN. The framework uses a number of methodological techniques to solve the many issues that appeared during the analysis. The experimental results demonstrate that the approach produced remarkable outcomes, such as a 96.27% binary classification accuracy.

In 2024 [17] provided an En-RfRsK ensemble ML approach for diabetes mellitus prognosis. The model was trained and tested using the PIMA diabetes dataset to analyze various human body attributes related to diabetes. The accuracy obtained by the En-RfRsK approach is 88.89%.

In 2024 [18] developed a DiabChatbot using an ML Chatbot for Early Diagnosis of diabetes and diet recommendations in an indian scenario. The comparison unequivocally demonstrates that the DiabChatBot outperforms DiaBot and Health Care Chatbot in all ML techniques with an accuracy of 98%.

In 2024 [19] presented a diabetes diagnosis with a CNN and high-frequency ultrasound (HFU). The CNN was applied to the signal's frequency spectra and spectrograms in order to find correlations between signal characteristics and changes in RBC characteristics brought on by glucose levels. Classification accuracy of 0.98 was achieved, confirming the efficacy of the CNN-based approach.

In 2025 [20] introduced an integrated intelligent system that combines Optical Character Recognition (OCR) and an LSTM-based chatbot to assist in the management and monitoring of diabetes. The proposed system processes diabetic test reports using OCR to extract key health indicators like HbA1c and VLDL levels. The system accurately classified users and provided personalized guidance using OCR and an LSTM-based chatbot.

In the literature review, current techniques have a number of drawbacks, including limited adaptability to diverse populations, lifestyle variations, and environmental factors, particularly outside the Indian context. The system only focuses on diabetes prediction without integrating continuous physiological monitoring or personalized feedback, which limits its effectiveness for real-time healthcare and early intervention. To overcome this problem, the DIA-CHAT approach is proposed for diabetes classification.

3 Proposed Methodology

In this paper, a novel DIA-CHAT approach is presented for diabetes classification, such as diabetes and non-diabetes. The input ECG signal and clinical input data are collected and preprocessed using the Discrete Wavelet Transform (DWT) to remove noise such as baseline wander and powerline interference. The preprocessed signals are then fed into the hybrid CNN-BiGRU approach, where CNN extracts spatial features and BiGRU captures temporal dependencies for accurate diabetes classification. Finally, the classification result is forwarded to the chatbot, which provides diet guidance for diabetic pregnant women. The overall workflow of the DIA-CHAT approach is illustrated in Figure 1.

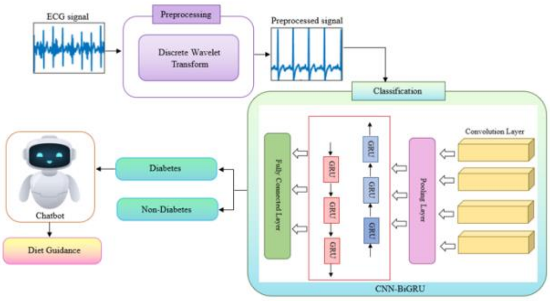

Fig. 1: Proposed DIA-CHAT methodology
Source: Authors' own creation

3.1 Dataset Description

In this research, the PTB-XL-physionet dataset was taken from the publicly available electrocardiography database for diabetes classification. PTB-XL consists of over 21,000 clinically annotated 12-lead ECG recordings collected from nearly 19,000 subjects. Each recording has a duration of 10 seconds and is sampled at 500 Hz. The dataset includes standardized diagnostic annotations provided by cardiologists, making it suitable for ECG signal preprocessing and deep learning–based analysis.

3.2 Preprocessing

The discrete wavelet transforms (DWTs) are based on dyadic multiresolution analysis using cascaded filter banks. Let $x[n]$ denotes the input signal, with $A_0[n] = x[n]$. At decomposition level j, the approximation and detail coefficients are obtained in equations (1) and (2).

$$A_j[n] = \sum_k h[k] \mathrm{A}_{j-1}[2n-k] \quad (1)$$

$$D_j[n] = \sum_k g[k] \mathrm{A}_{j-1}[2n-k] \quad (2)$$

where $h[k]$ and $g[k]$ denote the low-pass and high-pass analysis filters associated with the selected mother wavelet. A multilevel decomposition up to level L is employed to capture time–frequency characteristics of the ECG signal while maintaining computational efficiency. Here, n denotes the discrete coefficient index after downsampling, k represents the filter index, and j indicates the wavelet decomposition level.

Each filtering step requires convolution with finite-length filters, resulting in a computational complexity of $O(NL_f)$, where N is the signal length and L_f is the filter length. Due to downsampling by a factor of two at each level, the overall complexity of multilevel DWT decomposition is approximately $O(N)$, which makes it suitable for efficient biomedical signal preprocessing. The preprocessed images are fed into the diabetic classification model using a CNN-based BiGRU.

3.3 Classification

Convolutional neural networks (CNNs) are made up of convolutional and pooling layers. The convolutional layers use power load data to extract nonlinear local features, and the pooling layers compress these features to improve generalization. The ability of the model to effectively generalize and collect significant information is enhanced by this structure. An enhanced version of GRUs, termed Bidirectional Gated Recurrent Units (BiGRU), is made to process sequential data both forward and backward. They are important developments in Recurrent Neural Networks (RNNs), expanding their use in a variety of fields.

The CNN-BiGRU architecture is presented in Figure 2. The CNN layers first process the incoming data before extracting relevant geographical properties. A lower-dimensional representation is then created by combining these attributes. This condensed representation is fed onto the BiGRU layer, which enhances the recovered features by utilizing its ability to record sequential dependencies in both forward and backward directions. During preprocessing, the features are standardized and transformed into numerical embeddings to preserve the semantic connections between data points. These embeddings are then fed into the CNN-BiGRU architecture, which enhances the model's ability to recognize sequential trends by utilizing the BiGRU component to enhance the model's recognition of complex spatial patterns and the CNN component to enhance the prediction performance for diabetes classification.

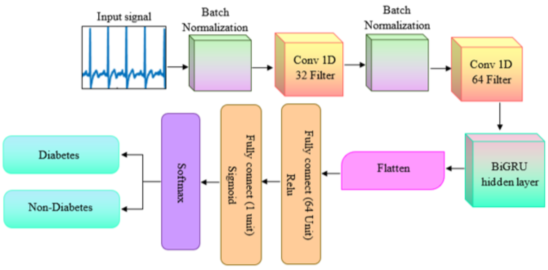

Fig. 2: Architecture of CNN-BiGRU
Source: Authors' own creation

The CNN consists of two sequential 1D convolutional layers followed by max-pooling operations for hierarchical feature extraction. Let the input feature sequence be represented in eqn (3).

$$X \in \mathbb{R}^{T\times F} \tag{3}$$

where T denotes the number of time steps and F represents the number of input features. The first convolution layer applies. $N_1 = 32$ filters with kernel size $k_1 = 3$, stride $s_1 = 1$, and padding $p_1 = 1$. The convolution output is expressed in eqn (4).

$$Y^{(1)} = \sigma\left(W^{(1)} * X + b^{(1)}\right) \tag{4}$$

where $W^{(1)}$ represents convolutional kernels, $b^{(1)}$ is the bias term, and σ denotes the ReLU activation function. A max-pooling layer with pooling size 2 is applied to reduce dimensionality and enhance translation invariance in Eqn (5). The resulting in an output dimension of $T \times 32$. Batch normalization preserves the dimensionality, and max-pooling with size 2 reduces the temporal dimension to ${}^{T}/_{2} \times 32$.

$$P^{(1)} = max\left(Y^{(1)}_{i:i+2}\right) \tag{5}$$

The second convolutional layer employs $N_2 = 24$ filters with kernel size $k_2 = 24$, stride $s_2 = 1$, and padding $p_2 = 1$ in eqn (6)

$$Y^{(2)} = \sigma\left(W^{(2)} * P^{(1)} + b^{(2)}\right) \tag{6}$$

Which produces an output dimension of ${}^{T}/_{2} \times 64$. After batch normalization and pooling, the resulting tensor becomes ${}^{T}/_{4} \times 64$, which is directly fed into the BiGRU layer as the sequential input representation.

The CNN-BiGRU handles the input diabetes dataset for binary classification using CNN and BiGRU. A matrix $X \in \mathbb{R}^{n*d}$, where n is the number of samples and d is the number of features, is used to describe the input ECG signal. Two 1D convolution layers (CL) are applied successively to the input in order to extract spatial characteristics.

$$H^{(1)} = ReLU(X * W_1 + b_1) \tag{7}$$

where $*$ indicates the convolutional operation, b_1 is the bias, and $W_1 \in \mathbb{R}^{k_1*d}$ is the kernel of size k_1. f_1 is the number of filters, and the output is $H^{(1)} \in \mathbb{R}^{n-k_1+1*f_1}$. Eq. (6) uses the convolution and the input. $H^{(1)}$ for the second CL.

$$H^{(2)} = ReLU\left(H^{(1)} * W_2 + b_2\right) \tag{8}$$

$$H^{(l)}_{BN} = \gamma\frac{H^{(l)}-\mu}{\sigma} + \beta \tag{9}$$

where γ and β are learnable scaling parameters, and μ are σ the batch mean and standard deviation. $H^{(2)}_{BN}$, The BiGRU layer output from the CL is fed into a BiGRU.

$$\vec{h}_t = GRU_{forward}(h_{t-1}, x_t) \tag{10}$$

where $GRU_{forward}$ uses a gating mechanism to update the hidden state and the forward time step is t.

$$\overleftarrow{h}_t = GRU_{backward}(h_{t+1}, x_t) \tag{11}$$

To enhance the mathematical completeness of the proposed model, the internal gating mechanisms of the Gated Recurrent Unit (GRU) used within the BiGRU architecture are explicitly defined. The GRU processes sequential information through reset and update gates that control information flow across time steps. Let the input sequence at time step t be x_t, and the hidden state is h_t. The update gate z_t and reset gate r_t are computed in eqns (12) and (13).

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{12}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{13}$$

where σ denotes the sigmoid activation function. The candidate's hidden state $\tilde{h}_t$ is defined in eqn (14).

$$\tilde{h}_t = \tan h(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{14}$$

$$h_t = (1 - z_t)\odot h_{t-1} + z_t \odot \tilde{h}_t \tag{15}$$

In the Bidirectional GRU, two parallel GRU layers process the sequence in forward and backward directions in equations (16) and (17).

$$\overrightarrow{h_t} = GRU\left(x_t, \overrightarrow{h_{t-1}}\right) \tag{16}$$

$$\overleftarrow{h_t} = GRU\left(x_t, \overleftarrow{h_{t-1}}\right) \tag{17}$$

The final BiGRU output is obtained through concatenation eqn in (18),

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (18)$$

where concatenation is shown by $[;]$. The number of hidden units, h, is the output, which is $h_{BiGRU} \in \mathbb{R}^{n*2h}$

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (19)$$

where concatenation is shown by $[;]$. The number of hidden units, h, is the output, which is $h_{BiGRU} \in \mathbb{R}^{n*2h}$. Equations (20-21) translate the features to higher-dimensional space using the fully connected output from the BiGRU layer and the fully connected layer (FCL).

$$H_{flat} = Flatten(H_{BiGRU}) \quad (20)$$

$$Z = ReLU(H_{flat}.W_{fc} + b_{fc}) \quad (21)$$

where $W_{fc} \in \mathbb{R}^{d\times64}$ and b_{fc} These are the weights and biases. The Dropout $(p = 0.5)$ is applied to prevent overfitting in eqn (22):

$$Z_{drop} = Dropout(Z) \quad (22)$$

$$y = Sigmoid(Z_{drop}.W_{out} + b_{out}) \quad (23)$$

where $W_{out} \in \mathbb{R}^{64\times1}$. Using a threshold of τ, the sigmoid activation produces a probability $y \in [0,1]$ that is classed as either diabetes or nondiabetes. A softmax activation could be used in place of the sigmoid function in equation (24) for multiclass extensions.

$$y = Softmax(Z_{drop}.W_{out} + b_{out}) \quad (24)$$

High prediction accuracy for diabetes classification is achieved by this architecture, which successfully blends CNN's spatial feature extraction, BiGRU temporal dependencies, and FCL robust classification. The diabetes classification task is formulated as a binary classification problem, and the binary cross-entropy (BCE) loss function is adopted as the objective function in the eqn (25).

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (25)$$

where y_i denotes the class label and $\hat{y}_i$ represents the predicted probability obtained from the sigmoid activation function. The classification result is sent to a Chatbot for a diet Plan.

3.4 Chatbot

The chatbot module is designed to interact with users by responding to queries related to diabetes and health management. An intents file with potential user inputs and matching predefined replies is used to train it. The chatbot responds with the appropriate response when a user's question and result match. The chatbot uses a recommender component to provide a customized diet plan if it determines that the user has diabetes.

The chatbot identifies user inputs such as symptoms, food preferences, glucose concerns, or meal timing questions and retrieves appropriate responses from a structured medical knowledge base and diet recommendation module. For example, if a user asks “What should I eat for breakfast with diabetes?”, the chatbot recommends low-glycemic foods such as whole-grain bread, boiled eggs, or vegetable oats. Similarly, when a user reports “My sugar level is high after lunch,” the chatbot suggests reducing refined carbohydrates and increasing fiber intake. The system also provides reminders for hydration, meal scheduling, and safe nutrition practices during pregnancy. This interactive framework ensures personalized guidance, improves patient engagement, and supports continuous dietary management alongside automated diabetes classification. Table 1 illustrates the food guidelines, including the recommended foods, foods to avoid, and their respective benefits for pregnant women with diabetes.

Table 1. Food guidelines

Meal Type	Recommended Foods	Foods to Avoid	Benefit
Early Morning (Before Breakfast)	Warm water with lemon (no sugar), a handful of soaked almonds or walnuts	Sweetened beverages, coffee on an empty stomach	Maintains hydration and controls morning glucose level
Breakfast	Whole-grain bread, vegetable oats, boiled egg, low-fat milk, sprouts	White bread, sugary cereals, and fried foods	Provides slow-release energy and stabilizes blood sugar
Mid-Morning Snack	Apple, pear, guava, buttermilk, unsweetened yogurt	Fruit juices, biscuits, chips	Keeps glucose stable between meals
Lunch	Brown rice or whole-wheat chapati, dal, leafy vegetables, grilled fish or tofu	White rice, potatoes, creamy gravies	Balanced meal with high fiber and protein
Evening Snack	Roasted chickpeas, vegetable soup, green tea without sugar	Cakes, pastries, sugary tea	Controls hunger and prevents sugar spikes
Dinner	Mixed vegetable salad, chapati, lentil soup, paneer/tofu	Rice, noodles, desserts	Light meal that aids digestion and overnight sugar control
Bedtime Snack	A glass of warm milk or a handful of nuts	Chocolates, sweet drinks	Prevents overnight hypoglycemia

Source: Authors’ own creation

4 Result and Discussion

In this section, the experimental configuration of the DIA-CHAT approaches was implemented using MATLAB 2020b, and the ensuing experimental findings are represented. The proposed DIA-CHAT to evaluate the model on the collected ECG signals, several measures were employed, including F1 score, recall, accuracy, specificity, and precision.

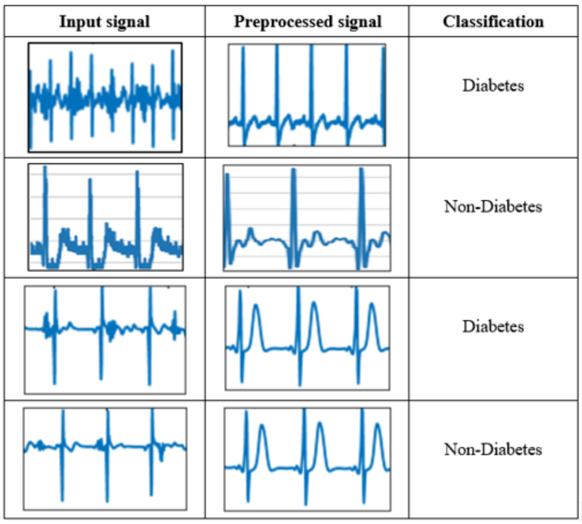

Fig. 3: Experimental result of the DIA-CHAT
Source: Authors' own creation

The result of the experiment approach DIA-CHAT is shown in Figure 3. In column 1, the input signals are gathered from the PTB-XL-physionet dataset. In column 2, DWT is used to remove baseline wander noises from the ECG signal, column 3, CNN-BiGRU is used for classification as diabetes and non-diabetes.

4.1 Performance Analysis

This section assessed the DIA-CHAT approach using a number of measurements from the collected dataset, including recall, specificity, F1 score, accuracy, and precision.

Accuracy measures the overall accuracy of the model's predictions. It is calculated as the percentage of all samples that were correctly predicted in eqn (26).

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{26}$$

The specificity of the model reveals whether it recognizes negative samples. This was calculated by dividing the total number of negatives by the predicted number of negatives.

$$Specificity = \frac{T_N}{T_N+F_P} \tag{27}$$

The precision quantifies the percentage of exact positive predictions. It emphasizes the extent to which the approach reduces false positives.

$$Precision = \frac{T_P}{T_P+F_P} \tag{28}$$

Recall evaluates a model's ability to identify true positive (TP) results. It is calculated as the ratio of the true positives to the sum of true positives and false negatives (FN).

$$recall = \frac{T_P}{T_P+F_N} \tag{29}$$

The F1 score is the harmonic mean of precision and recall, offering a balanced statistic in cases where the distribution of classes is dissimilar:

$$f_1 = 2\left(\frac{precision*recall}{precision+recall}\right) \tag{30}$$

where T_{pos} and T_{neg} indicates the true positives and negatives of the provided images, F_{pos} and F_{neg} display the sample images, false positives, and negatives.

Table 2. Performance analysis of the DIA-CHAT approach

Classes	Precision	F1 score	Accuracy	Specificity	Recall
Diabetes	97.23%	95.32%	99.62%	98.85%	98.36%
Non-diabetes	98.16%	97.65%	99.71%	98.65%	97.48%

Source: Authors' own creation.

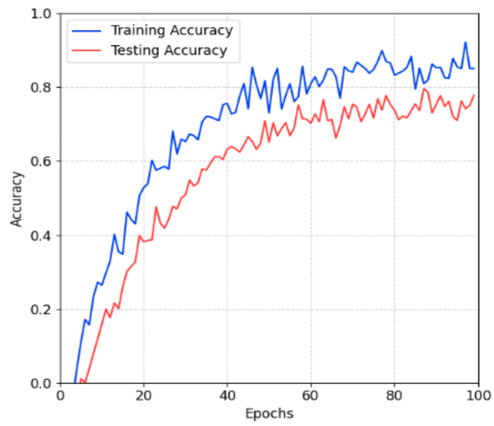

Fig. 4: Accuracy of the DIA-CHAT approach
Source: Authors' own creation

The recall, F1 score, specificity, accuracy, and precision of the DIA-CHAT approaches were assessed in Table 2. The DIA-CHAT method accuracy is 99.62% for diabetes and 99.71% for non-diabetes. The DIA-CHAT approach outperforms the existing approaches with an accuracy of 99.67%.

Figure 4 illustrates the accuracy of the training and testing, with accuracy on the y-axis and Epochs on the x-axis. The DIA-CHAT approach shows an accuracy level of 99.67% for times when considering the correctness of its evaluation and training curves. The loss graph plotted against epochs in Figure 5 displays that the loss falls with increasing epochs. The DIA-CHAT approach achieves high precision with a low loss of 0.33%.

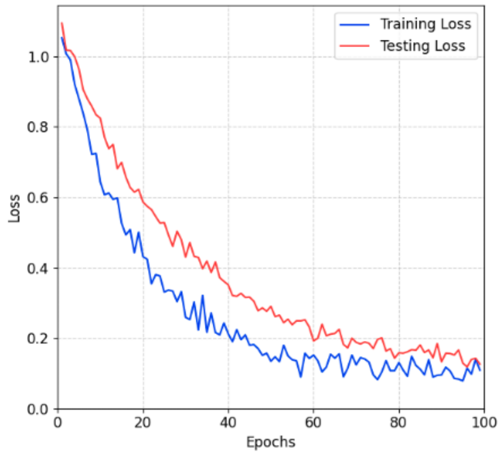

Fig. 5: Loss of the DIA-CHAT approach
Source: Authors' own creation

4.2 Comparative Analysis

The DIA-CHAT method's accuracy and efficiency were demonstrated by comparing it to other existing methods. The CNN-BiGRU classification is used to enhance the accuracy of diabetes Classification. The effectiveness of the DIA-CHAT strategy was evaluated using metrics of recall, F1 score, accuracy, and specificity. The accuracy rate shows that the proposed approach outperforms the current techniques. A comparison is performed between the DIA-CHAT approach and current approaches such as LightGBM [15], GAN [16], and CNN [19].

Table 3. Comparison of the existing approach and the DIA-CHAT approach

Techniques	Accuracy	Specificity	Precision	Recall	F1 score
LightGBM [15]	94.21 %	91.63%	90.05 %	91.25 %	90.36 %
GAN [16]	96.27 %	94.56%	93.24 %	95.25 %	91.11 %
CNN [19]	98.14 %	95.07%	92.37 %	93.17 %	94.61 %
CNN-BiGRU	99.67 %	98.75%	97.69 %	97.92 %	96.48 %

Source: Authors' own creation

Table 3 presents the various techniques of the existing model and compares the DIA-CHAT model. The CNN-BiGRU has an accuracy 94.21%, 96.27%, and 98.14%, better than the LightGBM [15], GAN [16], and CNN [19], respectively. The DIA-CHAT approach outperforms the current methods with an accuracy of 99.67%.

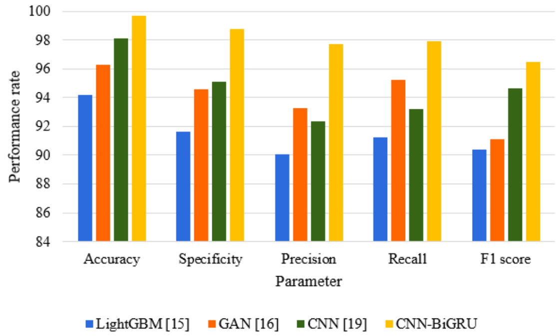

Fig. 6: Comparison of the existing approach
Source: Authors' own creation

The comparison of the CNN-BiGRU approaches and the current approach is illustrated in Figure 6. The DIA-CHAT approaches evaluation provided 99.67% accuracy, 98.75% specificity, 97.69% precision, 97.92% recall, and 96.48% F1 score. The CNN-BiGRU improves the accuracy range of 5.79%, 3.57%, and 1.56% better than LightGBM [15], GAN [16], and CNN [19], respectively. The DIA-CHAT methodology outperforms the current approaches with an accuracy of 99.67%.

Table 4. Accuracy comparison of the current model and the DIA-CHAT approach

Authors	Method	Accuracy
[14]	OD-DSAE	96.17%
[17]	En-RfRsK	88.89%
[18]	DiabChatbot	98.18%
Proposed	DIA-CHAT	99.67%

Source: Authors' own creation

Table 4 illustrates an accuracy comparison of current approaches and the DIA-CHAT approach. The DIA-CHAT approach maintains high accuracy levels of 99.67%. The DIA-CHAT approach enhances the total accuracy by 3.63%, 12.13%, and 1.52% better than OD-DSAE [14], En-RfRsK [17], and DiabChatbot [18], respectively. According to the comparison above, the DIA-CHAT approach has a higher accuracy than the existing models.

5 Conclusion

In this research, a novel DIA-CHAT approach was proposed for the diabetes classification using a CNN-BiGRU. The input signals are preprocessed using the DWT to remove the unwanted noise from the ECG signal. The CNN-BiGRU was used to extract the shape and slope features from the signal, while the BiGRU was used for the classification of diabetes to improve performance. Finally, the CNN-BiGRU is classifying such things as diabetes and non-diabetes. The performance of the DIA-CHAT approaches was assessed using metrics such as specificity, F1 scores, recall, accuracy, and precision. The DIA-CHAT approach accomplishes a higher accuracy of 99.67%. The CNN-BiGRU improves the accuracy range by 5.79%, 3.57%, and 1.56% better than LightGBM, GAN, and CNN, respectively. The DIA-CHAT approach enhances the total accuracy by 3.63%, 12.13%, and 1.52% better than OD-DSAE, En-RfRsK, and DiabChatbot, respectively. In future work, the DIA-CHAT approach will be enhanced for diabetes classification by implementing advanced optimization techniques to accurately identify diabetes and improve the chatbot's performance.

Acknowledgement:
The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

References:

[1] B. P. Lohani, A. Dagur, and D. Shukla, *An efficient approach for diabetes classification using feature selection and hyperparameter tuning*, Recent Advances in Electrical and Electronic Engineering, Vol. 18, No. 7, 2025, pp. 793–807.

[2] I. Abousaber, H. F. Abdallah, and H. El-Ghaish, *Robust predictive framework for diabetes classification using optimized machine learning on imbalanced datasets*, Frontiers in Artificial Intelligence, Vol. 7, 2025, pp. 1499530 https://doi.org/10.3389/frai.2024.1499530.

[3] M. Y. Shams, Z. Tarek, and A. M. Elshewey, *A novel RFE-GRU model for diabetes classification using PIMA Indian dataset*, Scientific Reports, Vol. 15, No. 1, 2025, pp. 982 https://doi.org/10.1038/s41598-024-82420-9.

[4] A. Ahilan, B. Pradeep Khanth. R. Ezhilarasi, and N. Muthukumaran, *Efficient luma modification based chroma down-sampling and novel luma down-sampling with adaptive interpolation*, Signal, Image and Video Processing, Vol. 18, No. 2, 2024, pp. 1415–1428 https://doi.org/10.1007/s11760-023-02814-6.

[5] J. Xing, *Enhancing gestational diabetes mellitus risk assessment and treatment through GDMPredictor: A machine learning approach*, Journal of Endocrinological Investigation, Vol. 47, No. 9, 2024, pp. 2351–2360 https://doi.org/10.1007/s40618-024-02328-z.

[6] P. Joshi, S. Rawat, A. Raj, and V. Jakhmola, *Machine learning approaches to predict gestational diabetes in early pregnancy*, Artificial Intelligence and Machine Learning for Women's Health Issues, Academic Press, 2024, pp. 107–120 https://doi.org/10.1016/B978-0-443-21889-7.00011-7.

[7] A. Agasthian, Rajendra Pamula, and L.A. Kumaraswamidhas, *Integration of monitoring and security based deep learning network for wind turbine system*, International Journal of System Design and Computing, Vol. 01, No.01, 2023, pp. 11-17.

[8] D. Santhakumar, K. D. Shree, M. Buvanesvari, A. S. Kumar, and A. O. Salau, *HD-MVCNN: High-density ECG signal-based diabetic prediction and classification using multi-view convolutional neural network*, Egyptian Informatics Journal, Vol. 28, 2024, pp. 100573 https://doi.org/10.1016/j.eij.2024.100573.

[9] L. Jenifer, Xiaochun Cheng, A. Ahilan, and P. Josephin Shermila, *A Novel Internet Of Things-Based Electrocardiogram Denoising Method Using Median Modified Weiner And Extended Kalman Filters*, International Journal of Data Science and Artificial Intelligence, Vol. 01, No. 02, 2023, pp. 10-20.

[10] S. K. Bigdeli, M. Ghazisaedi, S. M. Ayyoubzadeh, S. Hantoushzadeh, and M. Ahmadi, *Predicting gestational diabetes mellitus in the first trimester using machine learning algorithms*, BMC Medical Informatics and Decision Making, Vol. 25, No. 1, 2025, pp. 3 https://doi.org/10.1186/s12911-024-02799-3.

[11] A. Ahilan, N. Muthukumaran, and L. Jenifer, ECG Arrhythmia Measurement and Classification for Portable Monitoring, Measurement Science Review, Vol. 24, No. 4, 2024, pp.118-128. https://doi.org/10.2478/msr-2024-0017.

[12] D. Pan., *Effects of neonicotinoid pesticide exposure in the first trimester on gestational diabetes mellitus based on interpretable machine learning*, Environmental Research, Vol. 273, 2025, pp. 121168 https://doi.org/10.1016/j.envres.2025.121168.

[13] U. Juniarti, R. A. Setiawan, and R. R. Al-Hakim, *Machine learning for gestational diabetes mellitus: Comparing random forest,*

K-nearest neighbor and naive Bayes, Proceedings of ICHBS, Vol. 1, No. 1, 2024, pp. 280–295.
[14] A. Sumathi, S. Meganathan, and B. V. Ravisankar, *An intelligent gestational diabetes diagnosis model using deep stacked autoencoder*, Computer Materials and Continua, Vol. 69, No. 3, 2021, pp. 3109–3126.
[15] Y. Xiong, *Prediction of gestational diabetes mellitus in the first 19 weeks of pregnancy using machine learning techniques*, Journal of Maternal-Fetal & Neonatal Medicine, Vol. 35, No. 13, 2022, pp. 2457–2463 https://doi.org/10.1080/14767058.2020.1786517.
[16] X. Feng, Y. Cai, and R. Xin, *Optimizing diabetes classification with a machine learning-based framework*, BMC Bioinformatics, Vol. 24, No. 1, 2023, pp. 428 https://doi.org/10.1186/s12859-023-05467-x.
[17] B. A. Ng, *En-RfRsK: An ensemble machine learning technique for prognostication of diabetes mellitus*, Egyptian Informatics Journal, Vol. 25, 2024, pp. 100441. https://doi.org/10.1016/j.eij.2024.100441.
[18] P. Agrawal, S. Gandhi, and M. Agarwal, *DiabChatbot: A machine learning chatbot for early diagnosis of type II diabetes and diet recommendation*, International Conference on Advanced Computing and Communication Systems, Vol. 1, 2024, pp. 1526–1531. doi: 10.1109/ICACCS60874.2024.10716933.
[19] J. E. Lee, H. J. Jeon, O. J. Lee, and H. G. Lim, *Diagnosis of diabetes mellitus using high-frequency ultrasound and convolutional neural network*, Ultrasonics, Vol. 136, 2024, pp. 107167 https://doi.org/10.1016/j.ultras.2023.107167.
[20] E. Shriaarthy, *Transforming diabetes management through LSTM models, OCR and AI chatbot*, International Conference on Advances in Electrical, Electronics, Communication, Computing and Automation, 2025, pp. 1–9 doi: 10.1109/ICAECA63854.2025.11012235.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghost writing Policy)

- Ananthi A, conceived and designed the study, conducted the research, collected and analysed the data, and wrote the original draft of the manuscript.
- Kirubagari B, supervised the work, provided critical feedback, and revised the manuscript for intellectual content. Both authors reviewed and approved the final version.

Sources of Funding for Research Presented in a Scientific Article or the Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.