Smart Diabetes Management: Insulin Prediction Using Machine Learning

Mudavath Anil Kumar,
Digital Electronics and Communication Engineering,
Mahatma Gandhi Institute of Technology,
Hyderabad, India-500075.

DR.S Praveena,
Associate Professor,
Degital Electronics and Communication Engineering,
Mahatma Gandhi Institute of Technology,
Hyderabad, India -500075.

Abstract— **Diabetes mellitus requires accurate insulin dosage estimation to maintain optimal blood glucose levels and prevent complications such as hypoglycemia and hyperglycemia. Conventional insulin dosing methods are primarily based on predefined clinical rules and patient calculations, which often fail to capture the complex and dynamic relationship between physiological and lifestyle factors. This paper presents a machine learning-based approach for personalized insulin dose prediction using Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) models. The proposed framework utilizes the Code 34 diabetes dataset containing continuous glucose measurements, insulin administration records, meal information, and other time-dependent clinical observations. A comprehensive preprocessing pipeline, including data cleaning, normalization, temporal alignment, and feature engineering, is employed to improve prediction performance. The ANN model is designed to capture nonlinear relationships among clinical variables, whereas the LSTM model learns temporal dependencies in sequential glucose patterns. Experimental results demonstrate that both learning-based models consistently outperform conventional static insulin dosing rules, achieving RMSE improvements ranging from 26% to 48% across different patient and meal-based sequences. Furthermore, the hybrid prediction strategy provides marginal performance gains in selected cases while maintaining stable and reproducible results. These findings demonstrate the potential of deep learning techniques to support personalized insulin recommendation systems and contribute toward intelligent diabetes management in future digital healthcare applications.**

Index Terms — Artificial Neural Network (ANN), Diabetes Mellitus, Insulin Dose Prediction, Long Short-Term Memory (LSTM), Machine Learning, Personalized Healthcare.

I. Introduction

Diabetes mellitus is one of the most prevalent chronic metabolic disorders worldwide and is characterized by impaired insulin production or ineffective insulin utilization, resulting in abnormal blood glucose regulation. Long-term uncontrolled glucose levels can lead to severe complications, including cardiovascular diseases, nephropathy, neuropathy, and diabetic retinopathy, significantly affecting patients' quality of life. Effective insulin therapy plays a critical role in maintaining glycemic control, particularly for individuals with Type 1 diabetes and insulin-dependent Type 2 diabetes. In recent years, advances in continuous glucose monitoring (CGM), wearable sensors, and digital health technologies have enabled continuous collection of physiological data, creating new opportunities for data-driven decision support in diabetes management. These developments have accelerated the adoption of machine learning techniques for improving diabetes diagnosis, prediction, and personalized treatment strategies. Early studies have demonstrated the effectiveness of machine learning in diabetes prediction and risk assessment, highlighting its potential to support intelligent clinical decision-making [2], [6].

Despite these technological advancements, determining the appropriate insulin dosage remains a challenging task due to the complex interaction among blood glucose levels, carbohydrate intake, physical activity, insulin sensitivity, stress, and other physiological factors. Conventional insulin dosing methods, including standard correction rules such as the 1500 and 1800 rules, primarily rely on predefined formulas and patient self-calculations. Although these approaches are widely used in clinical practice, they cannot adequately capture the nonlinear and time-varying nature of glucose-insulin dynamics, often resulting in underestimation or overestimation of insulin requirements. Consequently, patients remain vulnerable to hypoglycemic and hyperglycemic events despite following established dosing guidelines. These limitations highlight the need for intelligent predictive models capable of adapting insulin recommendations according to individual patient characteristics and continuously changing physiological conditions [15].

Machine learning has emerged as a promising solution for addressing these challenges by learning complex relationships directly from historical patient data. Unlike conventional rule-based approaches, data-driven models can discover hidden nonlinear patterns and generate personalized insulin recommendations. Artificial Neural Networks (ANNs) are effective in modeling nonlinear relationships between multiple clinical variables and insulin dosage, whereas Long Short-Term Memory (LSTM) networks are specifically designed to capture temporal dependencies in sequential data such as continuous glucose measurements. Previous studies have demonstrated the capability of recurrent neural networks and LSTM architectures for blood glucose forecasting and real-time prediction, making them well suited for personalized diabetes management applications [11], [13]. Furthermore, adaptive learning frameworks have shown significant potential for improving treatment recommendations by continuously incorporating new patient information into the prediction process [16].

Motivated by these developments, this paper presents a machine learning-based framework for personalized insulin dose prediction using ANN and LSTM models trained on the Code 34 diabetes dataset. The proposed framework incorporates comprehensive data preprocessing, temporal alignment, and feature engineering to effectively model glucose-insulin interactions. A comparative evaluation is performed to analyze the predictive capabilities of both models using standard regression metrics and benchmark them against conventional static insulin dosing rules.

Experimental results demonstrate that the proposed learning-based models achieve substantial improvements in prediction accuracy while maintaining consistent performance across multiple patient and meal-based sequences. The findings indicate that intelligent machine learning models can serve as reliable decision-support tools for personalized insulin therapy and contribute toward the development of future AI-enabled diabetes management systems.

II. Related Work

Recent advances in machine learning have significantly influenced diabetes research, particularly in disease diagnosis, risk prediction, and personalized treatment planning. Early studies primarily focused on identifying diabetic patients using conventional machine learning algorithms such as Decision Trees, Support Vector Machines (SVM), Logistic Regression, and Random Forests trained on structured clinical datasets. These approaches demonstrated that data-driven models could achieve higher prediction accuracy than traditional statistical techniques while assisting clinicians in early disease diagnosis and risk assessment [3], [6]. Ensemble learning methods further improved predictive performance by combining multiple classifiers, resulting in greater robustness and generalization across diverse patient populations [4]. Similarly, comparative analyses of various data mining techniques revealed that no single algorithm consistently performs best for every diabetes dataset, emphasizing the importance of selecting models based on the characteristics of the underlying clinical data [10].

With the growing availability of electronic health records and continuous patient monitoring systems, deep learning has emerged as an effective alternative for modeling the complex nonlinear relationships associated with diabetes. Artificial Neural Networks (ANNs) have demonstrated superior capability in learning intricate interactions among physiological variables, enabling more accurate prediction of diabetic conditions compared with conventional machine learning algorithms [5]. Moreover, several studies have shown that deep neural architectures can effectively exploit large-scale clinical datasets without requiring extensive manual feature engineering, making them suitable for healthcare applications involving heterogeneous patient information [7]. These developments have encouraged the adoption of neural network-based approaches for more advanced prediction tasks beyond disease diagnosis.

Although disease prediction has received considerable attention, insulin dosage estimation presents additional challenges because glucose metabolism is inherently dynamic and depends on temporal interactions among glucose measurements, insulin administration, meals, and physical activity. Consequently, recurrent neural networks and Long Short-Term Memory (LSTM) architectures have gained popularity for modeling sequential physiological data. Martinsson et al. demonstrated the effectiveness of recurrent neural networks for automatic blood glucose prediction by capturing temporal glucose fluctuations from historical observations [11]. Similarly, Idriss et al. reported that LSTM networks achieved reliable glucose forecasting by learning long-term dependencies within continuous glucose monitoring data, making them particularly suitable for personalized diabetes management systems [13]. Adaptive prediction frameworks have also shown promising results in supporting real-time glucose estimation for Type 1 diabetes patients by continuously updating prediction models using incoming patient data [17].

Recent research has gradually shifted from generalized prediction models toward personalized and adaptive diabetes management. Personalized machine learning frameworks have demonstrated that individual physiological characteristics, dietary behavior, and lifestyle factors significantly influence glycemic responses, highlighting the limitations of population-based insulin recommendations [15]. Furthermore, dynamic treatment strategies based on deep learning have shown the ability to continuously adapt therapeutic decisions according to changing patient conditions, thereby improving long-term treatment effectiveness [16]. Despite these advancements, many existing studies primarily concentrate on diabetes diagnosis or glucose prediction, while comparatively fewer investigations address personalized insulin dosage prediction using both static clinical features and temporal glucose patterns. Motivated by this research gap, the present work performs a comparative evaluation of Artificial Neural Networks and Long Short-Term Memory networks for insulin dose prediction using the Code 34 diabetes dataset, aiming to develop a reliable machine learning framework capable of supporting personalized insulin recommendation in intelligent diabetes management systems.

III. Methodology

A. Overall Proposed Framework

The proposed framework is designed to predict personalized insulin dosage by combining the learning capabilities of Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks. The overall workflow begins with collecting patient records containing glucose measurements, insulin administration history, meal information, and other time-dependent clinical observations from the Code 34 diabetes dataset. The acquired data undergoes preprocessing and feature engineering to generate meaningful inputs for model training. The ANN model learns nonlinear relationships among clinical variables, whereas the LSTM model captures temporal dependencies in sequential glucose patterns. The predicted insulin doses are subsequently evaluated using standard regression metrics and compared with conventional static insulin dosing rules to assess the effectiveness of the proposed machine learning framework.

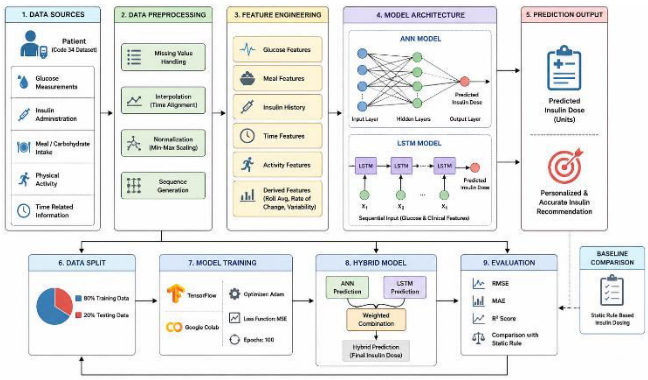

Fig.1 Overall System Architecture

The system architecture consists of five major stages: dataset acquisition, data preprocessing, feature engineering, model development, and performance evaluation. Initially, patient records are cleaned, normalized, and transformed into suitable input features. The processed data are then supplied to both ANN and LSTM models, where the ANN performs nonlinear regression while the LSTM analyzes sequential glucose variations. Finally, the predicted insulin doses are compared with actual insulin values and conventional dosing rules using regression-based evaluation metrics to determine the predictive performance of the proposed framework.

B. Dataset

The proposed insulin prediction framework utilizes the Code 34 diabetes dataset, which contains time-series clinical records collected from individuals undergoing insulin therapy. The dataset includes continuous glucose measurements, insulin administration records, meal-related information, and other patient observations that describe glucose-insulin dynamics over time. These records provide the temporal and physiological information required for developing personalized insulin prediction models. The primary input variables include blood glucose levels, previous insulin dosage, carbohydrate intake, physical activity, and time-related features, while the target variable is the insulin dose to be administered. The dataset is organized as chronological patient records, enabling both ANN and LSTM models to learn static feature relationships and temporal glucose patterns for accurate insulin dose prediction.

C. Data Preprocessing

Data preprocessing is an essential step in developing reliable machine learning models, as the quality of the input data directly influences prediction accuracy. The raw patient records were processed through multiple preprocessing stages to eliminate inconsistencies, improve data quality, and prepare the dataset for effective training of the ANN and LSTM models.

Missing Value Handling: The collected clinical records contained missing values resulting from irregular glucose measurements and incomplete patient logs. These missing entries were carefully handled to preserve data continuity while minimizing information loss. Records with excessive missing information were excluded, whereas minor missing observations were treated using appropriate imputation techniques to maintain the consistency and reliability of the glucose-insulin time series.

Interpolation: Since glucose and insulin measurements were recorded at irregular time intervals, temporal interpolation was applied to generate uniformly spaced observations. Linear interpolation was employed to estimate intermediate glucose values and align all physiological measurements to fixed time intervals. This temporal synchronization preserves the continuity of glucose trends and enables the LSTM model to effectively learn sequential dependencies from consistent time-series data.

Normalization: The numerical input variables exhibited different value ranges, which could negatively affect model convergence during training. Therefore, feature normalization was performed to scale the clinical variables into a comparable numerical range while preserving their relative relationships. This process prevents features with larger magnitudes from dominating the learning process, accelerates model convergence, and improves the overall stability and prediction performance of both ANN and LSTM models.

Sequence Generation: To enable temporal learning, the preprocessed data were transformed into sequential input windows representing historical glucose patterns. Each sequence contains consecutive glucose observations and their corresponding clinical features over a predefined time interval, while the associated insulin dose serves as the prediction target. This sequence generation strategy allows the LSTM model to capture long-term temporal dependencies, whereas the ANN utilizes the corresponding static feature representation for insulin dose prediction.

The resulting preprocessed dataset provides clean, normalized, and temporally aligned patient records that facilitate effective learning of both nonlinear feature relationships and sequential glucose dynamics, thereby improving the accuracy and robustness of insulin dose prediction.

D. Feature Engineering

Feature engineering was performed to extract meaningful clinical information from the preprocessed patient records and improve the predictive capability of the proposed models. The primary features include current blood glucose levels, meal-related information such as carbohydrate intake, previous insulin administration history, time-based attributes representing daily glucose variations, and physical activity that influences insulin sensitivity. In addition to these direct variables, several derived features, including glucose rate of change, rolling glucose averages, glycemic variability, and time-in-range indicators, were generated to better characterize glucose-insulin dynamics. These engineered features provide comprehensive physiological and temporal information, enabling the ANN to learn complex nonlinear relationships while allowing the LSTM model to effectively capture sequential glucose patterns for accurate insulin dose prediction.

E. Algorithms

The proposed insulin prediction framework employs two deep learning models to capture different characteristics of glucose-insulin dynamics. Artificial Neural Networks (ANN) are utilized to model complex nonlinear relationships among clinical features, whereas Long Short-Term Memory (LSTM) networks are designed to learn temporal dependencies from sequential glucose measurements. The combination of these complementary models enables comprehensive analysis of both static physiological variables and time-dependent glucose variations.

Artificial Neural Network (ANN): The ANN model is developed as a feed-forward regression network for predicting personalized insulin dosage from clinical input features. The architecture consists of an input layer that receives the engineered features, followed by two fully connected hidden layers with ReLU activation functions to learn nonlinear relationships among glucose levels, meal information, insulin history, and activity-related variables. A single neuron with a linear activation function is used in the output layer to generate the predicted insulin dose. The model is trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function, enabling efficient optimization while minimizing prediction errors. Owing to its simple architecture and fast inference capability, the ANN model provides accurate insulin dose estimation with relatively low computational complexity.

Long Short-Term Memory (LSTM): The LSTM model is designed to capture the temporal behavior of glucose-insulin dynamics by processing sequential patient records. The network receives fixed-length glucose sequences generated during preprocessing and consists of stacked LSTM layers followed by a dense output layer for continuous insulin dose prediction. The memory cells and gating mechanisms enable the network to preserve long-term dependencies while filtering irrelevant information from the input sequence. Similar to the ANN model, the LSTM is optimized using the Adam optimizer and Mean Squared Error (MSE) loss function. By learning historical glucose trends and temporal variations, the LSTM model provides improved prediction capability for time-dependent insulin requirements and supports personalized diabetes management.

IV. Results & Discussion

A. Experimental Setup

The proposed insulin prediction models were implemented using TensorFlow in the Google Colab environment, which provided the required computational resources for training and evaluation. The dataset was divided into 80% training and 20% testing subsets to assess the generalization capability of the models. Both the ANN and LSTM networks were trained using the Adam optimizer with the Mean Squared Error (MSE) loss function to minimize prediction errors. Model training was carried out for 100 epochs, with validation performed during training to monitor convergence and prevent overfitting. The performance of both models was subsequently evaluated using standard regression metrics and compared with conventional static insulin dosing rules.

B. Performance Comparison

The performance of the proposed ANN and LSTM models was evaluated using the Root Mean Squared Error (RMSE) and compared with conventional static insulin dosing rules across different patient and meal-based sequences. Lower RMSE values indicate higher prediction accuracy and better agreement between the predicted and actual insulin doses. The experimental results demonstrate that both machine learning models consistently outperform the traditional rule-based approach, highlighting their capability to learn complex glucose-insulin relationships from historical patient data. Among the evaluated models, the LSTM achieved superior performance in sequences with strong temporal dependencies, whereas the ANN produced comparable results for relatively stable glucose patterns.

Table 1 presents the quantitative comparison between the static insulin dosing rule and the proposed ANN and LSTM models. The results show that the learning-based approaches achieved substantial reductions in prediction error, with improvements ranging from 26% to 48% over the conventional dosing method.

Table 1. Overall Performance Comparison

Sequence	Static Rule RMSE	ANN RMSE	LSTM RMSE	Improvement over Static Rule (LSTM)
Patient 1	0.34	0.23	0.25	~26%
Patient 2	0.29	0.16	0.15	~48%
Breakfast	0.18	0.10	0.10	~44%
Lunch	0.20	0.11	0.11	~45%
Dinner	0.17	0.10	0.10	~41%

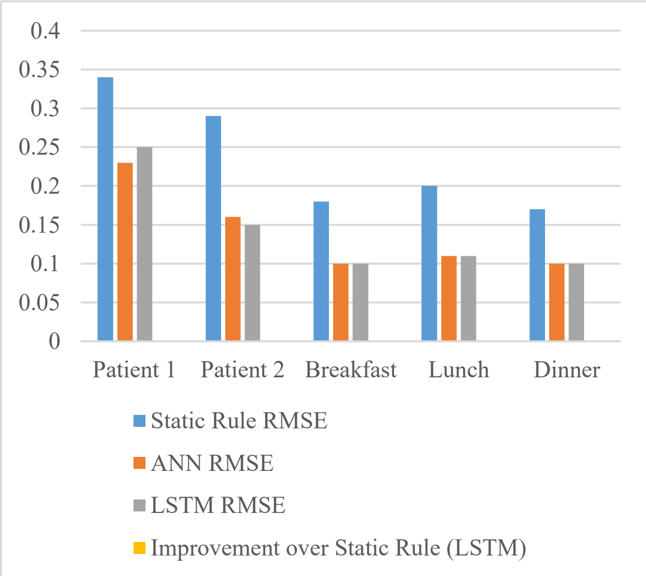

Fig.2 Performance Comparison Graph

Figure 2 visually compares the prediction performance of the three approaches across different evaluation sequences. It can be observed that both ANN and LSTM consistently achieve lower RMSE values than the conventional static rule, confirming the effectiveness of machine learning-based insulin prediction. While the ANN performs competitively for relatively stable glucose profiles, the LSTM demonstrates improved adaptability in capturing temporal variations, particularly for Patient 2, where it achieves the lowest prediction error.

To further improve prediction robustness, a hybrid framework combining the outputs of the ANN and LSTM models was evaluated. As shown in Table 2, the hybrid model either matched or slightly outperformed the individual models by leveraging the complementary strengths of both architectures. The greatest improvement was observed for Patient 2, where the hybrid model reduced the RMSE to 0.14, while maintaining comparable performance for the remaining sequences.

Table 2. Hybrid Model Performance Comparison

Sequence	ANN RMSE	LSTM RMSE	Hybrid RMSE
Patient 1	0.23	0.25	0.22
Patient 2	0.16	0.15	0.14
Breakfast	0.10	0.10	0.10
Lunch	0.11	0.11	0.10
Dinner	0.10	0.10	0.10

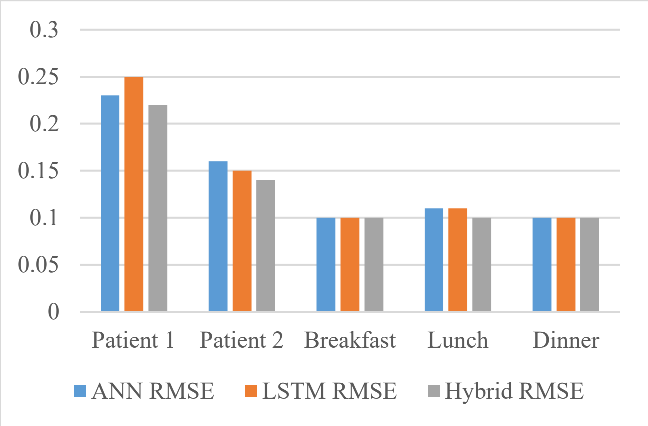

Fig.3 Hybrid Model Performance Comparison Graph

The learning behavior of both models was analyzed using the training and validation loss curves. The ANN exhibited rapid convergence during the early training stages and stabilized after approximately 30 epochs, whereas the LSTM continued to improve until around 70 epochs, reflecting its ability to learn temporal dependencies from sequential glucose data. The final training and validation losses indicate stable convergence with minimal evidence of overfitting.

Table 3. Learning Behavior of the Proposed Models

Model	**Final Train Loss**	**Final Validation Loss**	**Convergence Epoch**
ANN	0.038	0.043	~30
LSTM	0.027	0.038	~70

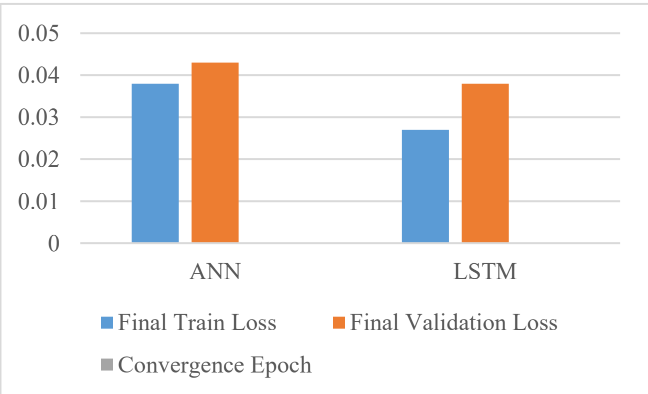

Fig.4 Learning Behavior of the Proposed Models Graph

Overall, the experimental results demonstrate that the proposed deep learning models provide more accurate insulin dose prediction than conventional static dosing rules. The ANN offers efficient nonlinear regression with fast convergence, while the LSTM effectively captures temporal glucose variations. Furthermore, the hybrid model combines the strengths of both approaches, producing the most consistent prediction performance across different patient and meal-based scenarios, thereby highlighting the potential of intelligent machine learning techniques for personalized diabetes management.

C. Discussion

The experimental results demonstrate that both ANN and LSTM models significantly outperform conventional static insulin dosing rules by learning patient-specific glucose-insulin relationships from historical clinical data. The ANN effectively models nonlinear interactions among physiological variables and provides fast, stable predictions with rapid convergence. In contrast, the LSTM captures temporal glucose fluctuations more effectively, resulting in improved performance for sequences exhibiting strong time-dependent patterns. The hybrid approach combines the complementary strengths of both models, achieving the lowest prediction errors in selected cases while maintaining consistent performance across different evaluation scenarios. Overall, the proposed machine learning framework offers a more accurate and personalized alternative to traditional rule-based insulin dosing methods, highlighting its potential for intelligent diabetes management and future clinical decision-support systems.

V. Conclusion

This paper presented a machine learning-based framework for personalized insulin dose prediction using Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks. The proposed approach utilized the Code 34 diabetes dataset and incorporated data preprocessing, feature engineering, and deep learning techniques to model complex glucose-insulin relationships. Experimental evaluation demonstrated that both ANN and LSTM consistently outperformed conventional static insulin dosing rules, achieving significant reductions in prediction error across different patient and meal-based sequences. The ANN effectively captured nonlinear relationships among clinical variables with faster convergence, while the LSTM provided improved performance for sequential glucose patterns by learning temporal dependencies. Furthermore, the hybrid approach combined the strengths of both models and produced the most consistent prediction performance in selected scenarios. The overall findings indicate that learning-based insulin prediction models can provide more accurate, adaptive, and personalized insulin recommendations than traditional rule-based methods, thereby supporting intelligent clinical decision-making and improving the effectiveness of diabetes management systems.

Future research can focus on validating the proposed framework using larger and more diverse clinical datasets collected from multiple healthcare centers. The integration of continuous glucose monitoring devices, wearable sensors, and real-time physiological data can further enhance prediction accuracy. In addition, incorporating advanced deep learning architectures and explainable artificial intelligence techniques can improve model interpretability, enabling reliable deployment in clinical decision-support systems and closed-loop insulin delivery applications.

REFERENCES

[1] A. M. Syed, M. U. Akram, T. Akram, M. Muzammal, S. Khalid, and M. A. Khan, "Fundus images-based detection and grading of macular edema using robust macula localization," IEEE Access, vol. 6, pp. 58784–58793, 2018.

[2] A. Cahn, A. Shoshan, T. Sagiv et al., "Prediction of progression from pre-diabetes to diabetes: development and validation of a machine learning model," Diabetes, vol. 36, no. 2, pp. 1–8, 2020.

[3] Veena Vijayan V. And Anjali C, Prediction and Diagnosis of Diabetes Mellitus, "A Machine Learning Approach",2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS) | 10- 12 December 2015 | Trivandrum.

[4] M. K. Hasan, M. A. Alam, D. Das, E. Hossain, and M. Hasan, "Diabetes prediction using ensembling of different machine learning classifiers," IEEE Access, vol. 8, pp. 76516–76531, 2020.

[5] S. Islam Ayon, and M. Milon Islam, "Diabetes prediction: a deep learning approach," International Journal of Information Engineering and Electronic Business, vol. 11, no. 2, pp. 21–27, 2019.

[6] M. Maniruzzaman, M. J. Rahman, B. Ahammed, and M. M. Abedin, "Classification and prediction of diabetes disease using machine learning paradigm," Health Information Science and Systems, vol. 8, no. 1, pp. 1–14, 2020.

[7] P. Suresh Kumar and V. Umatejaswi, "Diagnosing Diabetes using Data Mining Techniques", International Journal of Scientific and Research Publications, Volume 7, Issue 6, June 2017 705 ISSN 2250-3153, pp. 705-709.

[8] Ridam Pal, Dr. Jayanta Poray, and Mainak Sen, "Application of Machine Learning Algorithms on Diabetic Retinopathy", 2017 2nd IEEE International Conference on Recent Trends in Electronics Information & Communication Technology, May 19-20, 2017, India.

[9] Berina Alic, Lejla Gurbeta and Almir Badnjevic, "Machine Learning Techniques for Classification of Diabetes and Cardiovascular Diseases", 2017 6th Mediterranean Conference on Embedded Computing (MECO), 11-15 JUNE 2017, BAR, MONTENEGRO.

[10] Dr. M. Renuka Devi and J. Maria Shyla, "Analysis of Various Data Mining Techniques to Predict Diabetes Mellitus", International Journal of Applied Engineering Research ISSN 0973-4562 Volume 11, Number 1 (2016) pp 727-730 © Research India Publications. http://www.ripublication.com

[11] Martinsson, John, Alexander Schliep, Bjorn Eliasson, Christian Meijner, Simon Persson, and Olof Mogren. "Automatic blood glucose prediction with confidence using recurrent neural networks." In Khd@ ijcai. 2018.

[12] Minyechil Alehegn and Rahul Joshi, "Analysis and prediction of diabetes diseases using machine learning algorithm": Ensemble approach, International Research Journal of Engineering and Technology Volume: 04 Issue: 10 | Oct -2017

[13] T. E. Idriss, A. Idri, I. Abnane and Z. Bakkoury, "Predicting Blood Glucose using an LSTM Neural Network," 2019 Federated Conference on Computer Science and Information Systems (FedCSIS), 2019, pp. 35-41, doi: 10.15439/2019F159.

[14] Michael Kahn, MD, PhD, Washington University,St. Louis, MO, https://archive.ics.uci.edu/ml/datasets/diabetes (accessed on 10/06/2022).

[15] D. Zeevi et al., "Personalized nutrition prediction using machine learning," Nature, vol. 528, no. 7583, pp. 484–489, 2015.

[16] V. Borisov et al., "Deep learning for dynamic treatment regimes in chronic diseases," J. Med. Syst., vol. 45, no. 4, pp. 1–12, 2021.

[17] E. Daskalaki et al., "Real-time glucose prediction in type 1 diabetes using adaptive models," IEEE Trans. Biomed. Eng., vol. 63, no. 6, pp. 1211–1221, 2016.