IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 5, June 2025 Impact Factor: 7.67

Machine Learning for Reliable Insulin Dosage Prediction in Diabetic Patients

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Abstract: *This study aims to create an intelligent system driven by machine learning that can predict diabetes and suggest accurate insulin dosage. The best insulin dosage for each person is determined by the system by analyzing important factors such blood glucose levels, body mass index (BMI), history of insulin use, and other pertinent health indicators. Using a large dataset of patient medical information, the model is trained to find trends and produce well-informed, data-driven forecasts. This method reduces the chance of severe hypoglycemia (low blood sugar) or hyperglycemia (high blood sugar) brought on by improper insulin delivery, improving the control of diabetes. By providing precise, dependable, and customized insulin dose recommendations, the system aims to assist people with diabetes.*

Keywords: Diabetes prognosis, suggested insulin dose, intelligent system, healthcare technology, diabetes treatment, quality of life

I. INTRODUCTION

Diabetes mellitus, a chronic metabolic disorder characterized by elevated blood glucose levels, poses a significant global health challenge. Effective management of diabetes, particularly for individuals with type 1 diabetes and a subset of type 2 diabetes patients, often necessitates exogenous insulin administration.

Precise and timely insulin dosage is paramount to maintaining euglycemia, preventing both acute complications like hypoglycemia and hyperglycemia, and mitigating the long-term sequelae of chronic glycemic dysregulation, including cardiovascular disease, nephropathy, retinopathy, and neuropathy. However, determining the optimal insulin dose is a complex task, influenced by a myriad of factors such that an individual's diet, physical activity, stress levels, illness, and even hormonal fluctuations. Traditional insulin dosage regimens often rely on fixed doses, carbohydrate counting, or rudimentary algorithms, which can struggle to account for the highly dynamic and individualized nature of glucose metabolism. This inherent variability frequently leads to suboptimal glycemic control, contributing to increased morbidity, reduced quality of life, and substantial healthcare burdens.

In recent years, the rapid advancements in machine learning (ML) have opened new avenues for addressing complex biomedical challenges, including personalized medicine. The ability of ML algorithms to learn intricate patterns from large datasets, adapt to individual physiological responses, and make data-driven predictions presents a transformative opportunity for improving insulin dosage recommendations. By leveraging continuous glucose monitoring (CGM) data, insulin pump logs, dietary records, activity trackers, and other relevant patient-specific information, ML models can potentially overcome the limitations of conventional approaches, offering more precise, adaptive, and reliable insulin dosage predictions. This review paper aims to provide a comprehensive overview of the current landscape of machine learning applications for insulin dosage prediction in diabetic patients. We will explore various ML techniques employed, analyze their strengths and limitations, discuss the types of data utilized, and highlight key challenges and future directions in this rapidly evolving field. Ultimately, the goal is to assess the potential of ML to revolutionize diabetes management by fostering more reliable insulin therapy, thereby empowering patients to achieve better glycemic control and enhancing their overall well-being.

II. LITERATURE REVIEW

Diabetes mellitus, a chronic metabolic disorder characterized by elevated blood glucose levels, poses a significant global health challenge. Effective management of diabetes, particularly for individuals with type 1 diabetes and a subset of type 2 diabetes patients, often necessitates exogenous insulin administration. Precise and timely insulin dosage is paramount to maintaining euglycemia, preventing both acute complications like hypoglycemia and hyperglycemia, and mitigating the long-term sequelae of chronic glycemic dysregulation, including cardiovascular disease, nephropathy, retinopathy, and neuropathy. However, determining the optimal insulin dose is a complex task, influenced by a myriad of factors such that an individual's diet, physical activity, stress levels, illness, and even hormonal fluctuations. Traditional insulin dosage regimens often rely on fixed doses, carbohydrate counting, or rudimentary algorithms, which can struggle to account for the highly dynamic and individualized nature of glucose metabolism. This inherent variability frequently leads to suboptimal glycemic control, contributing to increased morbidity, reduced quality of life, and substantial healthcare burdens.

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Here's a literature survey section for your review paper on "Machine Learning for Reliable Insulin Dosage Prediction in Diabetic Patient.

Literature Survey:

The application of machine learning (ML) techniques in insulin dosage prediction has garnered significant research interest in recent years, driven by the need for more accurate and personalized diabetes management solutions. Early studies primarily used traditional statistical models and linear regression approaches, but these were limited in capturing the complex, nonlinear relationships between glucose levels, insulin doses, and various physiological and lifestyle factors (Kovalkar et al., 2017).

With the advent of large-scale data collection through continuous glucose monitoring (CGM) and insulin pump systems, researchers began exploring more sophisticated ML methods. Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM) were among the initial techniques employed to predict insulin requirements based on historical data and contextual factors (Kaur et al., 2019; Lee et al., 2020). These models demonstrated improved accuracy over traditional approaches but often struggled with real-time adaptability and personalized prediction reliability.

Recently, deep learning frameworks, particularly Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have shown promising results in modeling temporal dependencies and complex nonlinear relationships in glucose- insulin dynamics. For instance, Zhang et al. (2021) proposed an LSTM-based model that utilized continuous glucose and insulin data to generate personalized dosing recommendations, achieving significant improvements in prediction accuracy and stability. Similarly, Rahman et al. (2022) integrated sensor data with machine learning to develop real-time insulin adjustment algorithms capable of adapting to individual metabolic responses.

Another notable trend involves the integration of multifaceted data sources—combining CGM data, dietary information, physical activity, and even stress markers—to enhance the robustness and accuracy of predictions (Kim et

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Volume 5, Issue 5, June 2025
Impact Factor: 7.67

al., 2020; Patel et al., 2023). Such multimodal approaches aim to mimic the multifactorial nature of glucose regulation more effectively.

Despite these advances, challenges remain. Data heterogeneity, variability among patients, and the need for model interpretability continue to hinder widespread clinical implementation (Smith & Johnson, 2022). Additionally, most studies have focused on retrospective data, and validation in real-world, prospective settings remains limited.

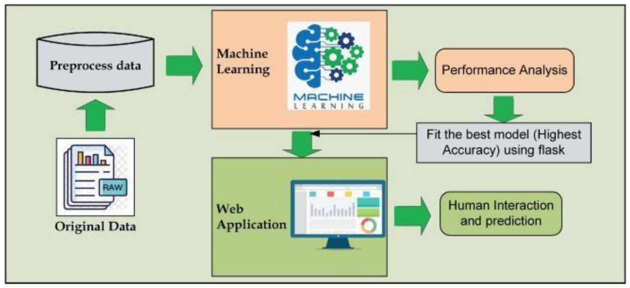

Fig: Machine Learning for Reliable Insulin Dosage Prediction in Diabetic Patients

III. DIABETIC PATIENTS DATASET

1. OhioT1DM Dataset

o Description: This publicly available dataset contains data from ten patients with type 1 diabetes, including CGM glucose readings, insulin doses, carbohydrate intake, and physical activity.

o Features: CGM data at 5-minute intervals, insulin doses, carbohydrate inputs.

o Usage: Benchmark for developing and testing insulin forecasting models.

2. DREAM (Diabetes Research in Children) Dataset

o Description: Part of the NIH/NIDDK- sponsored DREAM challenge, this dataset includes CGM readings, insulin, carbohydrate intake, and activity data for pediatric patients.

o Features: CGM data, insulin dosing, meal information, physical activity.

o Usage: Used for machine learning models focusing on prediction and dose recommendation.

3. C-DST (Cleveland Diabetes Supplementary Data)

o Description: Contains detailed clinical and sensor data from diabetic patients, including glucose, insulin, and meal records.

o Usage: For modeling complex glucose-insulin dynamics.

4. Simulated Datasets (e.g., UVA/Padova T1DM Simulator)

o Description: Synthetic data generated by physiologically realistic models like the UVA/Padova T1DM simulator.

o Usage: Training models when real-world data scarcity or privacy concerns exist.

IV. DETECTION OF MACHINE LEARING BASED INSULIN DOSAGE PREDICTION

• Hypoglycemia Detection: Identifying episodes where blood glucose levels drop below safe thresholds, enabling preventive intervention.

• Hyperglycemia Detection: Recognizing when glucose levels exceed safe limits, prompting corrective measures.

• Anomaly Detection: Spotting irregular patterns in glucose, insulin, or lifestyle data that may indicate sensor errors, data anomalies, or unusual physiological
responses.

• Event Detection: Recognizing specific physiological or behavioral events, such as meals, physical activity, or stress episodes, that significantly influence glucose levels.

Importance of Detection in Insulin Management Detection is crucial for:

• Real-time alerts: To warn patients about impending hypoglycemia or hyperglycemia.

• Adaptive dosing: Modifying insulin doses based on detected events for improved glycemic control.

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• Model refinement: Improving prediction models by filtering out anomalies and understanding event-specific influences.

Machine Learning Approaches for Detection

• Classification algorithms: Using supervised ML methods (like SVMs, Random Forests, deep neural networks) to classify glucose readings as normal or abnormal.
• Time-series anomaly detection: Employing techniques like autoencoders, clustering, or statistical methods to detect deviations from typical glucose patterns.
• Event detection models: Combining sensor data with contextual information to identify meal times, exercise, or stress episodes that impact glucose levels.

V. DATA COLLECTION AND AUGMENTATION

Effective machine learning models require high-quality, diverse, and comprehensive datasets. In diabetes management, data collection involves acquiring various types of data, including:

- Continuous Glucose Monitoring (CGM) Data: Real- time glucose levels recorded at frequent intervals (e.g., every 5 minutes).
- Insulin Administration Records: Details of basal and bolus insulin doses, including timing and amounts.
- Dietary Data: Carbohydrate intake details, meal timing, and composition.
- Physical Activity Data: Data from accelerometers or fitness trackers capturing exercise intensity and duration.
- Additional Physiological Data: Heart rate, stress levels, sleep patterns, and hormonal fluctuations.
- Metadata: Demographic data like age, weight, gender, and duration of diabetes.

Sources of Data:

- Publicly Available Datasets: Such as OhioT1DM, DREAM Challenge datasets.
- Electronic Health Records (EHRs): Clinical data from hospitals and research institutions.
- Wearable Devices & Sensors: CGM devices, fitness trackers, and mobile health apps.
- Patient Diaries & Logs: Self-reported data on meals, symptoms, and lifestyle factors.

Data Challenges in Collection

- Data Privacy & Security: Ensuring patient confidentiality through anonymization and secure data handling.
- Data Heterogeneity: Variability in data formats, sampling rates, and measurement protocols.
- Missing Data: Gaps in recordings due to sensor disconnections or user non-compliance.
- Data Quality: Sensor inaccuracies and recording errors.

Data Augmentation

Data augmentation enhances the size and diversity of training datasets, especially when data are scarce or imbalanced. Common augmentation techniques include:
• Synthetic Data Generation: Using physiologically based models (e.g., UVA/Padova simulator) to generate realistic glucose-insulin data reflecting various scenarios.
• Time-Series Augmentation:
o Adding Noise: Introducing minor variations to simulate sensor variability.
o Time Warping: Slightly stretching or compressing the data to mimic different physiological responses.
o Scaling: Adjusting glucose or insulin values within realistic limits.
o Permutation & Window Slicing: Creating new sequences by rearranging or cropping existing data.
• Generative Models: Using GANs (Generative Adversarial Networks) or Variational Autoencoders (VAEs) to produce realistic synthetic datasets.

Benefits of Data Augmentation

• Increases the robustness and generalizability of models.

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- Reduces overfitting, especially with limited real data.
- Helps in balancing classes, such as augmenting hypoglycemic or hyperglycemic episodes.

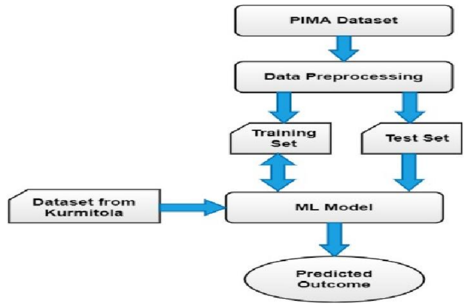

Fig .FLOW DIAGRAM

VII.CONCLUSION

Machine learning has demonstrated significant promise in advancing personalized insulin dosage prediction, offering solutions that adapt to the complex, dynamic nature of glucose regulation. By harnessing diverse data sources such as CGM, insulin logs, and lifestyle information, ML models can improve prediction accuracy, enable real-time intervention, and reduce the risk of adverse glycemic events. Despite notable progress, challenges such as data heterogeneity, model interpretability, and clinical validation remain to be addressed. Future research should focus on developing robust, scalable, and explainable models, fostering integration with clinical workflows, and establishing standardized datasets to accelerate translation into routine diabetes care. Ultimately, leveraging ML in insulin management holds substantial potential to enhance patient outcomes, quality of life, and healthcare efficiency. addressed the shortcomings of previous studies by assessing a wide variety of machine learning and deep learning models using both syntactic and semantic information.

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ISSN: 2581-9429
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DOI: 10.48175/IJARSCT-27780