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ARTIFICIAL INTELLIGENCE-BASED CLINICAL DECISION SUPPORT SYSTEM FOR PRIORITIZING MONITORING AND MANAGEMENT OF PATIENTS WITH DIABETES USING CONTINUOUS GLUCOSE MONITORING DATA

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Abstract

Diabetes mellitus remains a major global health challenge. This expanded paper discusses how artificial intelligence (AI) and machine learning can be integrated into Clinical Decision Support Systems (CDSS) to improve the interpretation of Continuous Glucose Monitoring (CGM) data. The proposed system analyzes glucose trends, identifies risk patterns, prioritizes patients requiring intervention, and supports healthcare professionals in decision-making. The study highlights the potential of AI to improve glycemic outcomes, optimize healthcare resources, and enhance patient quality of life.

Keywords: Artificial Intelligence (AI), Clinical Decision Support System (CDSS), Diabetes Mellitus, Continuous Glucose Monitoring (CGM), Diabetes Management, Explainable AI (XAI).

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Introduction

Diabetes affects hundreds of millions of people worldwide and is associated with significant morbidity and mortality [1]. Effective glycemic control reduces the risk of long-term complications, yet maintaining stable glucose levels remains difficult for many patients. Continuous Glucose Monitoring technologies provide a detailed picture of glucose behavior, but the sheer volume of data can overwhelm both patients and clinicians [2]. Artificial intelligence offers an opportunity to transform raw glucose measurements into actionable clinical insights. AI-based systems can identify patterns that may not be immediately visible and can provide recommendations that support timely intervention[3].

Literature Review

Recent studies have demonstrated the value of machine learning in diabetes care. Researchers have developed predictive models for hypoglycemia detection, insulin dose optimization, and glucose forecasting[4]. Advances in deep learning have enabled increasingly accurate analysis of physiological data[5]. Several investigations have reported improved clinical outcomes when decision-support tools are integrated into diabetes management programs. Despite these advances, challenges remain regarding interpretability, clinical validation, and implementation in routine healthcare settings[6].

Machine Learning Algorithms

Several machine learning techniques can be utilized, including decision trees, random forests, support vector machines, and neural networks[7]. These methods are trained using historical CGM datasets and validated against clinical outcomes. Feature engineering focuses on glucose variability, trends, fasting values, postprandial excursions, and hypoglycemic episodes. Model performance is assessed using accuracy, sensitivity, specificity, and area-under-the-curve metrics[8].

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Materials and Methods

The proposed CDSS uses CGM data as the primary input source. Data preprocessing includes noise filtering, handling missing values, and normalization. Machine learning algorithms evaluate glucose trends, variability, and temporal relationships between glucose measurements. The system calculates Time in Range (TIR), estimated HbA1c, glucose variability indices, and the frequency of abnormal glycemic events. Automated reports are generated to assist clinicians during follow-up visits.

System Architecture

The architecture consists of four main layers: data acquisition, preprocessing, machine learning analysis, and clinical decision support. The acquisition layer receives CGM sensor readings. The preprocessing layer prepares data for analysis. The machine learning layer identifies patterns and classifies risk levels. Finally, the decision-support layer generates recommendations and prioritization alerts for healthcare providers.

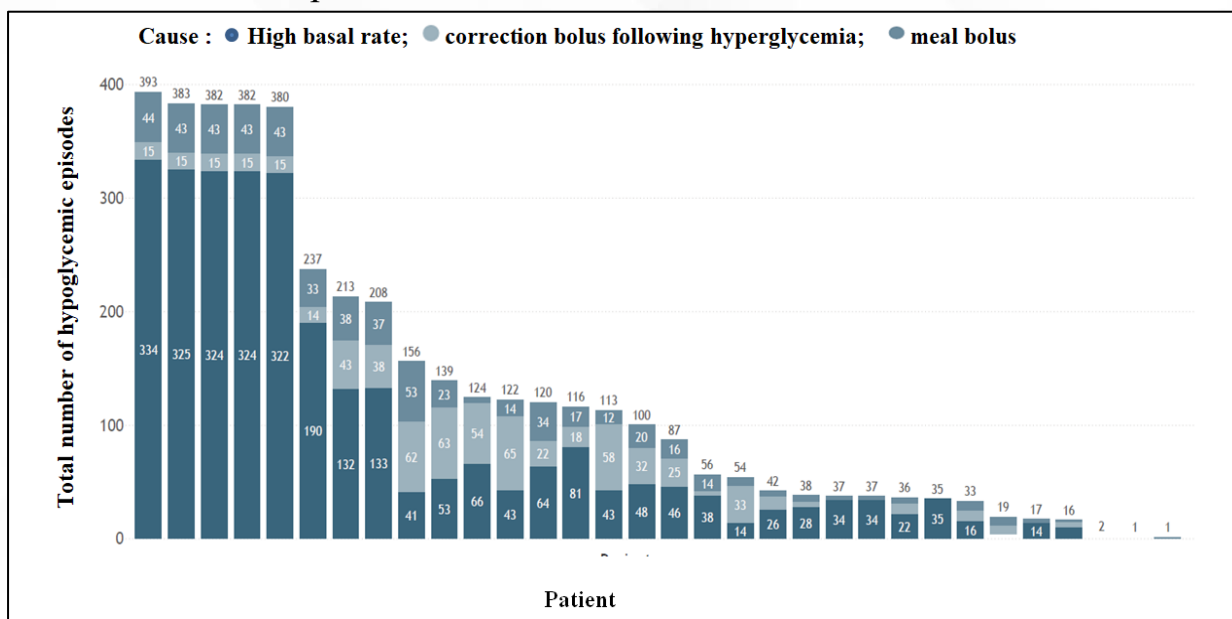


Figure1: Classification of patients according to the number of hypoglycemic episodes and their most probable cause.

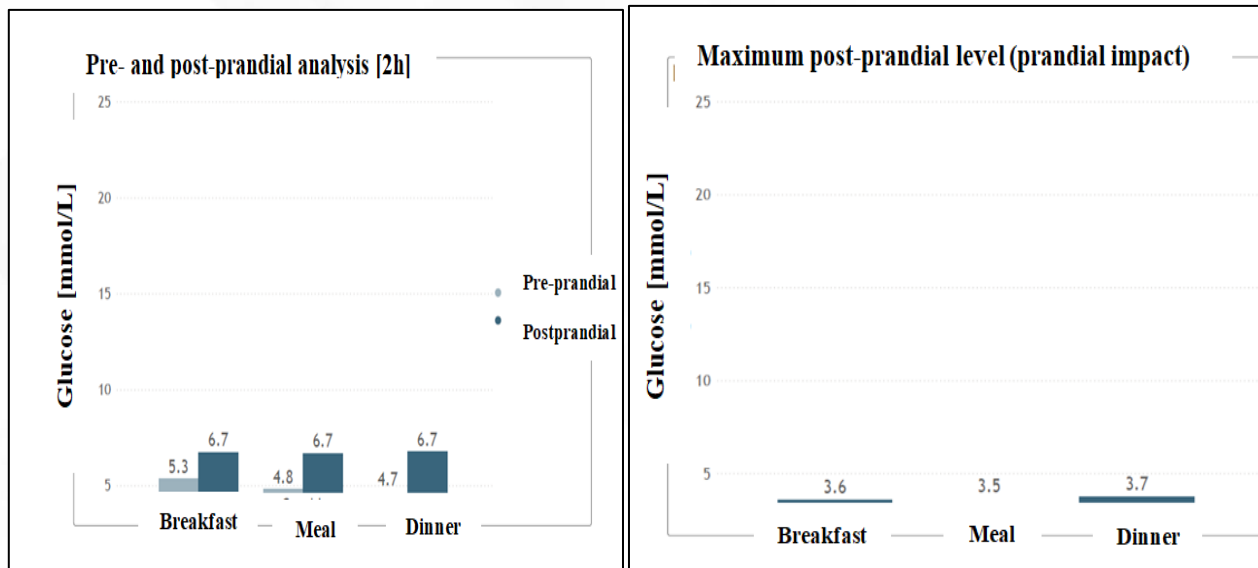
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Breakfast	Meal	Dinner	Total	Breakfast	Meal	Dinner	Total
1.37	1.87	2.08	1.83	3.59	3.47	3.72	3.57
Delta	Delta	Delta	Delta	Impact	Impact	Impact	Impact

Identified meals:	Breakfast	Meal	Dinner	All meals	Percentage of identified meals
	47	118	70	235	
Estimated meals:	Breakfast	Meal	Dinner	All meals	41% of the total estimated meals
	80	19	67	166	

Figure 2: Individual analysis of the pre- and postprandial glycemic profile.

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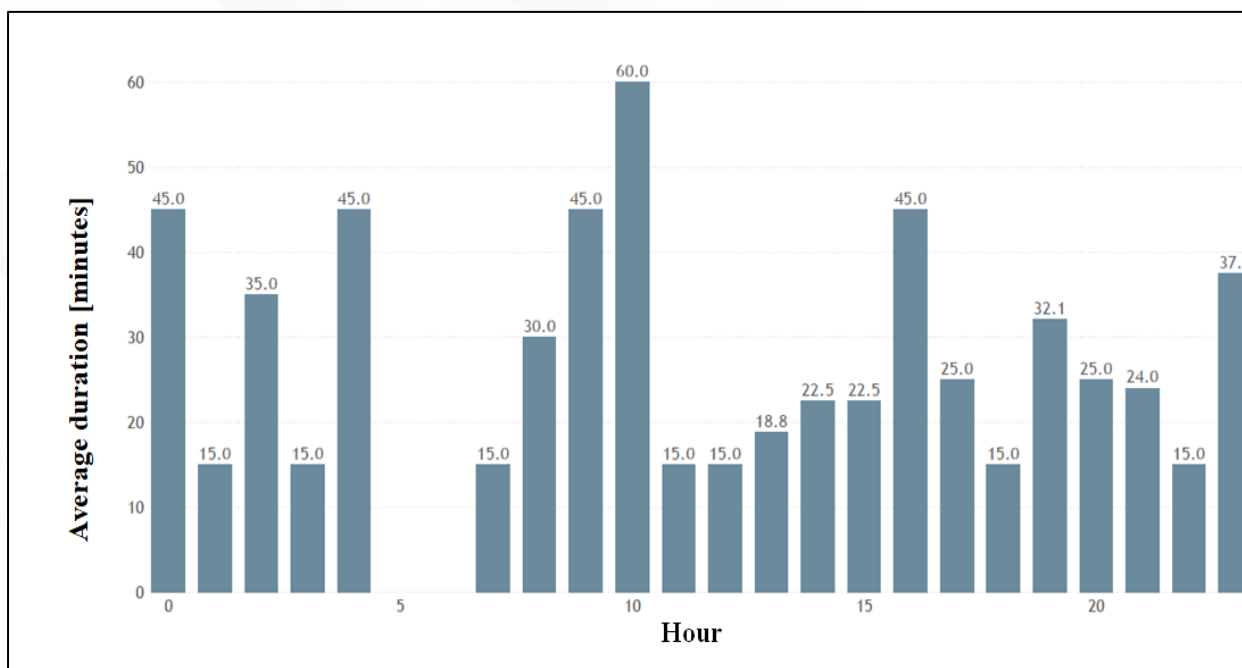


Figure 3: Mean duration of hypoglycemic episodes by time of day.

Results

The system demonstrated the ability to detect glycemic abnormalities and classify patients according to risk. Automated analysis reduced the burden of manual review and enabled more efficient identification of patients requiring clinical attention. Meal detection algorithms successfully identified postprandial glucose excursions, while fasting glucose analysis provided useful information regarding basal insulin adequacy.

Discussion

The findings support the growing role of AI in diabetes care. Automated interpretation of CGM data can enhance clinical efficiency and improve patient outcomes. Risk stratification allows healthcare professionals to allocate resources more effectively and focus on individuals with the greatest need. However,

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broader implementation requires robust validation studies, integration with electronic health records, and ongoing monitoring of algorithm performance.

Future Perspectives

Future developments may incorporate wearable devices, electronic health records, and patient-reported outcomes into unified AI platforms. Predictive analytics could enable proactive interventions before severe glycemic events occur. Explainable AI techniques may further increase clinician trust and facilitate regulatory approval. Integration with telemedicine services could expand access to specialized diabetes care in underserved regions.

Conclusion

Artificial intelligence has significant potential to transform diabetes management through automated analysis of CGM data. The proposed CDSS supports healthcare professionals by identifying high-risk patients, detecting glycemic abnormalities, and providing clinically relevant recommendations. Continued research and clinical validation are essential to maximize the benefits of AI-driven decision support in diabetes care.

References

1. Rawshani, Araz, et al. "Excess mortality and cardiovascular disease in young adults with type 1 diabetes in relation to age at onset: a nationwide, register-based cohort study." *The Lancet* 392.10146 (2018): 477-486.
2. Lind, Marcus, et al. "Continuous glucose monitoring vs conventional therapy for glycemic control in adults with type 1 diabetes treated with multiple daily insulin injections: the GOLD randomized clinical trial." *Jama* 317.4 (2017): 379-387.

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3. Battelino, Tadej, et al. "Clinical targets for continuous glucose monitoring data interpretation: recommendations from the international consensus on time in range." *Diabetes care* 42.8 (2019): 1593-1603.
4. Rama Chandran, Suresh, et al. "Beyond HbA1c: comparing glycemic variability and glycemic indices in predicting hypoglycemia in type 1 and type 2 diabetes." *Diabetes technology & therapeutics* 20.5 (2018): 353-362.
5. Famulla, Susanne, et al. "Glucose exposure and variability with empagliflozin as adjunct to insulin in patients with type 1 diabetes: continuous glucose monitoring data from a 4-week, randomized, placebo-controlled trial (EASE-1)." *Diabetes technology & therapeutics* 19.1 (2017): 49-60.
6. Dandona, Paresh, et al. "Efficacy and safety of dapagliflozin in patients with inadequately controlled type 1 diabetes: the DEPICT-1 52-week study." *Diabetes Care* 41.12 (2018): 2552-2559.
7. Ayodele, Taiwo Oladipupo. "Types of machine learning algorithms." *New advances in machine learning* 3.19-48 (2010): 5-1.
8. Pandey, Darpan, Kamal Niwaria, and Bharti Chourasia. "Machine learning algorithms: a review." *Mach. Learn* 6.2 (2019): 916-922.