Glycemic Oscillation Decomposition-Based Personalized Blood Glucose Prediction with Continuous Glucose Monitoring

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Abstract. With the increasing number of diabetes patients, the developments of continuous glucose monitoring (CGM) techniques and glucose prediction models become increasingly important. In this study, we propose a personalized blood glucose prediction approach via glycemic oscillation decomposition based on CGM data. We first utilize advanced data analytics techniques to decompose CGM data into multiple patterns through the oscillation pattern mining module. The temporal pattern learning module is then developed to capture the temporal dependency of glucose levels. We further aggregate multiple outputs into glucose predictions with improved accuracy. We conduct a comparison study between the proposed approach and other existing models using OhioT1DM dataset. Experimental results show that the proposed work can provide more accurate predictions for diabetic glucose levels compared to other methods. With improved prediction performance, the proposed approach facilitates personalized blood glucose management services for diabetes patients.

Keywords: Glucose prediction · Personalized healthcare · Time series analysis · Proactive healthcare

1 Introduction

Diabetes, a pervasive chronic metabolic disorder, remains a significant global health challenge, with its incidence steadily rising across many regions. In some areas, this increase is especially pronounced, driven by a combination of lifestyle changes, aging populations, and other risk factors. The global burden of diabetes not only affects public health systems but also impacts individuals' quality of

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life, as managing the condition requires constant monitoring and intervention. The rapid growth in diabetes prevalence highlights the urgent need for improved strategies in both prevention and treatment, particularly in regions experiencing the fastest rates of increase [1]. The regulation of blood glucose levels is governed by numerous factors, including dietary intake, physical activity, medication schedules, sleep quality, and overall health status. These factors are highly interdependent, interacting in complex and sometimes unpredictable ways that make accurate blood glucose prediction particularly difficult. This complexity significantly complicates the management of diabetes, where the primary objective is to keep blood glucose levels within a narrow, controlled range to prevent dangerous episodes of hyperglycemia or hypoglycemia. The challenge lies in accounting for these diverse and dynamic influences, which can vary not only from day to day but also between individuals, adding further difficulty to maintaining optimal glucose control.

Traditional diabetes management practices often involve periodic blood glucose measurements, which provide snapshots at discrete intervals. This approach lacks the continuity and detail needed for comprehensive disease management. The introduction of continuous glucose monitoring (CGM) technology has revolutionized this landscape by offering real-time, continuous tracking of blood glucose levels. This technology generates detailed time series data that significantly enhance the granularity and reliability of information available for diabetes management. Moreover, we have addressed the issue of missing data, ensuring the completeness of our analysis.

Despite the advancements in continuous monitoring, the accurate anticipation of future blood glucose levels continues to be a formidable scientific and clinical challenge. Existing methods mainly capture temporal patterns in time series data, including statistical model such as autoregressive integrated moving average (ARIMA) model [2], machine learning model such as XGBoost [3], deep learning models such as recurrent neural network (RNN) [4,5], DLinear and NLinear [6], N-BEATS [7], temporal convolutional network (TCN) [8] and time fusion transformer (TFT) [9]. These models often overlook the nuanced inter-individual variations in blood glucose dynamics. There is an evident need for a personalized predictive approach that can account for these individual-specific differences to forecast blood glucose levels with improved accuracy.

To address the above issues, our study introduces a novel personalized blood glucose prediction methodology. This method is anchored in the principle of glycemic oscillation decomposition, which meticulously analyzes and dissects blood glucose time series data to elucidate the subtleties of individual blood glucose dynamics [10]. By harnessing these personalized blood glucose features, we have developed individualized predictive models designed to forecast future blood glucose levels with high accuracy.

The objective of this study is to craft an effective, personalized blood glucose prediction system that promises more precise and prompt monitoring and management of blood glucose levels for diabetic patients. We plan to rigorously evaluate our methods efficacy through a series of experiments across diverse populations and scenarios, and compare its performance against established blood glucose prediction techniques. We are confident that the insights gleaned from this study will propel the field of diabetes management forward, potentially enhancing the provision of healthcare services and improving the quality of life for individuals living with diabetes [11–13].

2 Methodology

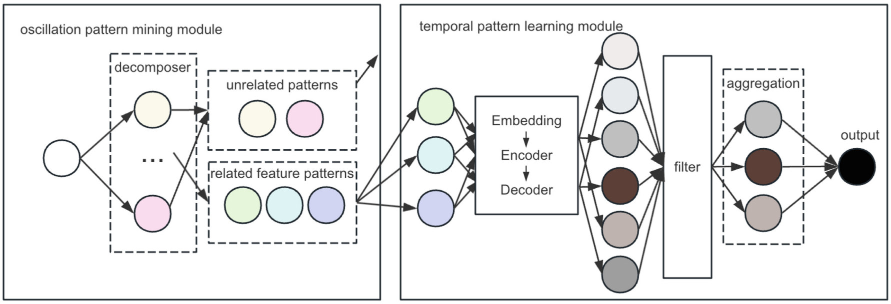

Fig. 1. Illustration of the proposed framework

2.1 Oscillation Pattern Mining

In the oscillation pattern mining module, data collected from CGM devices are subjected to an initial decomposition process to extract significant insights. This process commences with the addition of white noise to the original CGM data, which serves to enhance the robustness of the analysis by mitigating the effects of noise inherent in the data collection process. Subsequently, the signal with the added white noise is subjected to empirical mode decomposition, a method that effectively decomposes the data into multiple recognizable patterns. These patterns reflect the various influences on blood glucose levels, such as physiological responses to meals, physical activity, hormonal fluctuations, and other lifestyle factors. During the decomposition process, different white noise sequences are used for multiple iterations to ensure a comprehensive analysis that accounts for the stochastic nature of the data. The resulting patterns from these iterations are then averaged to reduce the influence of the added noise, providing a more accurate and reliable data representation [14]. These patterns are indicative of the complex interplay of factors that affect blood glucose levels, encapsulating specific trends and behaviors observed in the CGM data. The identification of these patterns is crucial for understanding the dynamics of glucose regulation, as they offer insights into how different variables impact glucose fluctuations over time and inform more effective management strategies.

Following the identification of these patterns, the next step involves filtering out irrelevant or insignificant ones. We retain only those patterns rich in features that contain essential information regarding trends in blood glucose levels. This rigorous filtering process ensures that subsequent analyses focus on the most informative patterns, likely to yield meaningful insights and enhance predictive accuracy. Once relevant patterns are identified, we forward them to a specialized module dedicated to temporal pattern learning.

2.2 Temporal Pattern Learning

In the temporal pattern learning module, decomposed patterns undergo transformation into mathematical formulations through a process known as embedding. This transformation facilitates a nuanced representation of the patterns suitable for effective processing by machine learning algorithms, allowing for deeper analysis and understanding. To further enhance our comprehension of these patterns, we utilize encoder-decoder architectures integral to our model's design. During training phases, the machine learning model learns to map input patterns to specific outputs, thereby establishing relationships between observed patterns and expected glucose responses. Throughout this training process, filtering steps are implemented to select only those outputs deemed meaningful or high quality. Additionally, aggregation techniques are employed to combine multiple outputs which aid in achieving a more accurate and robust final result. This integration process enhances the prediction reliability of our model, as illustrated in Fig. 1. The proposed systematic approach allows the oscillation pattern mining and temporal pattern learning modules to work synergistically, significantly enhancing the overall effectiveness in predicting blood glucose levels. This not only enhances predictive accuracy but also provides valuable tools for diabetes management.

3 Case Study

3.1 Dataset and Experiment Setting

The OhioT1DM dataset comprised extensive data from 12 individuals diagnosed with type 1 diabetes, including 5 females and 7 males. These patients were undergoing insulin pump therapy at the time of data collection. The CGM data were collected every 5 min over a period of 8 weeks for each patient [15]. We utilized this dataset in a comparison study to demonstrate the effectiveness and outstanding performance of the proposed approach. We compared our proposed approach with 8 representative models, including ARIMA [2], XGBoost [3], RNN [5], DLinear and NLinear [6], N-BEATS [7], TCN [8] and TFT [9]. All models were implemented in PyTorch 2.1.0 using the Darts framework. We utilized a single RTX4090D (24GB) GPU to accomplish all experiments.

3.2 Data Preprocessing

However, a significant challenge associated with this dataset was the presence of missing and discontinuous blood glucose values, which potentially impacted

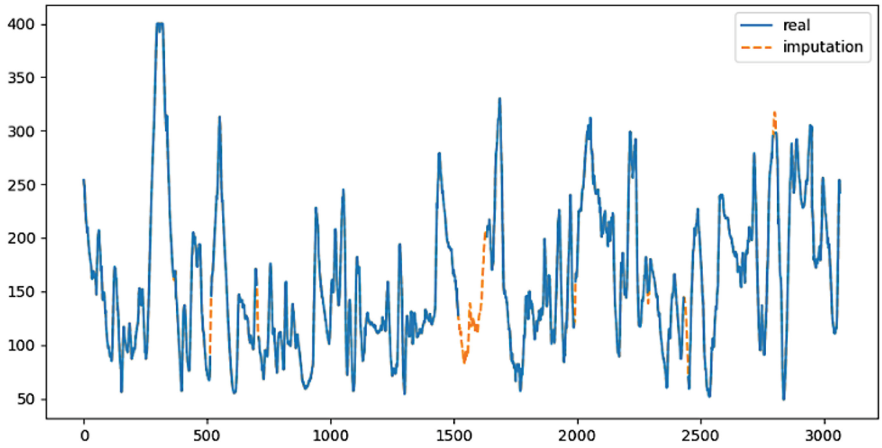

Fig. 2. The effectiveness of using interpolation to complete blood glucose data.

the accuracy of predictive models. To preserve the integrity of the proposed approach, we implemented a linear interpolation method to address these gaps. This technique estimated missing values by drawing a straight line between the known data points, as shown in Fig. 2, thereby creating a continuous curve that reflected the underlying trend more accurately. Our choice of linear interpolation was rooted in its simplicity and effectiveness for datasets with minor missingness. It provided a reasonable approximation for missing values without complicating the model or introducing bias.

By applying this method to both the training and testing datasets, we ensured that our model training was grounded in a complete and representative set of data, which is essential for developing a reliable predictive tool. In this work, we utilized historical glucose sequences to forecast future glucose sequences. We investigated different prediction horizons, including 60, 90 and 120 min.

To evaluate the efficacy of the proposed approach, we meticulously designed a comprehensive evaluation framework to gauge its performance across various temporal scales. This approach involved the establishment of distinct prediction windows, which allowed us to systematically evaluate the model's accuracy over different time horizons, ranging from short-term to long-term intervals. To quantitatively assess the model's predictive accuracy, we employed the mean absolute error (MAE) as our primary metric.

$$MAE = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} |y_i' - y_i| \tag{1}$$

3.3 Results

By calculating the MAE for each prediction window, we were able to obtain a clear and concise quantification of the model's performance in the context of short-term, medium-term, and long-term blood glucose level predictions. Our findings revealed that the model we proposed demonstrates superior predictive capabilities when compared to other state-of-the-art models across all considered prediction time frames. The outstanding performances demonstrated the efficacy and the robustness of the proposed approach. Most notably, the model's superiority was particularly pronounced in the domain of long-term predictions. In this critical area, our model exhibited a significant reduction in error rates when compared with other alternative models, as graphically depicted in Fig. 3. The enhanced performance of our model in long-term predictions was not only statistically significant but also clinically meaningful. It suggested that the proposed approach was able to capture the subtle nuances and complex dynamics of glucose metabolism over time. This capability to effectively manage glucose fluctuations over extended periods was of paramount importance in clinical settings. The proposed work had the potential to revolutionize diabetes management by enabling healthcare providers to make more informed decisions regarding treatment adjustments, lifestyle modifications, and personalized care plans. Furthermore, it empowered individuals with diabetes to engage in a more proactive and data-driven approach to their self-management, leading to improved health outcomes and a better quality of life for diabetes patients.

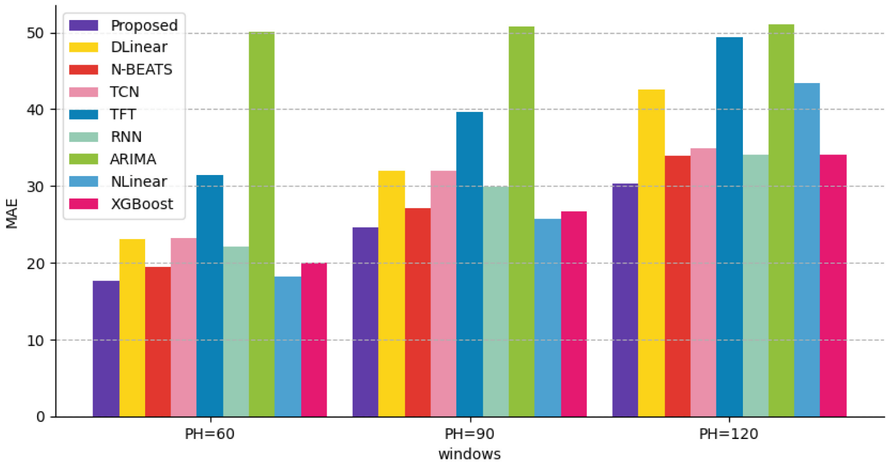

Fig. 3. Performance comparison results with alternative methods

4 Conclusion

In this study, the oscillation pattern mining module utilized CGM data to systematically decompose and analyze various distinct glucose fluctuation patterns. By dissecting these patterns, we were able to capture the intricate dynamics of glucose variations over time, facilitating a more nuanced understanding of the temporal behaviors in patients' glucose levels. The extracted oscillation patterns yielded critical insights into underlying mechanisms of glucose fluctuations. These patterns served as foundational inputs for the temporal pattern learning module, which adopted a personalized approach for blood glucose prediction. The proposed approach enabled a more robust and adaptive strategy for capturing the glucose dynamics of each patient. Notably, the proposed approach consistently demonstrated superior performance regarding prediction errors when compared with other state-of-the-art models. The proposed work not only improved prediction accuracy but also significantly advanced the timeliness of blood glucose monitoring. By delivering more precise and timely predictions, our method could elevate quality of life for diabetes patients by enabling more responsive and personalized strategies for managing blood glucose levels. These findings indicated that incorporating advanced data mining techniques alongside personalized modeling could lead to substantial enhancements in diabetes care.

In the future, we will delve even deeper into these different blood glucose vibration patterns. Our goal is not only to predict blood glucose trends but also to understand how patients' bodies react to various situations to improve the interpretability of blood glucose predictions. We will thoroughly investigate the cause-and-effect relationships behind these vibration patterns via advanced data mining techniques. We can then understand more precisely about the underlying personalized glucose dynamics in response to different time-varying activities such as food intake, exercise, medication use, sleep and stress.

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