Conv-GRU Temporal Refiner for Prandial Recommendations in Type 1 Diabetes

Patients with type 1 diabetes (T1D) require insulin therapy and dietary management to control their glycemic excursions. To aid in this, recent advances in machine learning (ML) for time series forecasting have improved the blood glucose (BG) prediction system. However, relatively few studies have addressed actionable recommendations for insulin dosing and carbohydrate intake. Moreover, existing approaches often rely on reinforcement learning (RL), which, despite its adaptability, is computationally intensive and requires a large memory footprint due to the large number of trainable parameters. To mitigate these limitations, this work proposes the convolutional gated recurrent unit (Conv-GRU) Temporal Refiner (CGTR) model. The proposed CGTR consists of two GRUs for coarse temporal feature extraction and a temporal refiner block. The refiner employs 1D CNN layers with a chain of dynamic filters, enabling efficient temporal attention-like modeling. In addition, a contrastive regularization loss is integrated that creates hard temporal samples via random masking and refines temporal modeling by minimizing prediction dissimilarity between contrastive samples. As a result, our CGTR avoids temporal overfitting, critical for real-time applications. Figure 1 shows an overview of the proposed CGTR model. The major contributions of this work are three-fold: (i) embedding GRUs for coarse temporal representation; (ii) introducing a CNN-based temporal refiner that approximates self-attention with linear complexity; (iii) applying contrastive loss with KLD minimization to enhance temporal robustness and mitigate overfitting.

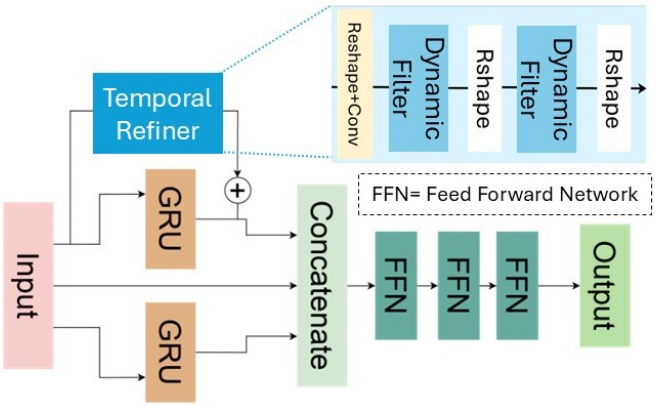

Figure 1: Overview of the proposed CGTR model, integrating dual GRUs with a temporal refiner block and dynamic filters, followed by feed-forward networks for final recommendation outputs.

Table 1:Performance (RMSE) Comparison

Bolus Recommendation			**Carbs Recommendation**	
	Inertial	Unrest.	Inertial	Unrest.
CGTR.best	1.78	**1.40**	**5.07**	**5.67**
LSTM.best	1.70	1.50	10.95	10.50
N-BEATS.best	**1.65**	1.51	9.92	10.07
Bolus Given Carbs			**Carbs Without Bolus**	
	Inertial	Unrest.	Inertial	Unrest.
CGTR.best	**0.393**	**0.195**	**12.11**	**11.92**
LSTM.best	0.94	1.00	13.75	14.94
N-BEATS.best	0.85	1.06	14.52	14.17

Table summarizes the root mean square error (RMSE) across four recommendation scenarios using CGTR and two baseline models. In our setup, CGTR operates on discrete temporal samples spaced 30 minutes apart, generating insulin bolus and carbohydrate recommendations to achieve target BG levels at specified postprandial or post-injection intervals. We evaluate the model on the OhioT1DM dataset [1], which contains eight weeks of recording of CGM, insulin logs, fitness band data, and self-reported life events from 12 individuals with type 1 diabetes. Compared with N-BEATS [2] and Chained LSTM [3], CGTR achieves an average error reduction of 29% and 28.3%, respectively, while requiring 25% fewer parameters than Chained LSTM. In the Carbs Recommendation (Inertial) setting, CGTR nearly halves the error compared to baselines, and in Bolus Given Carbs (Unrestricted), it achieves a fivefold improvement. Even in the challenging Carbs Without Bolus case, where insulin logs are missing, CGTR maintains a lower error than baselines. Overall, CGTR delivers a parameter-efficient and accurate framework for insulin and carbohydrate recommendations, with strong potential for real-time glycemic control in type 1 diabetes.

References

[1] C. Marling *et al.*, "The ohiot1dm dataset for blood glucose level prediction: Update 2020," in *Proceedings of the 5th International Workshop on Knowledge Discovery in Healthcare Data*, ser. CEUR Workshop Proceedings, vol. 2675, Santiago de Compostela, Spain, 2020.

[2] B. N. Oreshkin *et al.*, "N-BEATS: Neural basis expansion analysis for interpretable time series forecasting," in *Proceedings of the International Conference on Learning Representations (ICLR)*, 2019.

[3] J. Beauchamp *et al.*, "Lstms and deep residual networks for carbohydrate and bolus recommendations in type 1 diabetes management," *Sensors*, vol. 21, no. 9, p. 3303, 2021.