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A LSTM Approach to Blood Glucose Predictions for Personalized T1D Management

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The Lo & Zeng Labs will move to Syracuse University starting January 2025 (www.lo-zeng-labs.com)
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T1D Heterogeneity and Personalized Management

- Type 1 Diabetes (T1D) is a highly individualized condition. Glycaemic responses vary significantly between individuals, even with identical exogenous inputs (Fig. 1).
- Current blood glucose prediction algorithms, such as the UVA/Padova Type One Diabetes Mellitus Simulator (T1DMS)[1], rely on parameters averaged across multiple individuals and fail to account for inter-individual variability.
- Personalized algorithms are required to adapt to the unique physiological and metabolic differences among individuals with T1D.

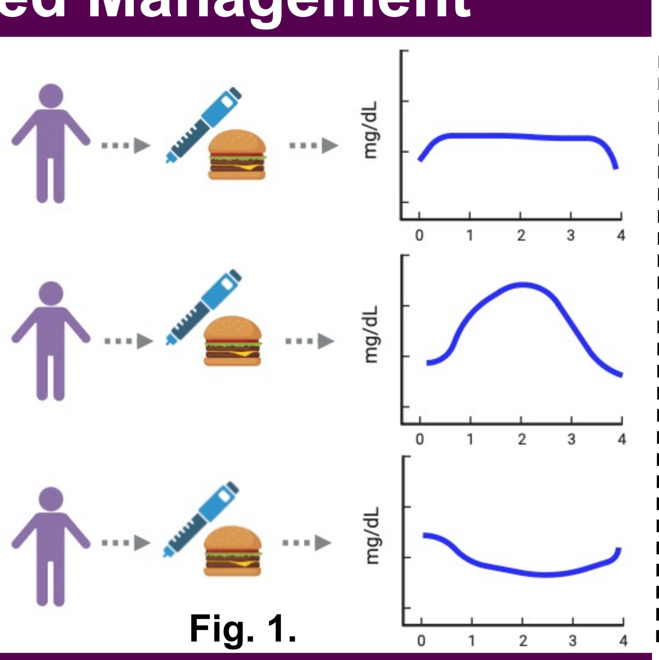
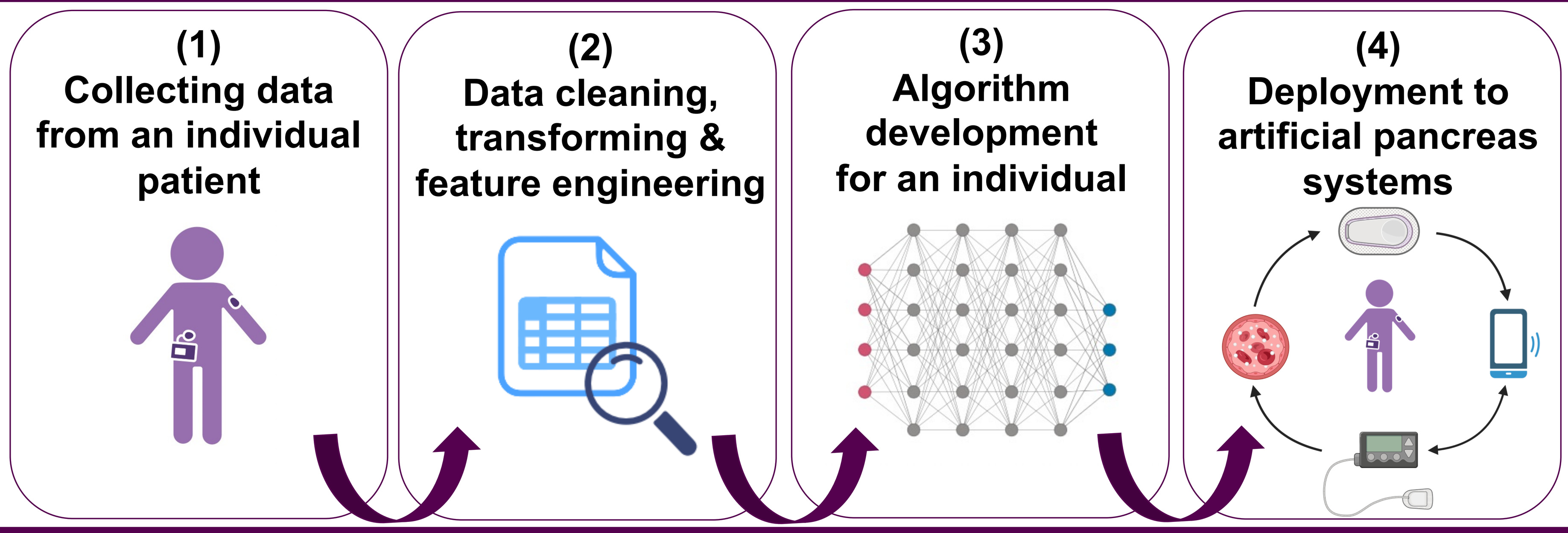


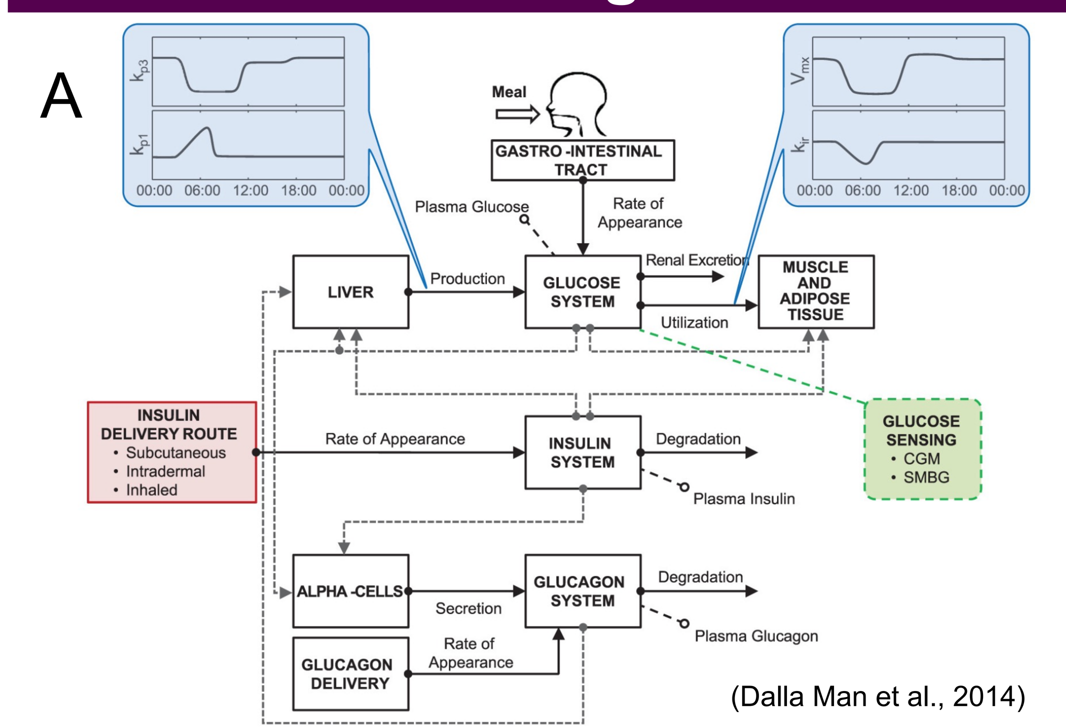
Fig. 1.

Pipeline: From Data to Decisions



Model Insights: Personalized vs Aggregate

A

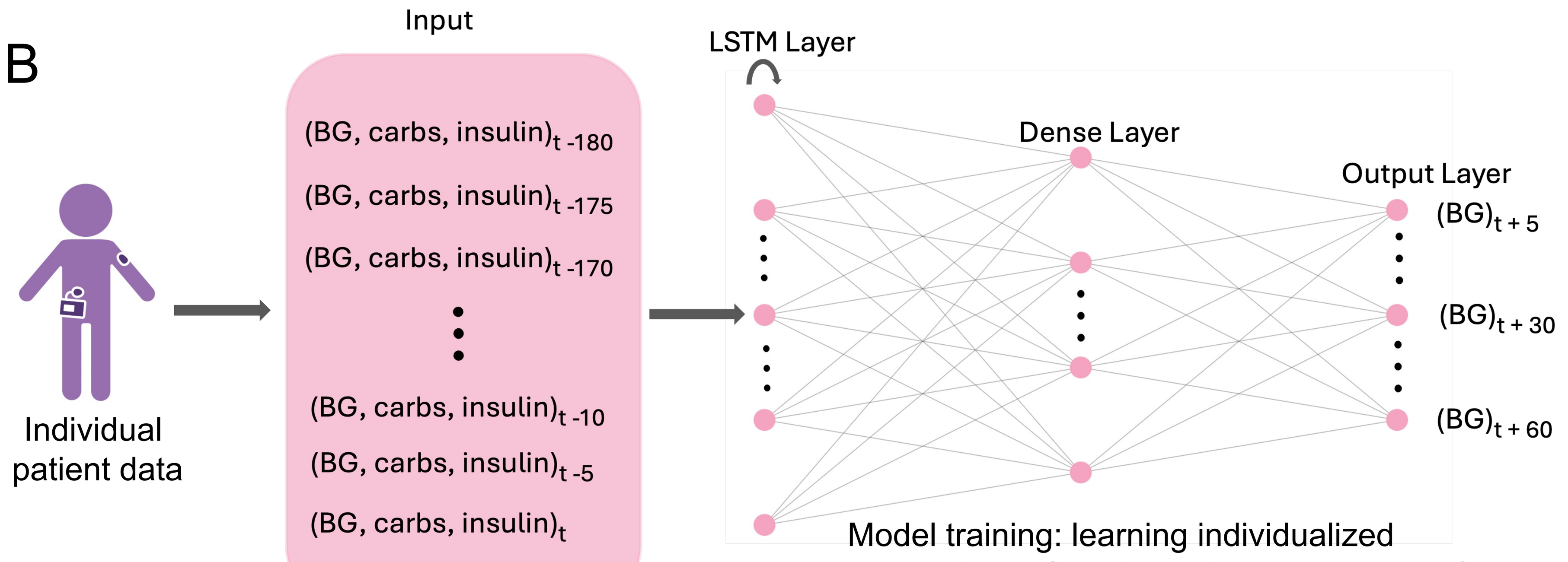


(Dalla Man et al., 2014)

$$\dot{G}_p(t) = EGP(t) + Ra(t) - U_{ii}(t) - E(t) - k_1 \cdot G_p(t) + k_2 \cdot G_t(t)$$
$$G_p(0) = G_{pb}$$
$$\dot{G}_t(t) = -U_{id}(t) + k_1 \cdot G_p(t) - k_2 \cdot G_t(t)$$
$$G_t(0) = G_{tb}$$
$$G(t) = \frac{G_p}{V_G}$$
$$G(0) = G_b$$

Parameters estimated from population-level data, representing average physiological behaviors across a cohort of people.

B



Model training: learning individualized parameters that reflect the unique responses of a specific person.

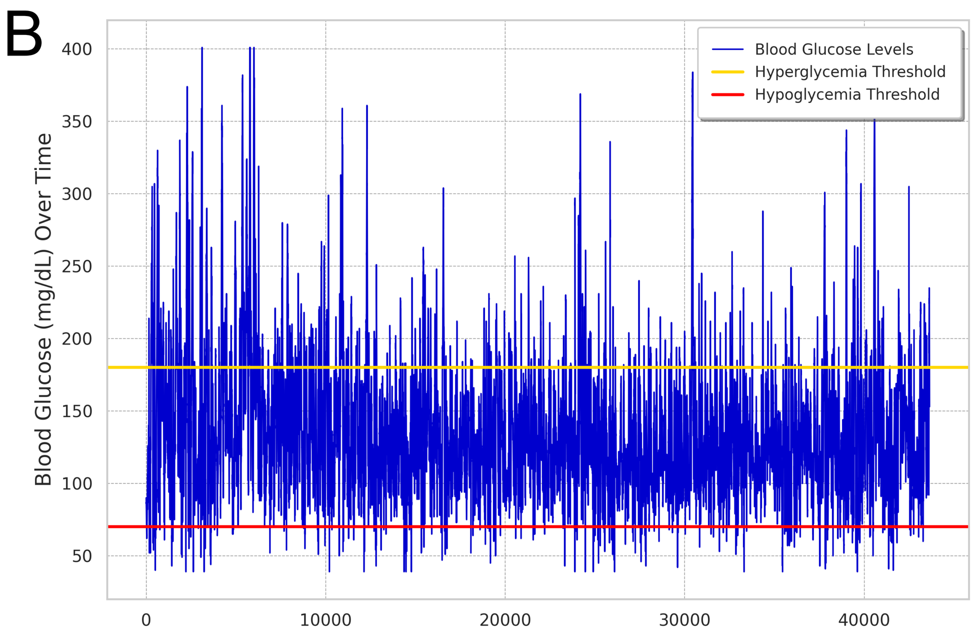
Fig 3. (A) Schematic representation of the UVA/Padova T1DMS framework. **(B)** Architecture of our LSTM neural network trained on individual patient data.

Data Preprocessing and Trends

A

	startDate	blood_glucose	time_diff	carbs	bolus	basal
	2018-03-04 10:54:00+00:00	101.0	5.0	72	0.0	0.5
	2018-03-04 10:59:00+00:00	97.0	5.0	0	0.0	0.5
	2018-03-04 11:04:00+00:00	96.0	5.0	24	4.0	0.5
	2018-03-04 11:09:00+00:00	91.0	5.0	0	0.0	0.5
	2018-03-04 11:14:00+00:00	88.0	5.0	0	0.0	0.5
	2018-03-04 11:19:00+00:00	82.0	5.0	0	0.0	0.5
	2018-03-04 11:24:00+00:00	80.0	5.0	0	0.0	0.5
	2018-03-04 11:29:00+00:00	80.0	5.0	0	0.0	0.5
	2018-03-04 11:34:00+00:00	78.0	5.0	0	0.0	0.5

B



C

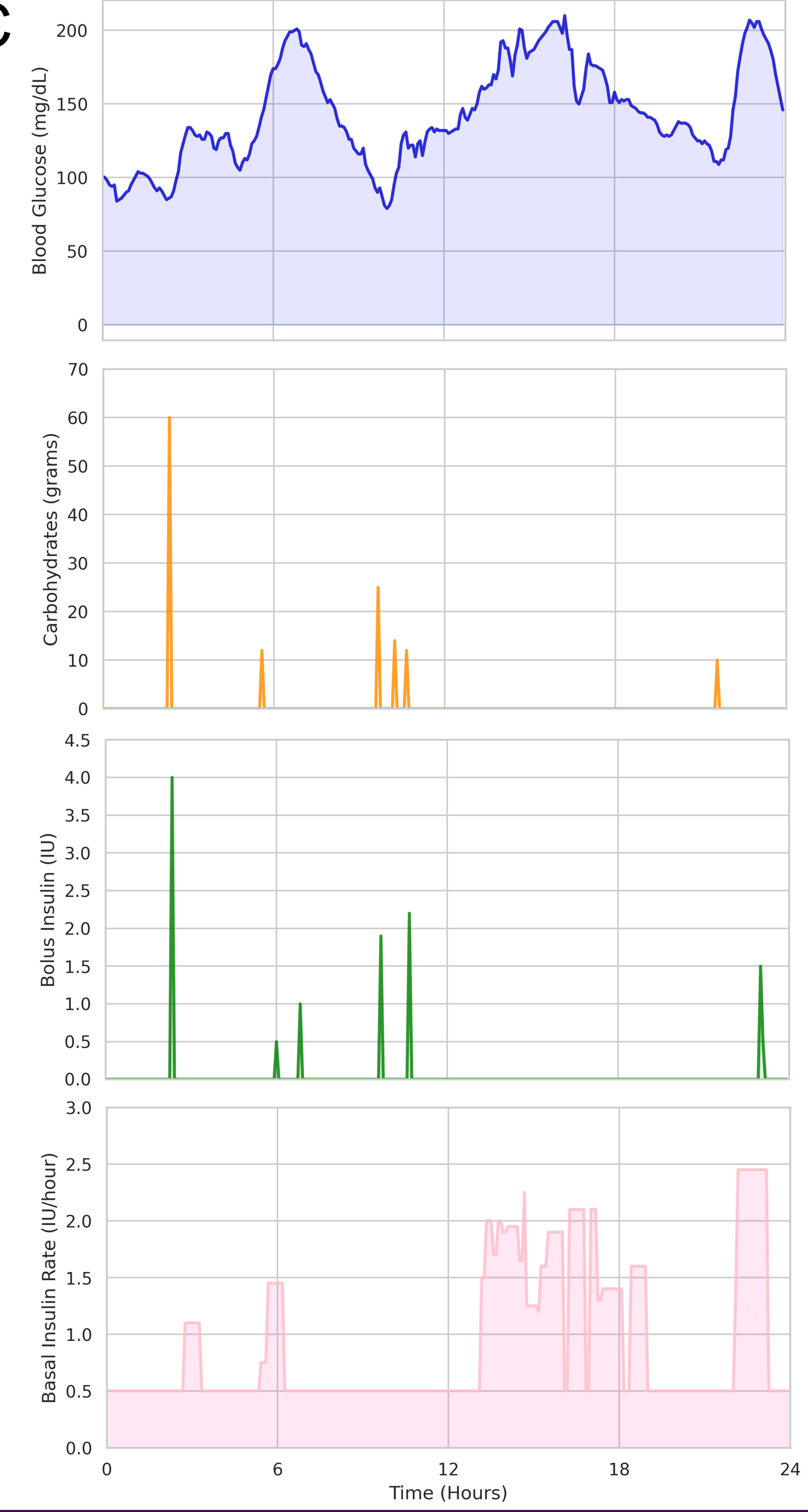


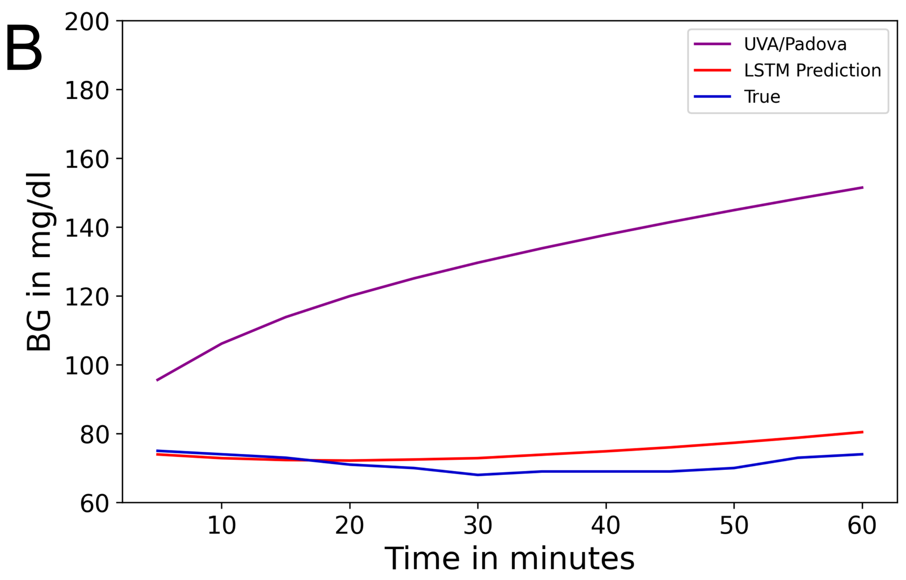
Fig 4. (A) Sample of the dataset after preprocessing, showing all features. (B) Blood glucose levels plotted across the entire dataset, with hyperglycaemia and hypoglycaemia thresholds indicated. (C) A 24 hour trend of blood glucose, carbohydrates, bolus insulin and basal insulin.

Model Validation

A

Model Type	RMSE 30 mins (mg/dl)	RMSE 60 mins (mg/dl)
LSTM	9.41	14.96
UVA/ Padova	42.43	52.76

B



C

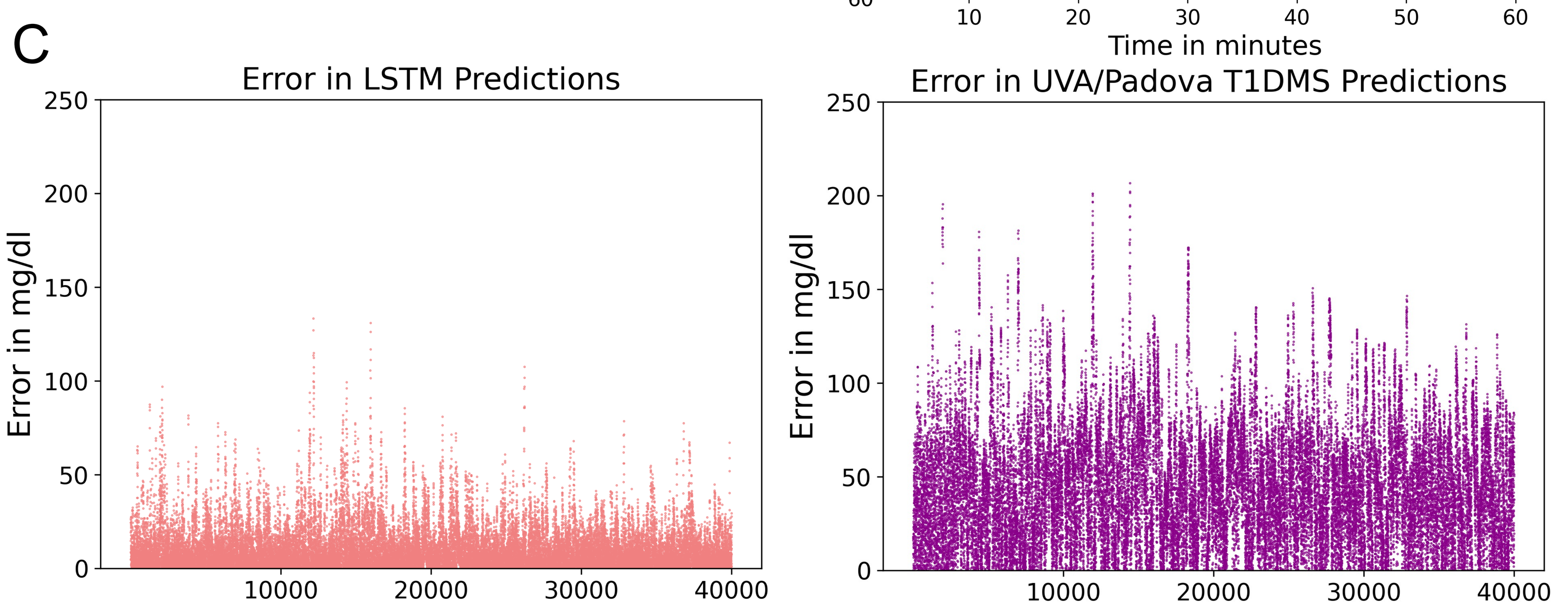


Fig 5. (A) Root mean squared error (RMSE) for LSTM and UVA/Padova Simulator for a 30 minute and 60 minute prediction horizon. (B) Comparison of predicted blood glucose levels with true values over a 60-minute horizon for both models. (C) Distribution of prediction errors for LSTM and UVA/Padova models, plotted for all individual predictions.

Evaluating Clinical Accuracy

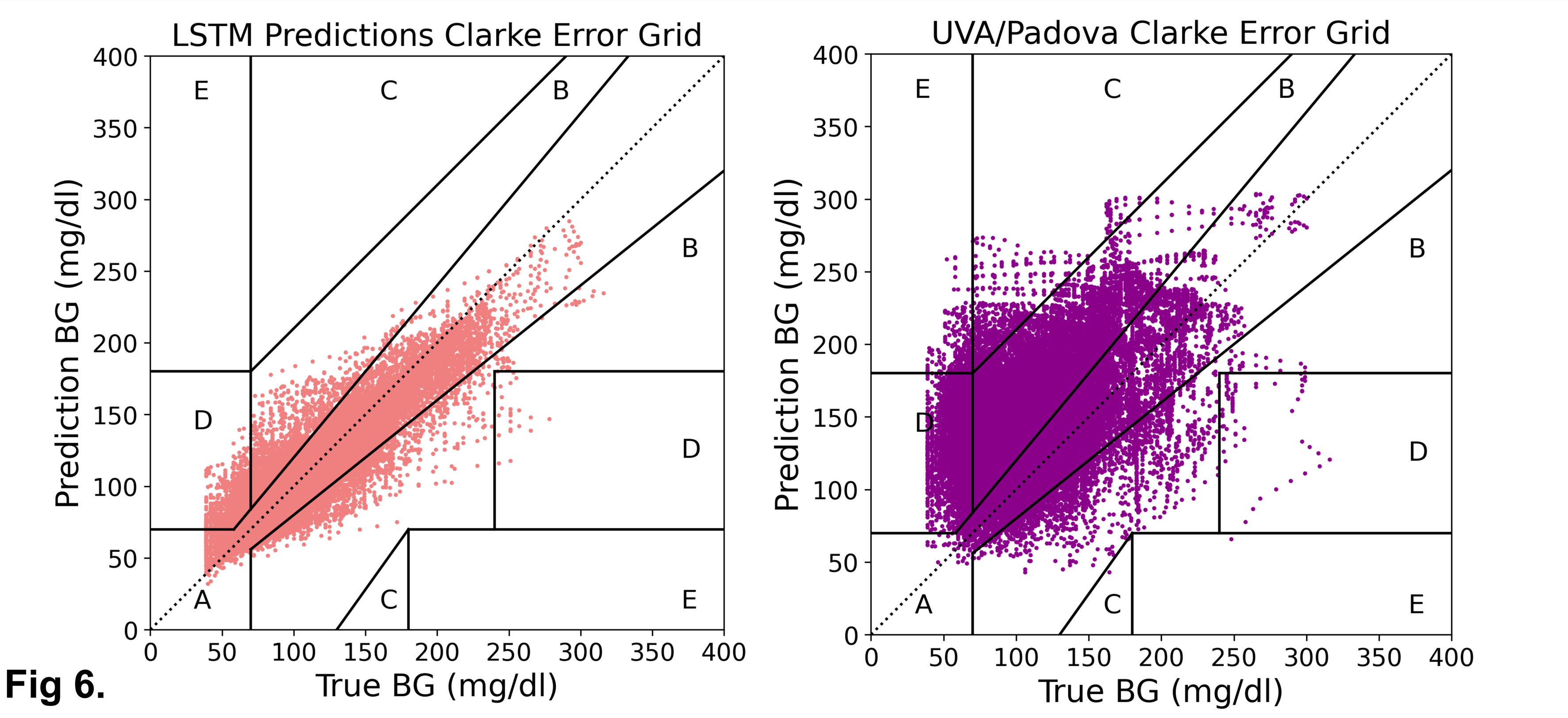


Fig 6.

Zone	LSTM (% readings)	UVA (% readings)
A: Predictions within 20% of the true sensor reading	88.09	27.62
B: Outside of 20% but would not lead to inappropriate treatment	8.63	60.98
C: Leading to unnecessary treatment	0.00	1.35
D: Potentially dangerous failure to detect hypoglycaemia or hyperglycaemia	3.26	9.43
E: Confuse treatment of hypoglycaemia for hyperglycaemia and vice versa	0.00	0.60

Summary and Future Work

- The UVA/Padova simulator has a RMSE approximately four times that of the LSTM model, and the LSTM model also has superior clinical performance. Unlike the simulator's fixed parameters, the LSTM adapts to an individual's trends, enabling more accurate forecasts.
- In future work, we will compare the forecast performance of LSTM models trained on aggregate patient data versus individual patient data for deployment in artificial pancreas systems.

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References: (1) Dalla Man et al., J Diabetes Sci Technol. 2014;8(1):26-34