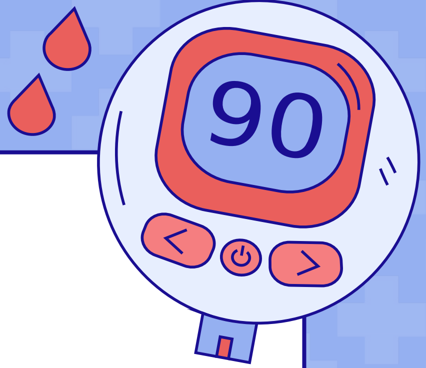
Lightning Talk: What Can You Do With AI?

AI-Driven Framework for Personalized Insulin Dosing and Safer Diabetes Management



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Everyday Insulin Decisions

- Type 1 Diabetes requires frequent insulin decisions each day
- Meals, activity, and residual insulin affect glucose outcomes
- Small dosing mistakes can quickly cause hypo- or hyperglycemia
- Most systems remain reactive and miss physiological context

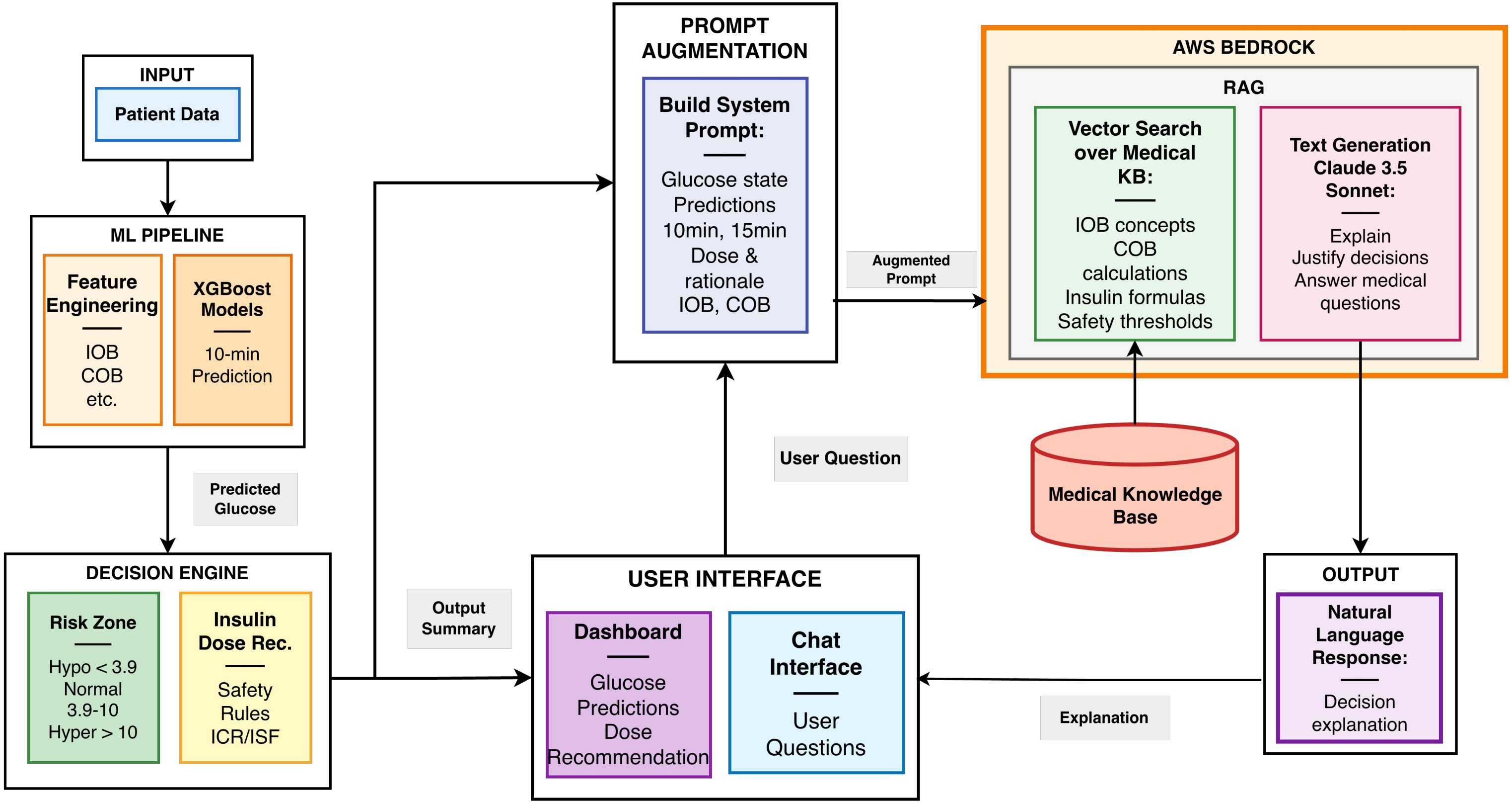
AI Roles in Insulin Decision Support

- Three components of system:

  - **Machine Learning Prediction**
  - **Rule based Decision & Safety Logic**
  - **LLM-based Explanation**

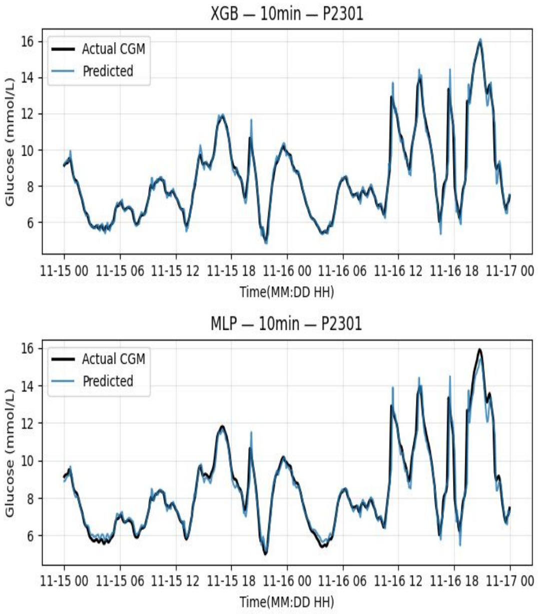
- AI supports clinicians without autonomous decision-making

System Architecture



ML for Short-Term Glucose Prediction

- Multimodal inputs capture glucose, insulin, meals, and activity
- Engineered physiological features improve short-term prediction accuracy
- XGBoost outperforms MLP model at 10–15 minutes



Predicted vs. actual CGM glucose traces for Patient P2301

Rule-Based Insulin Recommendation

Predicted Glucose

Risk Classification

Predicted glucose mapped to ADA risk zones

- Hypoglycemia (< 3.9 mmol/L)
- Euglycemia (3.9–10 mmol/L)
- Hyperglycemia (> 10 mmol/L)

Ensures clinical safety before dosing logic

Rule-Based Insulin Logic

(Clinically interpretable decision engine)

- IOB & carbs guide dosing
- Safety checks prevent stacking
- Clinically defined bolus rules

Decision Outcome

- Hypoglycemia → Insulin withheld
- Euglycemia → Meal bolus only
- Hyperglycemia → Correction considered

(Actionable but safe output)

*The work up to this module was published in IEEE CCWC 2026 conference.

What Can LLMs Do in Insulin Decision Support?

LLM for Explanation

- Explains insulin decisions using Retrieval-Augmented Generation
- Converts rules and predictions into clear language
- Does not predict glucose or insulin doses

LLM for Input Structuring*

- Interprets natural language meals and activities logs
- Converts text data into structured data
- Helps ML models

LLM for Safety Monitoring*

- Reviews system outputs across time
- Detects recurring hypo or hyper risk patterns
- Generates alerts for clinician review

LLMs act as support layers, not decision makers

*Future work

Prototype View of the Proposed System

Key Takeaways

ML predicts

Short-term glucose forecasting using multimodal CGM data

Rules decide

Rule-based dosing prevents hypoglycemia and insulin stacking

LLMs explain

LLM explains decisions without altering clinical outputs

Clinical Alignment

Risk zones follow ADA-based glycemic thresholds

Future Expansion

LLM input parsing and Multimodel dataset planned

Acknowledgments

This work is financially supported by ***CSUBIOTECH*** through the

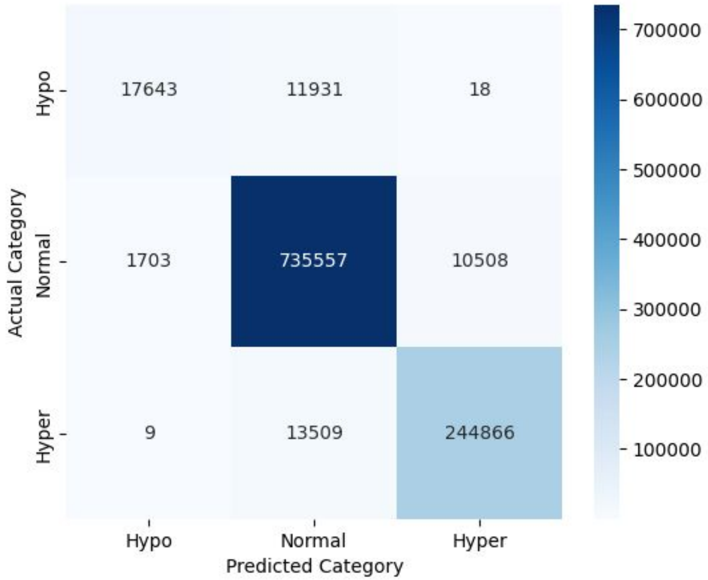
2025 Faculty–Graduate Student Research Collaboration Grant.

Thank You!

Backup Slide-1

Model	Horizon	MAE	RMSE	R^2
MLP	10 min	0.246	0.413	0.980
MLP	15 min	0.347	0.549	0.963
XGBoost	10 min	0.202	0.378	0.983
XGBoost	15 min	0.310	0.517	0.968

Model Performance

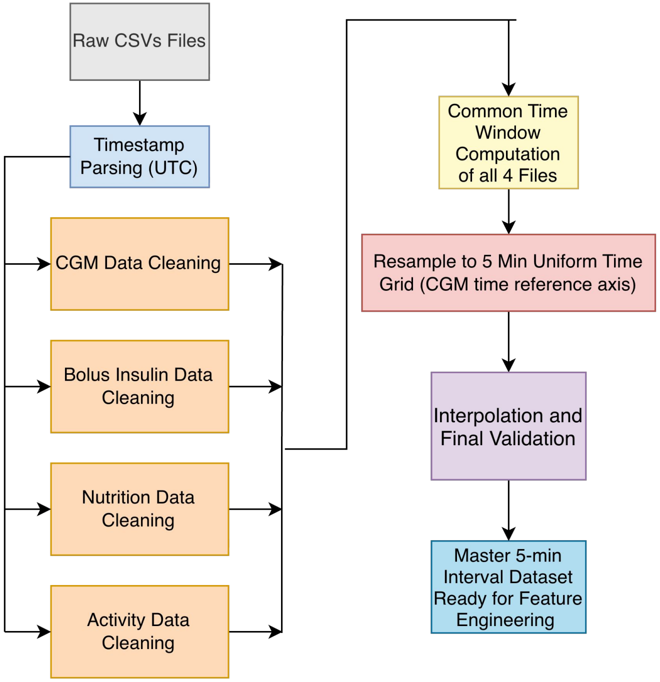


Risk Classification Confusion Matrix

Backup Slide-2

Feature	Description
Glucose Dynamics (6)	
glucose	Current CGM value (mmol/L)
glucose_lag_1/3/6	Glucose at t-5, t-15, t-30 min
delta_5	5-minute glucose change
glucose_roc	Rate of change (mmol/L/min)
Insulin (2)	
bolus	Current insulin dose (units)
IOB	Insulin-on-board (6h dual-phase convolution)
Carbohydrates (2)	
carbs	Current carb intake (grams)
COB	Carbs-on-board (3h delayed convolution)
Activity (2)	
met	Current metabolic equivalent
rolling_met_15	15-min average MET
Circadian (2)	
sin_time, cos_time	Time-of-day encoding (sin/cos of hour)

Engineered features for glucose prediction



Data preprocessing workflow