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Quantitative Biology > Quantitative Methods

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CGM Data Analysis 2.0: Functional Data Pattern Recognition and Artificial Intelligence Applications

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CGM 2.0	Traditional Statistical Pattern Analysis	Functional Data Pattern Analysis	Machine Learning Pattern Analysis	Artificial Intelligence Pattern Analysis
Approach	Visual, summary statistics	Statistical, models entire time series	Predictive modeling using algorithms	Integrates machine learning, deep learning, and advanced algorithms
Purpose	Identify obvious trends/patterns	Quantify, compare, and model complex dynamics	Predict future glucose levels and classify states	Predict risk, classify subtypes, optimize therapy,
Main Users	Clinicians	Statisticians, researchers	Data scientists, digital health developers	Researchers, health systems, digital therapeutics developers
Examples	AGP, time-in-range, mean, SD, GMI, GRI	Functional principal components, glucodensity	Clinically meaningful patterns from complex CGM data	AI-powered CGM or AI-powered closed-loop insulin delivery, image-based complication detection

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Prediction of metabolic subphenotypes of type 2 diabetes via continuous glucose monitoring and machine learning

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Check for updates

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USING ML ML TO IDENTIFY MECHANISMS OF METABOLIC SUBPHENOTYPES

- Gold standard metabolic testing combined with demographics established metabolic subphenotypes (muscle IR, hepatic IR, beta cell dysfunction, or decreased incretin effect)
- A variety of postprandial glucose concentrations was observed with 16 tests in 180 minutes
- OGTTs were analyzed with ML to predict the metabolic subphenotypes of the subjects who were apparently normoglycemic or had prediabetes

USING ML ML TO IDENTIFY MECHANISMS OF METABOLIC SUBPHENOTYPES

- The machine-learning models trained with glucose time series from in-clinic OGTTs predicted the subphenotypes with areas under the curve (AUCs) of 95% for muscle insulin resistance, 89% for β-cell deficiency and 88% for impaired incretin action
- For at-home OGTTs (vs in-clinic) model prediction performance was similar: muscle IR (AUC = 88%) and β-cell function (AUC = 84%)