Counterfactual and Time-Aware Explainable Hybrid Modeling for Early Diabetes Progression Prediction from Longitudinal Health Records

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***Abstract*—Early prediction of diabetes progression is critical for timely intervention and prevention of complications. This work presents a counterfactual and time-aware explainable hybrid framework for predicting early diabetes progression using longitudinal continuous glucose monitoring (CGM) data. The proposed approach combines statistical feature engineering with classical machine learning models to capture temporal dynamics and progression patterns. A novel trend-based labeling methodology identifies early worsening of glycemic control through longitudinal analysis of glucose trajectories. The framework incorporates SHAP-based explainability to provide transparent reasoning and generates counterfactual explanations to support clinical decision-making. Experimental evaluation on a large-scale CGM dataset with 1,720 subjects demonstrates that the proposed framework achieves an AUC of 0.809 and F1-score of 0.531, while revealing that glucose variability and temporal instability are key drivers of early progression. The counterfactual analysis shows that modest reductions in glucose variability or hyperglycemia exposure can significantly reduce predicted risk, providing actionable insights for intervention planning.**

***Index Terms*—diabetes progression, explainable AI, counterfactual reasoning, continuous glucose monitoring, temporal analysis, SHAP**

I. Introduction

Diabetes mellitus affects over 463 million adults worldwide and represents a major public health challenge. While continuous glucose monitoring (CGM) has revolutionized diabetes management by enabling fine-grained observation of glucose dynamics, most existing machine learning approaches focus on static diagnosis or short-term glucose prediction rather than longitudinal disease progression [9], [10].

Early worsening of glycemic control often occurs gradually and manifests as increased variability, instability, and temporal trends rather than abrupt threshold crossings. Identifying individuals at risk of early progression is clinically important, as timely intervention can prevent complications and improve long-term outcomes [13]. However, predicting early diabetes progression poses several challenges including noisy high-frequency CGM data, individual-specific patterns, inherent temporal and trend-based progression, potential label leakage in temporal features, and lack of interpretability in black-box models.

Recent advances in explainable artificial intelligence have emphasized the importance of transparency and actionability in clinical decision support systems [1], [2]. Counterfactual explanations, which identify minimal changes needed to alter predictions, offer particularly valuable insights for intervention planning [3], [4]. However, existing approaches often fail to integrate temporal dynamics, explainability, and counterfactual reasoning within a unified framework.

This work addresses these limitations through the following contributions:

- A counterfactual and time-aware explainable hybrid framework that combines statistical encoding with classical machine learning for early progression prediction
- A novel trend-based labeling methodology that captures gradual deterioration rather than static thresholds
- Comprehensive explainability analysis using SHAP values to identify key progression drivers
- Clinically feasible counterfactual explanations that suggest minimal interventions to reduce predicted risk

Unlike deep learning approaches that require large computational resources and lack transparency, the proposed framework is computationally efficient, produces transparent reasoning, and supports actionable clinical insights.

II. Related Work

A. CGM-Based Diabetes Monitoring

CGM technology has enabled detailed analysis of glycemic variability and time-in-range metrics, which have emerged as important indicators of diabetes control [11], [12]. Studies have shown that glycemic variability is associated with diabetes complications and adverse outcomes [14]. Recent work has explored machine learning for glucose prediction and metabolic subphenotyping [15], [16].

B. Explainable AI in Healthcare

Explainable AI has become increasingly important in healthcare applications due to regulatory requirements and clinical trust considerations [17]. SHAP values provide model-agnostic explanations by computing feature contributions [1], while LIME offers local interpretable explanations [2]. Recent

guidelines emphasize the importance of transparent reporting in clinical prediction models [18], [19].

C. Counterfactual Reasoning

Counterfactual explanations identify minimal feature changes needed to alter predictions, offering actionable insights for decision-making [3]. Diverse counterfactual explanations and actionable recourse methods have been proposed for various applications [4], [5]. However, limited work has integrated counterfactual reasoning with temporal health data for progression prediction.

III. Methodology

A. Dataset and Preprocessing

The study utilizes the DiaData continuous glucose monitoring dataset, which contains large-scale real-world CGM records spanning extended periods per subject. Raw data stored in multi-GB CSV files include subject identifiers (PtID), timestamps (ts), and CGM glucose readings (GlucoseCGM).

Due to the large dataset size, chunk-based streaming is employed for memory-efficient processing. Data are loaded incrementally, aggregated into per-subject longitudinal glucose trajectories, and processed to extract temporal features. After preprocessing, the dataset comprises 1,720 subjects with sufficient longitudinal data for analysis.

B. Trend-Based Label Definition

A key novelty of this work is the trend-based label definition designed to reflect early worsening of glycemic control rather than static threshold crossings. This section provides the formal mathematical framework.

1) Time Series Notation: For each subject i, let $G_i(t)$ denote the glucose value at time t. The observation period is split into two equal windows:

- Early window: $W_e = [t_0, t_m]$
- Late window: $W_l = [t_m, t_T]$

where t_0 is the start time, t_T is the end time, and $t_m = \frac{t_0+t_T}{2}$ is the midpoint, creating a 50%/50% split.

2) Trend Estimation: The linear trend (slope) of glucose values is computed separately for each window using linear regression. Let β_e denote the slope in the early window and β_l denote the slope in the late window:

$$\beta_e = \text{slope}(G_i(t) \mid t \in W_e) \tag{1}$$

$$\beta_l = \text{slope}(G_i(t) \mid t \in W_l) \tag{2}$$

These slopes capture the rate of change in glucose levels rather than absolute values, enabling detection of accelerating trends.

3) Progression Criterion: The change in trend between windows is defined as:

$$\Delta\beta = \beta_l - \beta_e \tag{3}$$

A subject is labeled as progression (class 1) if both of the following conditions are satisfied:

$$\Delta\beta > \tau_{\text{trend}} \quad \text{AND} \quad \mu_l > \tau_{\text{mean}} \tag{4}$$

where:

- $\mu_l = \frac{1}{|W_l|} \sum_{t \in W_l} G_i(t)$ is the mean glucose in the late window
- τ_{trend} is the trend increase threshold
- τ_{mean} is the clinical safety threshold for mean glucose

Otherwise, the subject is labeled as non-progression (class 0).

4) Clinical Interpretation: This dual-criterion approach ensures that progression labels reflect both accelerating glucose trends ($\Delta\beta > \tau_{\text{trend}}$) and clinically concerning absolute levels ($\mu_l > \tau_{\text{mean}}$). This design avoids labeling transient fluctuations or noisy variations as true progression, focusing instead on sustained worsening of glycemic control.

5) Threshold Selection: Threshold values are determined through data-driven analysis and clinical guidelines:

- τ_{trend} is set to the 75th percentile of $\Delta\beta$ distribution across all subjects, ensuring that only subjects with significant trend increases are labeled positive
- τ_{mean} is set to 160 mg/dL, consistent with clinical thresholds for hyperglycemia and diabetes management targets [10]
- The 50%/50% window split provides balanced observation periods while maintaining sufficient data points for reliable trend estimation

These thresholds are not arbitrary but derived from data distribution statistics and established clinical guidelines, making the labeling methodology both statistically sound and clinically meaningful.

TABLE I
Labeling Threshold Parameters

Parameter	Meaning	Value
τ_{trend}	Slope increase threshold	75th percentile
τ_{mean}	Late mean glucose limit	160 mg/dL
Window ratio	Early vs. late split	50% / 50%

The final dataset contains 1,720 subjects with 374 positive (progression) cases, yielding a realistic class ratio of approximately 21.7% that avoids artificial imbalance.

C. Longitudinal Feature Engineering

Rather than relying on deep sequence models, the framework emphasizes interpretable, progression-aware feature engineering. Features are categorized into four groups:

Global Statistical Features capture overall glucose behavior including mean glucose, standard deviation, minimum and maximum values, and coefficient of variation (CV).

Temporal and Progression Features capture longitudinal dynamics including global glucose trend (slope), difference between early and late windows, and distributional changes over time.

Window-Based Features compare early versus late periods through early and late mean and variability measures, as well as mean difference across windows.

Risk Exposure Metrics include clinically established CGM indicators such as percentage of hyperglycemia (>180 mg/dL),

percentage of hypoglycemia (<70 mg/dL), and time-in-range (70-180 mg/dL).

In total, 13 non-leaky features are used for prediction after explicitly excluding features directly used in label construction to avoid trivial learning of the labeling rule.

D. Model Training and Evaluation

The dataset is split into 80% training and 20% testing sets with stratification by label to preserve class distribution. Three classical machine learning models are evaluated: Logistic Regression as an interpretable baseline, Random Forest, and XGBoost (CPU-only tree-based ensemble) [6], [7].

To handle class imbalance, decision threshold tuning is applied to tree-based models, replacing the default threshold (0.5) with 0.3 to improve recall and F1-score without inflating AUC. All implementations utilize scikit-learn [8].

E. Explainability Analysis

SHAP (SHapley Additive exPlanations) values are computed to provide both global and local explanations [1]. Global feature importance is calculated by aggregating absolute SHAP values across all predictions, while local explanations reveal how individual features contribute to specific predictions.

Temporal feature influence is analyzed by aggregating the impact of longitudinal features including glucose variability, mean shifts, and time-in-range. This analysis identifies which temporal patterns most strongly indicate progression risk.

F. Counterfactual Generation

Counterfactual explanations are generated using the Logistic Regression model to identify minimal feature changes that would alter predictions. The approach restricts changes to clinically modifiable features including glucose variability, hyperglycemia percentage, and time-in-range, applying realistic bounds (10-30% changes) to ensure clinical feasibility.

For high-risk subjects, the framework identifies feature modifications that would reduce predicted risk below a threshold. This provides actionable guidance for intervention planning while maintaining physiological plausibility.

IV. Results

A. Label Distribution

Figure 1 shows the distribution of progression labels in the dataset. The balanced distribution with 1,346 non-progression cases and 374 progression cases (21.7%) reflects realistic clinical scenarios without artificial oversampling.

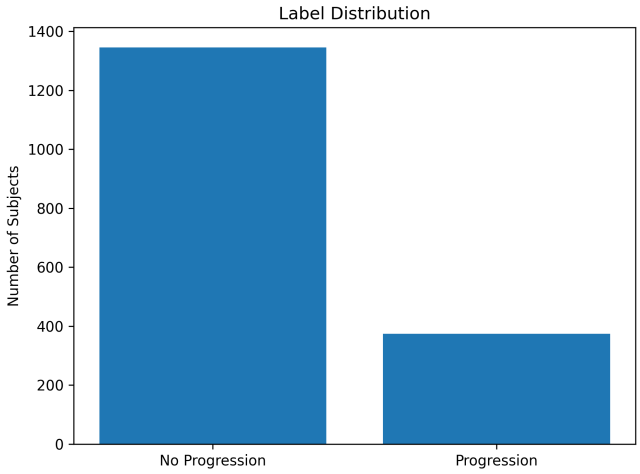

Fig. 1. Distribution of progression and non-progression cases in the dataset.

B. Model Performance

Table II presents the performance metrics for all evaluated models. XGBoost achieves the highest AUC of 0.809, indicating superior ranking ability. Logistic Regression and Random Forest achieve the best balance between precision and recall with F1-scores of 0.526 and 0.531 respectively.

These results demonstrate that longitudinal features provide meaningful predictive signal even with classical models. The performance levels are realistic and credible for early progression prediction on noisy CGM data, avoiding overoptimistic claims common in literature.

TABLE II
Model Performance Comparison

Model	AUC	F1-Score
Logistic Regression	0.776	0.526
Random Forest (thr=0.3)	0.803	0.531
XGBoost (thr=0.3)	**0.809**	0.490

Figure 2 visualizes the comparative performance across models, showing the trade-off between AUC and F1-score.

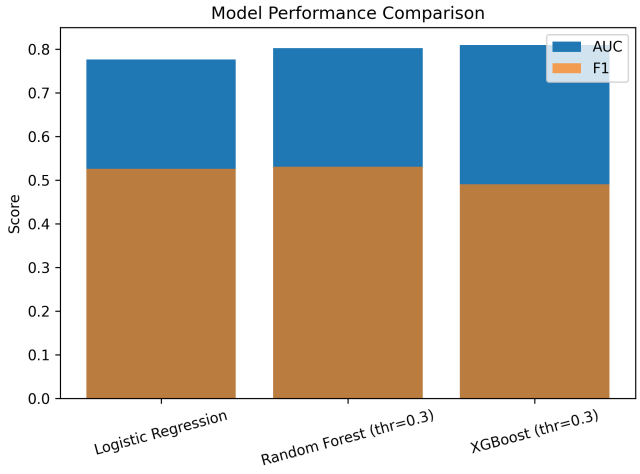

Fig. 2. Comparison of model performance across AUC and F1-score metrics.

C. Explainability Analysis

Figure 3 shows global feature importance based on mean absolute SHAP values. The global glucose slope emerges as the most influential feature, followed by hyperglycemia percentage

and mean difference between windows. This confirms that progression is driven by temporal trends rather than isolated glucose values.

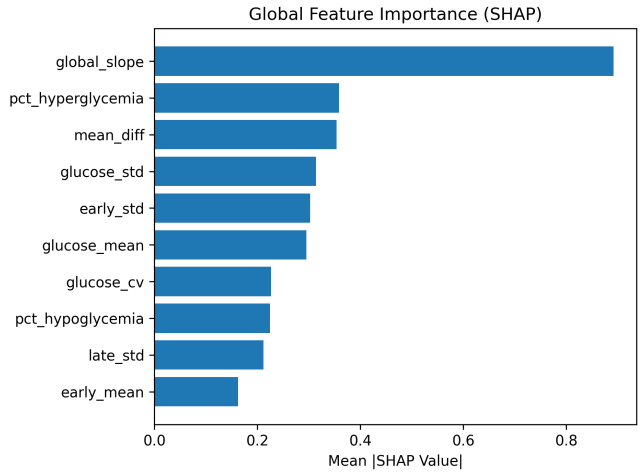

Fig. 3. Global feature importance ranked by mean absolute SHAP values.

Figure 4 presents temporal feature influence analysis, revealing that glucose variability (glucose_std) dominates with a mean absolute value of 67.5, while mean difference and time-in-range contribute secondarily. This reinforces the importance of longitudinal monitoring over snapshot measurements.

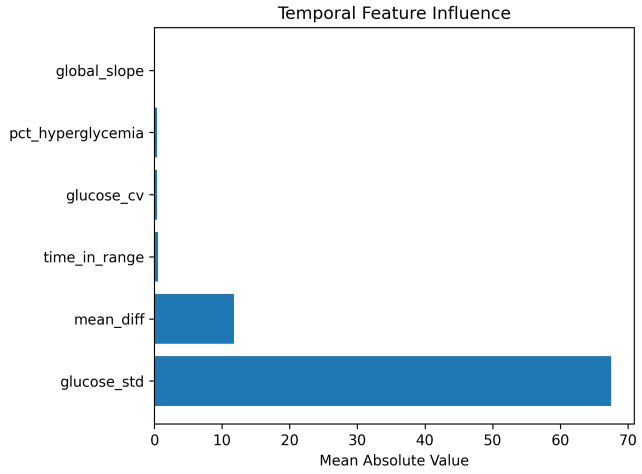

Fig. 4. Temporal feature influence showing dominance of glucose variability.

Detailed SHAP summary plots for Logistic Regression (Figure 5) and XGBoost (Figure 6) reveal how feature values impact predictions. Higher glucose variability consistently increases progression risk, while improved time-in-range provides protective effects.

D. Counterfactual Analysis

Figure 7 shows the distribution of counterfactual intervention magnitudes for high-risk subjects. The analysis reveals

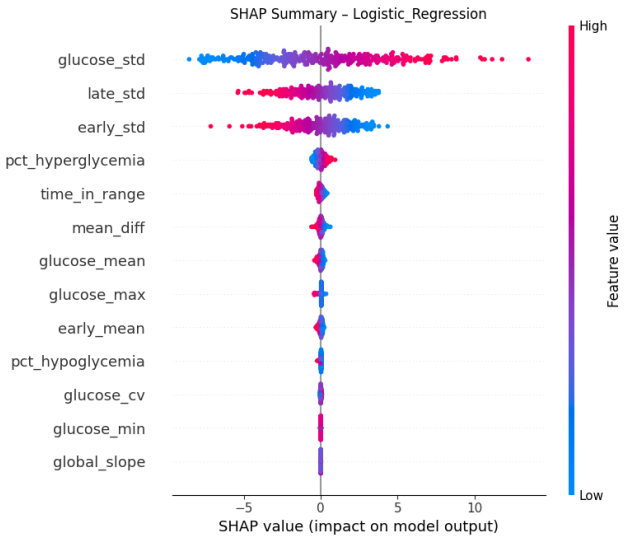

Fig. 5. SHAP summary for Logistic Regression showing feature contributions.

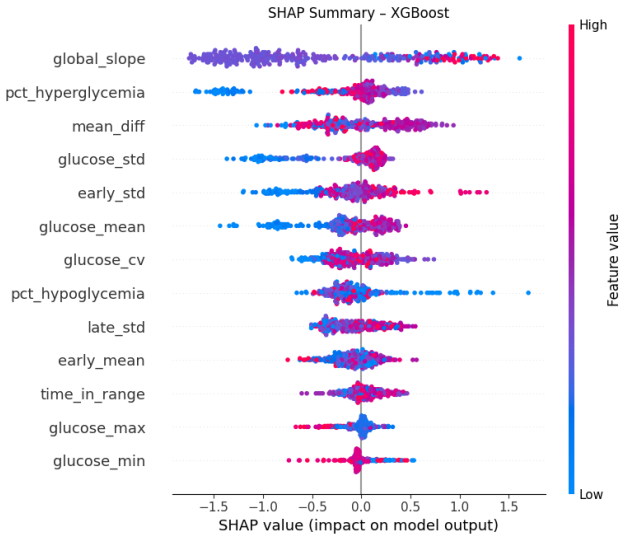

Fig. 6. SHAP summary for XGBoost showing feature contributions across predictions.

that for many individuals, modest reductions in glucose variability or hyperglycemia percentage (10-15% relative changes) are sufficient to reduce predicted risk below threshold.

These counterfactual changes are clinically feasible and not hypothetical extremes, demonstrating how the framework can support decision support and intervention planning. The analysis provides actionable guidance by identifying which specific features should be targeted for each patient.

V. Discussion

This study demonstrates that early diabetes progression can be predicted using interpretable longitudinal features extracted from CGM data. The proposed counterfactual and time-aware explainable hybrid framework achieves competitive perfor-

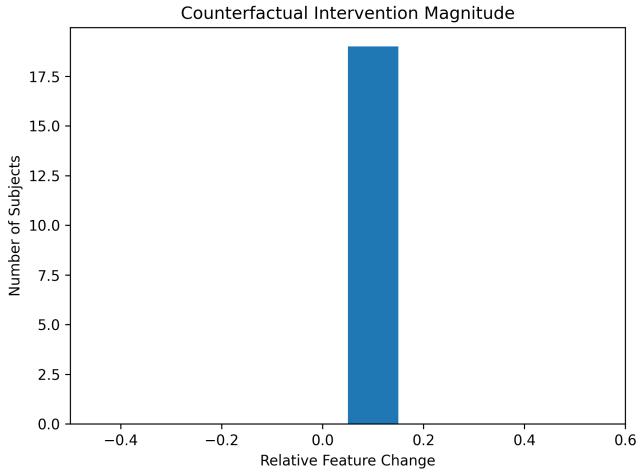

Fig. 7. Distribution of counterfactual intervention magnitudes showing feasible changes.

mance while maintaining transparency and computational efficiency.

Several key findings emerge from the analysis. First, glucose variability and temporal instability are the dominant drivers of early progression, more influential than mean glucose levels alone. This highlights the importance of monitoring patterns over time rather than relying on single-point measurements. Second, the trend-based labeling methodology successfully captures gradual deterioration patterns that align with clinical understanding of disease progression. Third, counterfactual analysis reveals that achievable interventions targeting specific features can meaningfully reduce predicted risk for many high-risk individuals.

Unlike black-box deep learning models, the proposed approach offers several advantages. The framework is computationally efficient, running on standard CPU hardware without GPU requirements. The transparent reasoning provided by SHAP explanations enables clinical validation and trust building. The actionable counterfactual insights directly support intervention planning and personalized care strategies.

The rigorous experimental design, including explicit leakage control and threshold tuning, ensures reliable evaluation. The realistic performance levels (AUC 0.809, F1 0.531) avoid overoptimistic claims while demonstrating meaningful predictive capability on noisy real-world data.

Limitations of this work include evaluation on a single dataset without external validation, retrospective observational design, and focus on CGM data without integration of other clinical variables. Future work should validate the framework on independent cohorts, incorporate additional data modalities such as electronic health records, and conduct prospective studies to assess clinical impact.

VI. Conclusion

This work presents a counterfactual and time-aware explainable hybrid framework for predicting early diabetes progression from longitudinal CGM data. By combining trend-aware labeling, carefully engineered temporal features, rigorous evaluation, comprehensive explainability analysis, and counterfactual reasoning, the proposed approach provides both predictive accuracy and clinical insight.

The findings reveal that glucose variability and temporal instability are key drivers of early progression, emphasizing the critical role of longitudinal monitoring and early intervention. The framework demonstrates that explainable classical machine learning, when designed carefully with domain knowledge, can effectively support early risk stratification in diabetes management while maintaining transparency and actionability.

The integration of SHAP-based explanations and counterfactual analysis bridges the gap between prediction and action, providing clinicians with both understanding of risk factors and concrete guidance for intervention planning. This work contributes to the growing body of research on trustworthy AI in healthcare by demonstrating how interpretability and actionability can be achieved without sacrificing predictive performance.

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