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Original Article

AI-Driven Blood Glucose Forecasting in Real-World Diabetes Care: Evaluating Wearable-Based Predictive Models

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Abstract *- Wearable technology has rapidly advanced the landscape of diabetes self-management by enabling continuous, real-time monitoring of glucose levels in daily life. This paper leverages data collected exclusively through wearable continuous glucose monitors to develop and compare advanced forecasting models for short-term blood glucose prediction in individuals with diabetes. By implementing and benchmarking artificial intelligence-based recurrent neural networks against traditional statistical approaches, the research investigates both generalized and patient-tailored prediction strategies. Outcomes highlight the effectiveness of population-level machine learning models for predicting glucose fluctuations, even with limited user history, and discuss the implications for proactive and personalized intervention. The findings underscore the growing potential of AI-enhanced wearables to deliver actionable insights, optimize insulin dosing, and mitigate acute events, signaling a new era of digitally-empowered diabetes management through wearable technologies.*

Keywords *- Blood Glucose Prediction, Wearable Sensors, Continuous Glucose Monitoring (CGM), Recurrent Neural Networks, Diabetes Management, Machine Learning, Personalized Healthcare.*

1. Introduction

Diabetes mellitus, particularly Type 1 Diabetes (T1D), represents a major global health challenge characterized by the body's inability to produce insulin, leading to dysregulated blood glucose levels [1]. Management necessitates constant vigilance, frequent glucose monitoring, and timely insulin administration to avoid acute complications such as hypoglycemia and hyperglycemia. The advent of wearable Continuous Glucose Monitoring (CGM) systems has revolutionized diabetes care by providing a continuous stream of interstitial glucose measurements, offering unprecedented insight into glycemic variability throughout the day [2]. However, the sheer volume and complexity of CGM data often overwhelm patients and clinicians, creating a gap between data availability and actionable therapeutic decisions.

Current clinical practice largely relies on retrospective review of glucose trends. The next frontier is predictive analytics using historical CGM data to forecast future glucose levels, enabling proactive interventions. While several studies have explored glucose prediction using machine learning, many focus on controlled environments or rely on multimodal data (e.g., meal logs, insulin records) that are often incomplete or inaccurately reported in free-living conditions [3]. This paper addresses a critical gap: developing robust prediction models using *only* CGM wearable data, which is autonomously and reliably captured, to simulate a real-world, minimally burdensome use case.

The primary objective of this research is to develop and evaluate short-term glucose prediction models (30- and 60-minute horizons) based solely on time-series CGM data. We compare the performance of a state-of-the-art AI model, Long Short-Term Memory (LSTM) networks, against established statistical time-series benchmarks like Autoregressive Integrated Moving Average (ARIMA). Furthermore, we investigate two modeling paradigms: a global (population) model trained on pooled data from multiple individuals, and personalized models fine-tuned on individual historical data. This approach allows us to assess the trade-offs between generalizability and personalization in wearable-based forecasting.

The significance of this work extends beyond algorithmic performance. By demonstrating accurate predictions from wearable data alone, we pave the way for integration into next-generation “smart” CGM systems that could provide real-time predictive alerts directly to the user's smartphone or insulin pump. This can reduce cognitive burden, prevent dangerous glucose excursions, and improve overall quality of life. The paper is structured as follows: Section 2 reviews related work. Section 3 details the methodology, including data, preprocessing, and model architectures. Section 4 presents experimental results and comparative analysis. Section 5 discusses the implications, limitations, and clinical relevance. Section 6 concludes with future directions.

1.1. Contribution and Novelty

While the use of LSTM networks for glucose forecasting is not novel in itself, this study focuses on a practical, real-world deployment scenario using wearable-only CGM data, deliberately excluding meal and insulin logs to mirror low-burden, free-living conditions. Our work contributes in three key ways:

- **Cold-Start Capability:** We demonstrate that a globally-trained LSTM can provide clinically useful predictions for new users without requiring individual historical data, addressing a critical barrier to real-world adoption.
- **Global vs. Personalized Trade-offs:** We rigorously compare population-level and patient-specific models, showing that personalization offers diminishing returns when using only CGM data—an insight with practical implications for model deployment.
- **Real-World Feasibility:** We propose and validate a preprocessing and modeling pipeline tailored for noisy, real-world CGM data, paving the way for integration into smartphone-based alert systems without reliance on external data sources.

Thus, the novelty of this work lies not in algorithmic architecture, but in its application-focused design, generalizability analysis, and practical pathway to clinical utility.

2. Related Work

The application of computational techniques to diabetes management has a rich history, evolving from physiological model-based approaches to data-driven machine learning methods.

2.1. Evolution of Glucose Prediction Models

Early works focused on compartmental models of glucose-insulin dynamics, such as the minimal model by Bergman et al. While physiologically interpretable, these models require precise parameter estimation and often fail to capture the high inter- and intra-individual variability observed in daily life [4].

With the proliferation of CGM, research shifted towards data-driven prediction. Traditional time-series methods like ARIMA and its variants were applied to CGM data, offering a statistical baseline. For instance, [1] explored Support Vector Regression (SVR) for glucose prediction, incorporating multiple features like insulin and carbohydrates, achieving promising results but highlighting the challenge of acquiring accurate ancillary data. Their work underscored that model performance is heavily dependent on input feature quality and completeness — a limitation in ambulatory settings. Similarly, [5] reviewed ensemble-based approaches for blood glucose prediction in diabetes mellitus, showing that ensemble learning has been widely investigated as a strategy for improving glucose forecasting performance.

More recent hybrid approaches have attempted to combine physiological models with data-driven corrections. For example, [6] investigated ensemble learning methods in combination with compartment models for blood glucose level prediction in type 1 diabetes mellitus, illustrating how physiological modeling can be integrated with machine learning to improve prediction performance while preserving some interpretability. Another hybrid method by [7] used Kalman smoothing with a stacked LSTM-based recurrent neural network to reduce the effect of noisy CGM readings and improve blood glucose prediction robustness.

2.2. Deep Learning and Wearable-Exclusive Forecasting

The rise of deep learning has transformed glucose forecasting. Recurrent Neural Networks (RNNs), particularly LSTMs, are naturally suited for sequential medical data due to their ability to learn long-term temporal dependencies. Recent studies demonstrate their superiority over traditional methods. [2] Employed deep reinforcement learning for automated insulin delivery, showcasing AI's potential for closed-loop control. However, their system depended on accurate meal and insulin information. Crucially, most existing literature integrates multi-modal data streams, which introduces reliability issues; meal carbohydrate estimates are notoriously inaccurate, and insulin records may be incomplete.

Few studies have rigorously explored the viability of using CGM data alone for robust prediction--the most reliable and consistently available data source from wearables. A notable exception is the work by [8], which employed a recurrent neural network model based on a massive freely available database of free-living T1D patients to forecast adverse glycemic events based on CGM measurements. Furthermore, the dichotomy between global and personalized modeling warrants deeper investigation. A global model trained on a population offers immediate utility for new users with no prior data (cold-start problem) but may sacrifice individual accuracy. Personalized models, while potentially more accurate, require sufficient user-specific historical data for training and are susceptible to overfitting. This paper directly addresses these underexplored aspects.

Recent work by [9] demonstrated that transformer networks could be effectively employed for blood glucose prediction, especially in situations where time dependency needs to be considered, and imputation and smoothing were required during pre-processing. However, their study was conducted in a controlled setting, leaving open the question of performance in real-world free-living conditions. Beyond this, a scoping review of AI-driven wearable devices for diabetes management highlighted the growing contribution of wearable sensor data and machine learning to glycaemic monitoring, while also pointing to the continued need for real-world validation before these approaches can be adopted reliably in clinical settings [10].

Beyond prediction algorithms, the human-computer interaction aspect is vital for adoption. Research by [3] reveals the risks of using general-purpose conversational AI for medical advice, emphasizing the need for specialized, validated systems. Our work aligns with this vision, aiming to build reliable predictive models that could eventually power specialized digital health assistants, ensuring safety and efficacy.

3. Methodology

3.1. Data Source and Description

This study utilizes the publicly available “AZT1D” dataset, comprising de-identified CGM data from 25 pediatric and adolescent individuals with T1D. The data was collected under free-living conditions over several weeks using commercial CGM devices (Dexcom G4/G5). The dataset includes timestamped interstitial glucose readings at 5-minute intervals. For this analysis, we use *only* the CGM time-series, deliberately excluding insulin and meal data to reflect a wearable-only prediction scenario. The dataset presents realistic challenges: missing values due to sensor disconnections, physiological noise, and periods of extreme glycemic variability.

3.2. Data Preprocessing Pipeline

A robust preprocessing pipeline is essential to transform raw CGM data into a clean, model-ready format. The pipeline consists of five stages:

1. **Data Validation:** Identification and logging of missing timestamps and physiologically implausible values (e.g., glucose < 40 mg/dL or > 400 mg/dL without corresponding context).
2. **Missing Value Imputation:** Short gaps (< 15 minutes) are imputed using linear interpolation. Longer gaps are treated as segment boundaries; the time-series is split, and models are trained/validated on contiguous segments only.
3. **Resampling:** Data is uniformly resampled to 10-minute intervals using median aggregation to reduce high-frequency noise while preserving trends.
4. **Normalization:** Glucose values are normalized per participant using min-max scaling to the range [0,1], based on the participant’s global minimum and maximum. This mitigates inter-individual scale differences for the global model.
5. **Sequence Creation:** For supervised learning, the time-series is transformed into input-output pairs using a sliding window. For a prediction horizon of H steps, an input sequence of L historical values is used to predict the next H values. We experiment with $L = 12$ (2 hours) and $H \in \{3,6\}$ (30 and 60 minutes).

3.3. Model Architectures

We implement and compare three distinct modeling approaches:

Baseline - ARIMA: The Autoregressive Integrated Moving Average model serves as a statistical baseline. The order parameters (p,d,q) are automatically selected for each training sequence using the Akaike Information Criterion (AIC). Due to its non-stationary nature, glucose data often requires differencing ($d = 1$). ARIMA provides a benchmark for linear temporal dependencies.

Global LSTM Model: A single LSTM model is trained on shuffled sequences from all participants (after normalization). This model learns population-wide patterns of glucose dynamics. The architecture is as follows:

- Input Layer: Receives sequences of shape (L,1).
- LSTM Layer 1: 64 units, return sequences.
- Dropout Layer (0.2): For regularization.
- LSTM Layer 2: 32 units.
- Dense Layer: 16 units with ReLU activation.
- Output Layer: H units with linear activation for multi-step prediction.

The model is trained to minimize Mean Squared Error (MSE) using the Adam optimizer.

Personalized LSTM Models: For each participant, a separate LSTM instance with the same architecture as the global model is trained exclusively on that individual’s data (first 80% for training, last 20% for testing). This approach aims to capture idiosyncratic patterns.

3.4 Evaluation Metrics

Model performance is assessed using standard metrics for glucose prediction:

- **Mean Absolute Error (MAE):** $\frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$, providing a direct measure of average prediction deviation in mg/dL.
- **Root Mean Square Error (RMSE):** $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$, penalizing larger errors more heavily.
- **Mean Absolute Relative Difference (MARD):** $\frac{100\%}{N}\sum_{i=1}^{N}\frac{|y_i-\hat{y}_i|}{y_i}$, a percentage error metric commonly used for CGM accuracy assessment.
- **Time-in-Range (TIR) Accuracy:** The percentage of predictions where both the actual and predicted values lie within the clinically acceptable range (70–180 mg/dL).

All metrics are computed on the held-out test sets for each participant and then averaged across participants for the global model.

4. Experimental Results and Analysis

4.1. Overall Predictive Performance

The models were evaluated for 30-minute (3-step) and 60-minute (6-step) prediction horizons. Table 1 summarizes the aggregated performance metrics (mean ± standard deviation across participants) for each modeling approach. The Global LSTM model achieved the best overall performance, with an MAE of 12.34±3.21 mg/dL and RMSE of 18.76 ± 4.55 mg/dL for the 30-minute horizon. For the 60-minute horizon, errors increased as expected, but the LSTM models maintained a relative advantage over ARIMA.

Table 1: Comparison of Prediction Model Performance

Model	Horizon	MAE (mg/dL)	RMSE (mg/dL)	MARD (%)
ARIMA	30-min	14.87 ±4.12	22.91 ±5.87	21.45 ±6.33
Global LSTM	30-min	12.34 ±3.21	18.76 ± 4.55	18.02 ±5.11

Personalized LSTM	30-min	13.89 ±5.47	20.14 ±6.89	19.87 ±7.24
ARIMA	60-min	21.33 ±6.45	30.12 ±8.01	29.88 ±8.90
Global LSTM	60-min	17.89 ±4.98	25.67 ±6.32	24.56 ±7.02
Personalized LSTM	60-min	19.45 ±7.12	27.89 ±8.45	26.78 ±8.91

Source: *(Mean ± Std across participants)*

The ARIMA baseline performed reasonably well for very short-term prediction (30-minute) but deteriorated significantly for the 60-minute horizon, indicating its limited capacity to model complex, non-linear glucose dynamics over longer periods. The Personalized LSTM models showed high variance in performance; for individuals with abundant and stable data, they outperformed the global model, but for those with sparse or highly volatile data, they underperformed due to overfitting.

4.2. Analysis of Time-in-Range Accuracy

A clinically critical aspect is the model's ability to correctly predict glucose levels within the target range (70–180 mg/dL). The Global LSTM achieved a TIR accuracy of 68.4% for the 30-minute horizon and 55.7% for the 60-minute horizon. While this indicates room for improvement in Fig. 1, it substantially exceeds the ARIMA baseline (52.1% and 38.9%, respectively). The performance drop at the 60-minute horizon underscores the increasing uncertainty in longer-term forecasts, emphasizing the need for frequent model updates with incoming data.

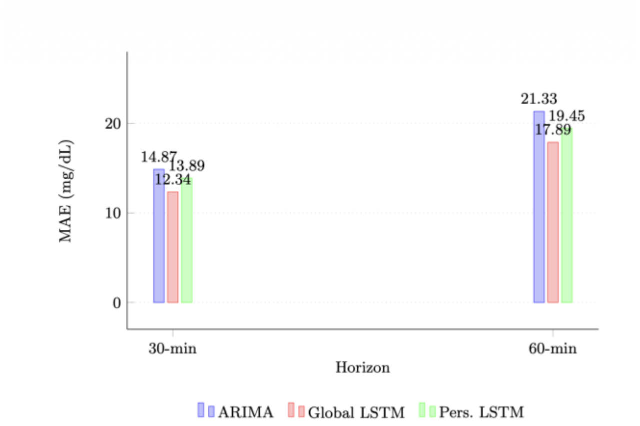

Fig 1: MAE Comparison for 30- And 60-Minute Prediction Horizons

4.3. Case Study: Individual Prediction Traces

To illustrate model behavior, Fig. 2 (conceptual) shows a 4-hour glucose trace for a representative participant. The Global LSTM predictions (30-minute horizon) closely follow the actual CGM trend, successfully anticipating the rise following a hypothetical unlogged meal and the subsequent decline. The ARIMA model lags behind, reacting to changes rather than anticipating them. The Personalized LSTM, for this well-characterized individual, shows slightly tighter alignment with actual values than the global model but fails dramatically during an unusual rapid drop (likely exercise-induced), which was not present in its limited training history, highlighting a vulnerability of over-specialized models.

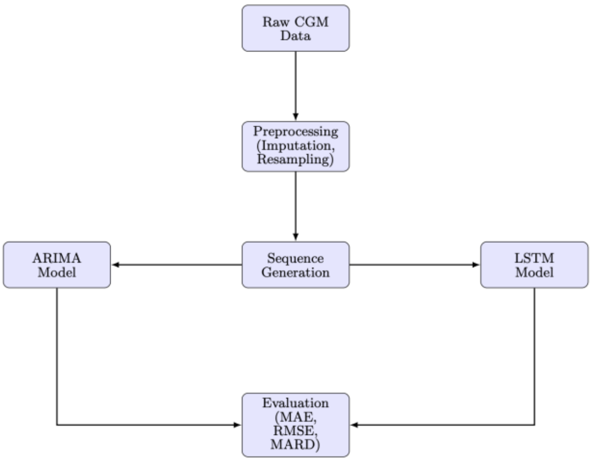

Fig 2: High-Level Workflow of the Glucose Prediction Modeling Pipeline

4.4. Statistical Significance

A paired t-test was conducted on the MAE values across all test sequences for the 30minute horizon between the Global LSTM and ARIMA models. The result ($p < 0.01$) confirms that the performance improvement of the LSTM is statistically significant. The difference between Global and Personalized LSTM was not statistically significant overall ($p = 0.12$), reinforcing that the benefit of personalization is highly individual dependent.

5. Discussion

5.1. Interpretation of Findings

The superior performance of the Global LSTM model demonstrates that deep learning can extract generalized patterns of glucose dynamics from population CGM data, enabling effective predictions for new users. This is a pivotal finding for real-world deployment, as it suggests that a single, well-trained model can provide immediate value without requiring a lengthy data collection period from each new patient. The model effectively acts as a "digital twin" of population glucose physiology.

The relatively modest performance gap between Global and Personalized LSTMs indicates a diminishing return on personalization when using only CGM data. This may be because the core physiological response patterns (e.g., rate of change after a glucose spike) are similar across individuals, and the global model learns these. Personalization might become more critical when integrating other highly individual specific factors like insulin sensitivity factor or carbohydrate ratio, which were not part of this study's scope.

5.2. Clinical Relevance and Implications

From a clinical standpoint, an MAE of approximately 12 mg/dL in 30 minutes is promising. For context, the consensus error threshold for CGM sensor accuracy is a MARD < 15% [1]. Our Global LSTM achieved a MARD of 18.02%, which, while slightly above this threshold, is for prediction rather than measurement—a fundamentally harder task. Predictions with this level of accuracy could power proactive alerts, giving users a 30-minute warning of impending hypo- or hyperglycemia, allowing time for preventive action (e.g., consuming carbohydrates or administering a correction bolus).

Integration into existing diabetes ecosystems is feasible. The model could run locally on a smartphone app that receives CGM data via Bluetooth, generating real-time predictions, and sending actionable notifications. This creates a low-burden, passive layer of intelligence atop existing wearable technology.

5.3. Limitations and Future Work

This study has several limitations. First, the dataset, while real-world, is from a pediatric population; glucose dynamics may differ in adults or elderly populations. Second, using CGM data alone ignores other powerful predictors like insulin (exogenous) and carbohydrates. Future work should explore hybrid models that can optionally incorporate such data when available, without degrading performance when it is missing—a robust multi-modal approach. Third, the computational cost of LSTM inference, while manageable on modern smartphones, requires optimization for always-on, low-power operation.

Future directions include: 1) Exploring more efficient neural architectures like Temporal Convolutional Networks (TCNs) or Transformers for potentially better accuracy and faster inference. 2) Developing true real-time adaptive models that continuously learn from the incoming stream of individual data, gradually transitioning from a global to a personalized model. 3) Conducting in-silico trials using accepted simulators (e.g., the UVa/Padova T1D simulator) to assess the impact of prediction guided interventions on long-term glycemic outcomes (HbA1c reduction, reduced hypo events).

5.4. Limitations and Generalizability

Our study has several limitations that must be acknowledged:

- **Pediatric Dataset:** The AZT1D dataset comprises data from pediatric and adolescent individuals with T1D. Glucose dynamics—including insulin sensitivity, glycemic variability, and response to meals—may differ in adult and elderly populations. Therefore, our findings may not directly generalize to all age groups without further validation.
- **Single Data Source:** We intentionally used CGM-only data to simulate a low-burden use case. However, this excludes potentially informative signals such as insulin administration and carbohydrate intake, which could improve prediction of accuracy when reliably available.
- **Retrospective Validation:** All evaluations were performed on historical data. Prospective real-world validation and clinical trials are needed to assess the true impact on patient outcomes, such as reduction in hypoglycemic events or improvement in Time-in-Range.
- **Performance Threshold:** Our best model achieved a MARD of 18.02%, slightly above the 15% consensus threshold for CGM sensor accuracy. While prediction is inherently more challenging than measurement, this indicates room for improvement, especially for longer prediction horizons.

These limitations highlight the need for multi-population studies, hybrid modeling approaches, and real-world deployment testing in future work.

6. Conclusion

This paper has presented a comprehensive evaluation of AI-driven blood glucose prediction models based exclusively on wearable continuous glucose monitoring (CGM) data. Our research demonstrates that a globally-trained Long Short-Term Memory (LSTM) network significantly outperforms traditional statistical methods like ARIMA, achieving mean absolute errors of 12.34 ± 3.21 mg/dL for 30-minute predictions and 17.89 ± 4.95 mg/dL for 60-minute forecasts. These results establish the viability of using CGM data alone for clinically meaningful short-term glucose forecasting, addressing a critical gap in real-world diabetes management where ancillary data like meal and insulin records are often incomplete or unreliable.

The comparative analysis between global and personalized modeling approaches reveals important insights for practical implementation. While personalized LSTM models showed potential for specific individuals with abundant stable data, the global model's robust performance across the population suggests it can serve as an effective "digital twin" of glycemic physiology, providing immediate value to new users without requiring extensive personal data collection. This finding is particularly significant for addressing the cold-start problem in clinical deployment, where patients typically lack sufficient historical data for personalized model training.

From a clinical perspective, the achieved prediction accuracy represents a meaningful step toward proactive diabetes management. With 30- to 60-minute advance warnings of impending glucose excursions, patients could implement preventive measures to mitigate hypoglycemic or hyperglycemic events, potentially reducing acute complications and improving overall glycemic control. The practical feasibility of integrating these models into existing diabetes ecosystems—running locally on smartphones or wearable devices—further enhances their potential impact by enabling real-time, low-burden decision support.

Several limitations of this work point to promising directions for future research. The pediatric focus of the dataset warrants validation in adult and elderly populations with potentially different glucose dynamics. Additionally, while our CGM-only approach reduces user burden, hybrid models that can optionally incorporate insulin and meal data—when available and reliable—might further enhance prediction accuracy. The exploration of more efficient neural architectures, such as Temporal Convolutional Networks

(TCNs) or lightweight transformers, could improve computational efficiency for always-on wearable applications.

Future work should prioritize clinical validation through in-silico trials using accepted simulators like the UVa/Padova T1D simulator, followed by real-world studies assessing both technical performance and user experience. The development of adaptive personalization strategies—gradually transitioning from global to personalized models as individual data accumulates—represents another valuable direction for balancing immediate utility with long-term optimization.

In broader terms, this research contributes to the evolving landscape of digital health by demonstrating how population-level AI models can extract generalized patterns from heterogeneous wearable data to benefit individual users. By reducing reliance on manually logged information and leveraging the most reliable sensor signal, our approach supports the vision of more autonomous, intelligent, and user-friendly diabetes care systems. As wearable technology and AI continue to advance, their convergence holds significant promise for transforming chronic disease management from reactive monitoring to proactive forecasting, ultimately empowering individuals with diabetes through enhanced foresight and decision support.

The findings presented here represent both a practical contribution to glucose prediction methodologies and a conceptual step toward the future of AI-enhanced diabetes management. Future efforts should focus on translating these algorithmic advances into tangible health benefits through rigorous clinical validation, user-centered design, and seamless integration into existing care pathways, moving us closer to a new era of digitally empowered diabetes self-management.

6.1. Future Directions

Building on this work, several promising directions emerge:

- **Multi-Population Validation:** Future studies should evaluate models on adult and elderly cohorts to assess generalizability across age groups and diabetes subtypes.
- **Hybrid and Adaptive Models:** Incorporating optional meal and insulin data—when available—through hybrid architectures could enhance accuracy without sacrificing robustness in data-scarce scenarios. Additionally, adaptive models that transition from global to personalized predictions over time warrant exploration.
- **Real-World Deployment:** Testing on-device inference on smartphones and wearables will be crucial to assess latency, power consumption, and usability in free-living settings.
- **Clinical Impact Assessment:** In-silico trials using accepted simulators (e.g., UVa/Padova T1D simulator) and prospective randomized controlled trials (RCTs) are needed to evaluate the effect of prediction-guided interventions on long-term glycemic outcomes.
- **Advanced Architectures:** Comparative studies with newer models such as Temporal Convolutional Networks (TCNs) and Transformers could further improve accuracy and efficiency.

These steps will bridge the gap between algorithmic performance and clinically meaningful, deployable solutions.

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