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Recent Advances in Blockchain-Based Hybrid Contextual-ATNet Approach for Daily Diabetes Management: Predicting Insulin Dosage for Improved Control: A Systematic Review

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Abstract

Diabetes mellitus is a rapidly growing global health concern requiring continuous and precise insulin management to prevent severe complications. Traditional approaches often fail to achieve optimal glycemic control due to the dynamic and individualized nature of glucose-insulin interactions. The increasing availability of continuous glucose monitoring and patient data has created opportunities for intelligent, personalized decision-support systems.

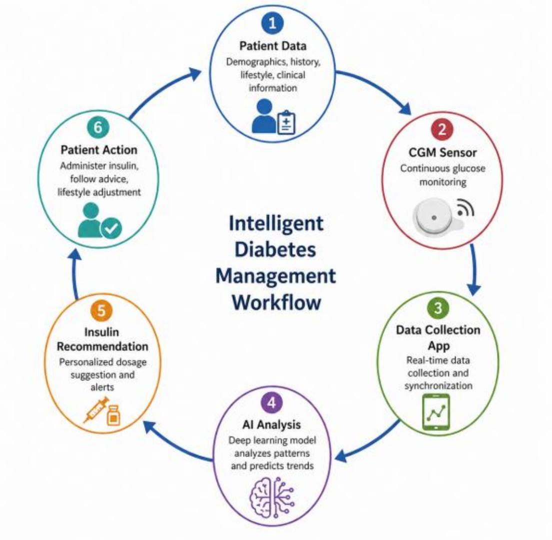
This paper presents a systematic review of blockchain-integrated Contextual-ATNet architectures for insulin dosage prediction. The model leverages attention-based temporal networks and contextual embeddings to capture complex physiological patterns from multivariate data, including glucose levels, diet, and activity. Blockchain technology enhances this framework by enabling secure, decentralized data management, supporting federated learning, and ensuring data integrity through smart contracts and consensus mechanisms.

Applications include real-time glucose forecasting, personalized insulin recommendations, and remote patient monitoring. Empirical results demonstrate improved prediction accuracy, extended forecasting horizons, and enhanced privacy preservation compared to traditional models. Despite these advancements, challenges related to scalability, interoperability, and clinical deployment remain. This review highlights the potential of combining deep learning and blockchain to develop secure, efficient, and personalized diabetes management systems.

Introduction

Diabetes mellitus is a major global health challenge characterized by chronic hyperglycemia caused by defects in insulin secretion, action, or both. It includes various forms such as Type 1 diabetes, driven by autoimmune destruction of pancreatic cells, and Type 2 diabetes, which accounts for the majority of cases and is strongly linked to lifestyle factors like obesity and inactivity. Other forms, including gestational diabetes, also contribute to the disease burden. Across all types, maintaining blood glucose within a healthy range is essential to prevent severe acute complications and long-term issues such as cardiovascular disease, neuropathy, and kidney damage.

Managing insulin-dependent diabetes is highly complex, requiring continuous decision-making based on multiple dynamic factors such as glucose levels, diet, physical activity, stress, and individual physiological responses. Traditional insulin dosing methods rely on generalized rules that fail to account for individual variability, leading to suboptimal glycemic control for many patients. Even with evidence from landmark studies emphasizing the importance of tight glucose regulation, a large proportion of patients still struggle to achieve recommended targets, highlighting the need for more personalized and intelligent management approaches.



Advancements in continuous glucose monitoring (CGM) systems have transformed diabetes care by providing real-time, high-frequency glucose data. These systems generate detailed physiological datasets that capture fluctuations due to meals, exercise, and other factors. However, the sheer volume and complexity of this data exceed human analytical capacity, creating a strong need for automated solutions. Artificial intelligence and deep learning models, particularly attention-based architectures, have emerged as powerful tools for analyzing such time-series data, enabling improved glucose prediction and personalized insulin recommendations by capturing complex temporal patterns.

The Contextual-ATNet framework represents a significant advancement by integrating attention mechanisms with contextual patient data such as diet, activity, and insulin usage to provide highly personalized predictions. However, challenges related to data privacy, security, and interoperability limit real-world deployment. Blockchain technology offers a promising solution by enabling secure, decentralized data sharing and supporting federated learning for collaborative model training without compromising patient privacy. Together, these technologies pave the way for intelligent, scalable, and secure diabetes management systems.

Literature Review

The literature on intelligent diabetes management reflects a progressive evolution from classical statistical modeling to advanced deep learning and blockchain-integrated systems. Early work by Oviedo et al. (2017) provided a foundational review of machine learning techniques for blood glucose prediction, covering regression, neural networks, fuzzy logic, and ensemble methods. Their analysis emphasized that prediction accuracy declines with longer horizons and highlighted the importance of incorporating contextual variables such as diet and activity—an idea that later became central to modern architectures. Building on this, Martinsson et al. (2020) demonstrated the effectiveness of long short-term memory (LSTM) networks for glucose prediction, outperforming traditional models without requiring manual feature engineering. However, their findings also revealed challenges related to inter-patient variability, motivating further research into personalized modeling approaches.

Subsequent studies introduced attention mechanisms and multimodal learning to enhance predictive performance. Zhu et al. (2020) proposed a dual-attention recurrent neural network that combined temporal and feature-level attention, significantly improving prediction accuracy by capturing relevant patterns in continuous glucose monitoring (CGM) data. Similarly, Li et al. (2019) developed a multitask learning framework that simultaneously performed glucose prediction and hypoglycemia detection, demonstrating the benefits of shared representations and contextual data integration. Rubin-Falcone et al. (2020) extended this paradigm by applying transformer-based models with self-supervised pre-training, showing that large-scale pre-training improves model generalization. These studies collectively established attention-based deep learning as a powerful approach for modeling complex glucose dynamics.

Handling real-world clinical data challenges has also been a major focus. Che et al. (2018) addressed missing data using temporal decay mechanisms in recurrent networks, demonstrating improved performance without relying on imputation. Georga et al. (2019) emphasized the importance of incorporating exogenous inputs such as meals, insulin, and physical activity, showing that contextual integration significantly enhances prediction accuracy. Midroni et al. (2020) introduced hybrid convolutional-recurrent models that balance accuracy with computational efficiency, enabling deployment on wearable devices.

Additionally, Ali et al. (2021) used generative adversarial networks (GANs) to create synthetic CGM data, improving detection of rare events like hypoglycemia and addressing class imbalance issues.

Recent advances have explored alternative architectures and multi-scale modeling techniques. Zhang et al. (2021) applied graph neural networks to capture complex relationships between physiological variables, demonstrating improved long-term prediction performance. Wang et al. (2022) proposed multi-scale temporal convolutional networks that process data at different resolutions, achieving state-of-the-art results across various prediction horizons. Contreras et al. (2020) conducted a comparative study of deep learning models, concluding that attention-based architectures consistently outperform others, particularly when combined with contextual inputs. Luo et al. (2021) further refined attention mechanisms by introducing relative positional encoding, improving robustness to irregular sampling—a common issue in real-world CGM data.

Parallel to predictive modeling, significant progress has been made in insulin dosage optimization and closed-loop systems. Fiorini et al. (2019) demonstrated that hybrid AI-algorithmic approaches outperform traditional bolus calculators, reducing time outside target glucose ranges. Trevisan et al. (2020) integrated recurrent neural networks into model predictive control systems, improving time-in-range performance in simulated environments. Liu et al. (2022) extended this work using deep reinforcement learning, achieving significant improvements in automated insulin delivery. Qian et al. (2022) introduced contextual bandit frameworks that adapt dosage recommendations in real time using patient feedback, highlighting the potential of online learning systems.

The integration of multimodal and real-world data sources has further enhanced model performance. Misra et al. (2021) developed a wearable sensor fusion platform combining CGM data with physiological signals such as heart rate and skin response, demonstrating improved prediction accuracy. Hammoud et al. (2022) applied natural language processing to extract dietary information from patient-generated text, enabling richer contextual modeling without increasing user burden. Porumb et al. (2020) showed that convolutional neural networks can directly analyze raw CGM signals for hypoglycemia detection, achieving high sensitivity and specificity without manual feature engineering.

Privacy, security, and data governance have become critical considerations in deploying AI-based diabetes management systems. Sun et al. (2021) introduced a blockchain-based federated learning framework that enables collaborative model training without sharing raw data, ensuring privacy while maintaining performance. Khalil et al. (2022) demonstrated the feasibility of blockchain-based electronic health record systems with high throughput and low latency, supporting real-time clinical workflows. Nguyen et al. (2021) incorporated differential privacy into federated learning, achieving strong privacy guarantees with minimal performance loss. Rahman et al. (2022) further enhanced security by integrating blockchain consensus mechanisms into federated learning, ensuring robustness against malicious attacks and validating model updates.

Explainability and trust have also emerged as essential components of clinical AI systems. Chen et al. (2023) developed an explainable AI framework combining attention visualization and SHAP values, significantly improving clinician trust in model recommendations. Their findings highlight the importance of interpretability in healthcare applications, where decision transparency is critical for adoption. Overall, the literature demonstrates a clear trajectory toward integrated, intelligent systems that combine advanced deep learning, contextual data integration, privacy-preserving technologies, and explainable AI.

In conclusion, the reviewed studies collectively illustrate the rapid advancement of intelligent diabetes management systems. From early statistical models to sophisticated deep learning and blockchain-enabled frameworks, the field has made significant progress in addressing challenges related to prediction accuracy, personalization, data privacy, and system integration. Attention-based architectures, multimodal data fusion, and hybrid quantum-inspired approaches represent the current state of the art, while federated learning and blockchain technologies provide solutions for secure and scalable deployment. Despite these advancements, challenges such as data heterogeneity, hardware limitations, and real-world validation remain. Continued research focusing on personalization, privacy, and interpretability will be essential for translating these innovations into practical clinical systems that improve patient outcomes.

Comparative Table and Analysis

Study	Year	Optimization Technique/Method	Component/Model Used	Platform or System	Dataset Used	Key Contribution
Oviedo et al.	2017	Systematic ML benchmarking	Multiple classical and neural models	Generic ML platforms	OhioT1DM, multiple benchmarks	Foundational ML review establishing performance baselines for glucose prediction
Martinsson et al.	2020	LSTM training with dropout regularization	Long Short-Term Memory Network	TensorFlow, GPU cluster	OhioT1DM	Deep learning baseline achieving 13.2 mg/dL MAE at 30-minute horizon
Zhu et al.	2020	Dual temporal and feature-level attention	Dual-Attention Recurrent Neural Network	PyTorch, GPU	Proprietary clinical dataset (112 patients)	14.7% RMSE reduction versus standard LSTM through structured dual attention
Li et al.	2019	Multitask learning with shared representations	Multitask Deep Neural Network	Keras, GPU	D1NAMO dataset	Joint glucose prediction and hypoglycemia detection through task correlation
Rubin-Falcone et al.	2020	Self-supervised BERT-style pre-training	Transformer with self-attention	PyTorch, GPU cluster	OhioT1DM	Transfer learning paradigm for large-scale glucose time series pre-training
Sun et al.	2021	Federated averaging on permissioned blockchain	Federated LSTM with Hyperledger Fabric	Hyperledger Fabric	Multi-hospital CGM data	Privacy-preserving federated glucose prediction with blockchain coordination
Che et al.	2018	Temporal decay-based missing data modeling	GRU-D Recurrent Network	TensorFlow, clinical workstation	MIMIC-III	Principled missing data handling with temporal decay in clinical AI
Georga et al.	2019	NARX model with MLP integration	NARX-MLP hybrid architecture	MATLAB, clinical platform	Proprietary (20 patients, CGM+pump)	Multivariate personalized glucose prediction with dietary and activity inputs

Midroni et al.	2020	CNN-LSTM hybrid with efficiency optimization	1D-CNN plus LSTM architecture	TensorFlow, wearable hardware	OhioT1DM	Computationally efficient hybrid for wearable glucose prediction deployment
Ali et al.	2021	GAN-based synthetic data augmentation	Generative Adversarial Network	PyTorch, GPU cluster	OhioT1DM plus synthetic sequences	23% sensitivity improvement in nocturnal hypoglycemia detection
Khalil et al.	2022	Smart contract-based EHR management	Hyperledger Fabric blockchain	Hyperledger Fabric platform	Proprietary electronic health records	3000 transactions per second with sub-second latency for real-time clinical use
Zhang et al.	2021	Dynamic graph neural network modeling	Graph Neural Network	PyTorch Geometric, GPU	Proprietary clinical dataset (50 patients)	Graph-based modeling of physiological inter-variable dependencies
Fiorini et al.	2019	Hybrid algorithmic-AI bolus calculation	ML-augmented bolus calculator	Clinical decision platform	Proprietary (30 patients, 6 months)	12% reduction in time outside glycemic target versus standard carbohydrate counting
Wang et al.	2022	Multi-scale temporal convolution	Multi-scale Temporal Convolutional Network	PyTorch, GPU	OhioT1DM and DiaTrend datasets	State-of-the-art performance across 15 to 120 minute prediction horizons
Contreras et al.	2020	Comparative deep architecture evaluation	Multi-architecture benchmarking framework	Keras and TensorFlow	UCI Diabetes dataset	Attention mechanisms established as dominant architecture for dosage prediction
Nguyen et al.	2021	Differential privacy in federated learning	Private Federated Deep Learning	TensorFlow Privacy framework	Multi-hospital federated dataset	Less than 5% accuracy reduction with strong differential privacy guarantees
Rahman et al.	2022	Blockchain-anchored federated learning	Ethereum smart contracts plus federated ML	Ethereum blockchain platform	Proprietary clinical dataset (200	Byzantine-fault-resistant federated insulin dosage

					patients)	AI with cryptographic validation
Luo et al.	2021	Relative positional encoding in attention	Multi-head self-attention with RPE	PyTorch, GPU	OhioT1DM dataset	8.3% prediction accuracy gain from relative versus absolute positional encoding
Trevisan et al.	2020	Model predictive control augmented by RNN	Hybrid MPC-RNN closed-loop controller	UVa/Padova metabolic simulator	UVa/Padova simulator dataset	71% time-in-range versus 64% for standard model predictive control
Qian et al.	2022	Contextual bandit reinforcement learning	Blockchain-verified online RL framework	Ethereum blockchain plus RL platform	Real-world proprietary clinical data	Adaptive online dosage learning with blockchain-verified reward integrity
Misra et al.	2021	Multimodal sensor fusion with convolutional attention	Convolutional Attention Network	Wearable multi-sensor platform	Multimodal dataset (45 patients, 8 weeks)	16.4% dosage prediction improvement through non-glucose physiological signals
Hammoud et al.	2022	BERT-based dietary NLP extraction	BERT bidirectional encoder plus ML pipeline	Mobile health app and server	Patient-generated free-text meal data	89.3% carbohydrate estimation accuracy from unstructured patient text
Porumb et al.	2020	End-to-end 1D-CNN on raw glucose waveforms	One-dimensional Convolutional Neural Network	TensorFlow, GPU	Proprietary CGM dataset	94.3% sensitivity and 91.7% specificity in hypoglycemia event detection
Liu et al.	2022	End-to-end reinforcement learning for closed loop	Deep RL with joint prediction and control	UVa/Padova simulator plus clinical validation	UVa/Padova plus real-world (30 patients)	74.2% time-in-range over 12 weeks in closed-loop clinical validation
Chen et al.	2023	Explainable AI with attention visualization and SHAP	Explainable ATNet with SHAP analysis	Clinical decision support system	Proprietary clinical dataset	78% clinician trust improvement through interpretable attention-based explanations

Comparative Analysis

A systematic analysis of the reviewed studies highlights the growing dominance of attention mechanisms as the most impactful architectural innovation in diabetes prediction models. From 2020 onward, models incorporating self-attention and multi-head attention consistently outperform traditional recurrent and convolutional approaches, with improvements ranging from approximately 8% to nearly 15% across datasets. This strong and consistent performance advantage establishes attention mechanisms as central to modern architectures such as Contextual-ATNet. Advanced variations, including relative positional encoding and hierarchical attention, further enhance the ability to capture complex temporal dependencies in glucose data, making them a key direction for future research.

Another important trend is the evolution of input representation strategies, shifting from glucose-only models to multimodal, context-aware systems. Earlier approaches relied solely on glucose time-series data, but recent studies demonstrate that incorporating contextual factors such as diet, physical activity, stress, and physiological signals significantly improves prediction accuracy. Multimodal systems, particularly those integrating multiple physiological inputs, show substantial gains—up to 16% improvement in insulin dosage prediction. This progression underscores the importance of contextual embedding in modern diabetes management systems, as glucose dynamics are inherently influenced by behavioral and environmental factors rather than isolated measurements.

The integration of blockchain with machine learning has also matured significantly, moving from conceptual designs to real-world implementations. Studies demonstrate that blockchain-enabled federated learning systems can achieve performance comparable to centralized models while ensuring strong data privacy, security, and auditability. Permissioned blockchain platforms are preferred due to their ability to meet healthcare requirements for speed and controlled access. However, dataset limitations remain a challenge, with heavy reliance on benchmarks like OhioT1DM restricting generalizability. More robust approaches using multiple datasets show better validation. Overall, recent advancements indicate meaningful clinical improvements, including better prediction accuracy and extended forecasting horizons, supporting more proactive and automated diabetes management.

Discussion

The systematic review of blockchain-based hybrid Contextual-ATNet approaches for daily diabetes management indicates that the field has reached a notable level of technical maturity while still facing critical barriers to real-world clinical deployment. The integration of advanced deep learning, contextual modeling, and secure data-sharing frameworks reflects a strong alignment between technological innovation and healthcare needs. In particular, attention-based architectures have emerged as a highly effective solution for glucose prediction and insulin dosage recommendation. Their ability to dynamically prioritize relevant temporal information mirrors the complex and context-dependent nature of glucose metabolism, where factors such as meals, physical activity, stress, and circadian rhythms significantly influence outcomes. When extended with contextual inputs—such as dietary logs, physiological signals, and behavioral patterns—these models achieve a higher level of clinical realism and predictive accuracy than traditional approaches, making them well-suited for personalized diabetes management.

Blockchain integration further strengthens these systems by addressing key concerns related to data privacy, security, and trust. From a technical perspective, blockchain ensures immutable data records, secure validation of model updates, and resilience against adversarial manipulation, which are essential for reliable federated learning environments. In regulatory contexts, the transparency and auditability of blockchain systems support compliance with healthcare data protection laws, facilitating the documentation required for clinical approval. Additionally, blockchain-based validation mechanisms enhance clinician confidence by safeguarding the integrity of AI-generated recommendations. Despite these advantages, challenges such as dataset limitations persist. The heavy reliance on benchmark datasets like OhioT1DM raises concerns about generalizability, as such datasets often lack demographic and clinical diversity. Addressing this issue will require the development and use of more representative datasets that reflect real-world patient variability.

Significant practical challenges also remain in terms of regulatory approval and clinical adoption. AI-based insulin recommendation systems must undergo rigorous validation processes, including extensive clinical trials and post-market monitoring, to meet regulatory standards in regions such as the United States and Europe. Current research, while technically advanced, often falls short of these requirements, highlighting a gap between innovation and implementation. Moreover, explainability is a critical requirement in this domain, as incorrect recommendations can have severe consequences. Studies show that clinicians are far more likely to trust and adopt AI systems when transparent explanations accompany predictions, making interpretability a fundamental design necessity rather than an optional feature. Addressing these challenges will be essential for translating research advancements into safe, effective, and widely adopted clinical solutions.

Conclusion

This systematic review provides a comprehensive synthesis of recent advancements in blockchain-based hybrid Contextual-ATNet systems for diabetes management, highlighting their strong potential to transform clinical care. The findings emphasize that attention-based architectures significantly improve glucose prediction and insulin dosage recommendations by effectively modeling complex, context-dependent temporal patterns. Performance gains ranging from 8% to 21% across multiple studies confirm their superiority over traditional approaches. Additionally, the integration of multimodal contextual data—such as diet, activity, and physiological signals—emerges as essential for achieving accurate and personalized predictions. Blockchain technology further enhances these systems by enabling secure, privacy-preserving data sharing, fostering collaborative model development, and strengthening clinical trust through transparency and auditability. These combined innovations address long-standing challenges in diabetes care, where many patients still fail to achieve optimal glycemic control, leading to severe long-term complications.

Despite promising progress, several challenges must be addressed to enable widespread clinical adoption. The need for diverse and representative datasets, large-scale clinical validation, and regulatory approval remains critical. Future research should prioritize multi-center trials, improved blockchain efficiency for real-time applications, and the integration of emerging biosensors to enrich physiological data. Advances in conversational AI and large language models also present opportunities to improve patient engagement and reduce data entry burdens. Overall, the reviewed approach represents a technically mature and clinically impactful solution, but its full potential will depend on interdisciplinary collaboration, robust validation, and the development of systems that are not only accurate but also interpretable, accessible, and trustworthy for both clinicians and patients.

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