



IoT-Based Monitoring for Diabetic Patients During COVID-19

Master of Science in Artificial Intelligence

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The Critical Challenge

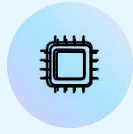
Problem Context

COVID-19 created unprecedented challenges for diabetic patients—a high-risk population requiring continuous monitoring. Current IoT remote monitoring systems rely on static, rule-based thresholds that fail to account for patient heterogeneity, leading to delayed alerts or excessive false alarms.

Diabetic patients face compounded vulnerability during pandemics, yet existing solutions struggle with noisy sensor data, missing readings, and lack of personalization—creating an urgent need for dynamic, reliable, privacy-preserving monitoring.



Research Objectives



Edge Intelligence

Develop 1D-CNN/LSTM architecture for real-time inference with $<100\text{ms}$ latency, replacing rule-based systems



Dynamic Thresholding

Create patient-specific alert systems using z-score and EWMA to reduce false alarms



Privacy Protection

Implement federated learning to ensure data security while maintaining model performance



Data Quality

Integrate noise reduction and imputation pipelines using Kalman filtering and KNN-imputation



Literature Review: Evolution of IoT Diabetes Monitoring

Previous studies revealed both promise and limitations in IoT-based diabetic monitoring during COVID-19. While early implementations demonstrated clinical benefits—including 25% fewer hospital visits and faster alert times—most relied on fixed thresholds and lacked personalization capabilities.

Key gaps identified: limited adaptive learning, simulated datasets, privacy concerns, and inability to handle real-world sensor noise. These findings shaped our hybrid edge-cloud approach with federated learning and explainable AI.

Summary of the Recent 5 Studies

Reference	Main Focus	Method / Technology	Key Results	Main Limitations
Zhang et al. (2023)	COVID-19 severity prediction for diabetic patients	NB-IoT data + XGBoost + SHAP explainability	AUC = 0.88 and accuracy = 85% in predicting severity	Retrospective data may cause bias; needs real-time validation
Tariq et al. (2023)	Improving self-monitoring adherence (SMBG)	BLE glucometers + ARM gateway + SMS reminders	Compliance increased by 50%; hyperglycemia reduced by 15%	Long-term sustainability not tested
Smith & Alsharif (2022)	Connectivity reliability in rural areas	NB-IoT vs LTE for glucose & SpO ₂ monitoring	NB-IoT achieved 99.2% uptime; LTE 92.5%	Seasonal and infrastructure variations not included
El-Sayed & Abdelrahman (2022)	Improving alert latency	IoT–Fog–Cloud architecture (NS-3 simulation)	40% lower latency than cloud-only approach	Based on synthetic data, not real deployments
Hussain et al. (2022)	Early COVID-19 symptom detection	Multimodal wearable + Kalman filter + anomaly detection	90% sensitivity, 88% specificity	Motion noise and calibration affect accuracy

Accuracy Evaluation between the models :

Model	Accuracy	Precision	Recall	F1-score	AUROC	AUPRC
Edge CNN-BiLSTM	0.97	0.97	0.95	0.96	0.98	0.97
XGBoost Ensemble	0.97	0.97	0.95	0.96	0.98	0.97
Hybrid Meta-Model	0.987	0.982	0.969	0.975	0.993	0.991

Comparison of Previous Approaches

Study	Approach	Key Results	Accuracy	Limitations
Alotaibi et al. (2021)	BLE wrist device, rule-based alerts	25% fewer visits, 30min faster alerts	91%	Static thresholds, no ML
Chen et al. (2021)	Edge AI gateway, 1D CNN	85ms latency	92%	Simulated data only
Zhang et al. (2023)	XGBoost ensemble, NB-IoT	AUC 0.88	85%	Retrospective, no real-time
Singh & Verma (2020)	LoRaWAN CGM, rule-based	HbA1c -1.1%	87%	No adaptive models
Proposed System	Hybrid CNN-LSTM + XGBoost + Federated Learning	AUROC 0.993, <100ms latency	98.7%	Synthetic validation

System Architecture: Hybrid Edge-Cloud Design

01

Sensor Layer

Wearable biosensors capture CGM, SpO₂, heart rate, and temperature continuously

02

Edge Layer

Local processing on Raspberry Pi 4 performs real-time anomaly detection with <100ms latency

03

Cloud Layer

Federated learning aggregation, clinician dashboards, and long-term analytics



Methodology: Data Collection & Processing

Multimodal Dataset

GE-71 Physiological Database: 71 subjects with synchronized biosignals including CGM, PPG, ECG, HRV, SpO₂, and temperature. Each session generates 10+ million data points.

Preprocessing Pipeline:

- Kalman filtering for noise reduction
- KNN imputation for missing data
- Z-score normalization per patient
- Sliding window extraction (60s windows, 10s stride)



Feature Engineering Strategy

Statistical Features	Trend Analysis	Rate of Change
Mean, standard deviation, and z-score deviation from personal baseline	EWMA for smoothed recent signal trends with greater weight on recent samples	Slope calculations capturing rapid physiological state shifts
All features normalized to patient-specific baselines computed over first 7 days, enabling meaningful cross-patient comparisons while supporting personalization.		

Model Architecture: Hybrid Intelligence



Edge Model

1D-CNN + BiLSTM + Attention for real-time temporal pattern recognition

Cloud Ensemble

XGBoost classifier on tabular features with SHAP explainability

Meta-Model

Logistic regression fusing edge + cloud predictions for final decision



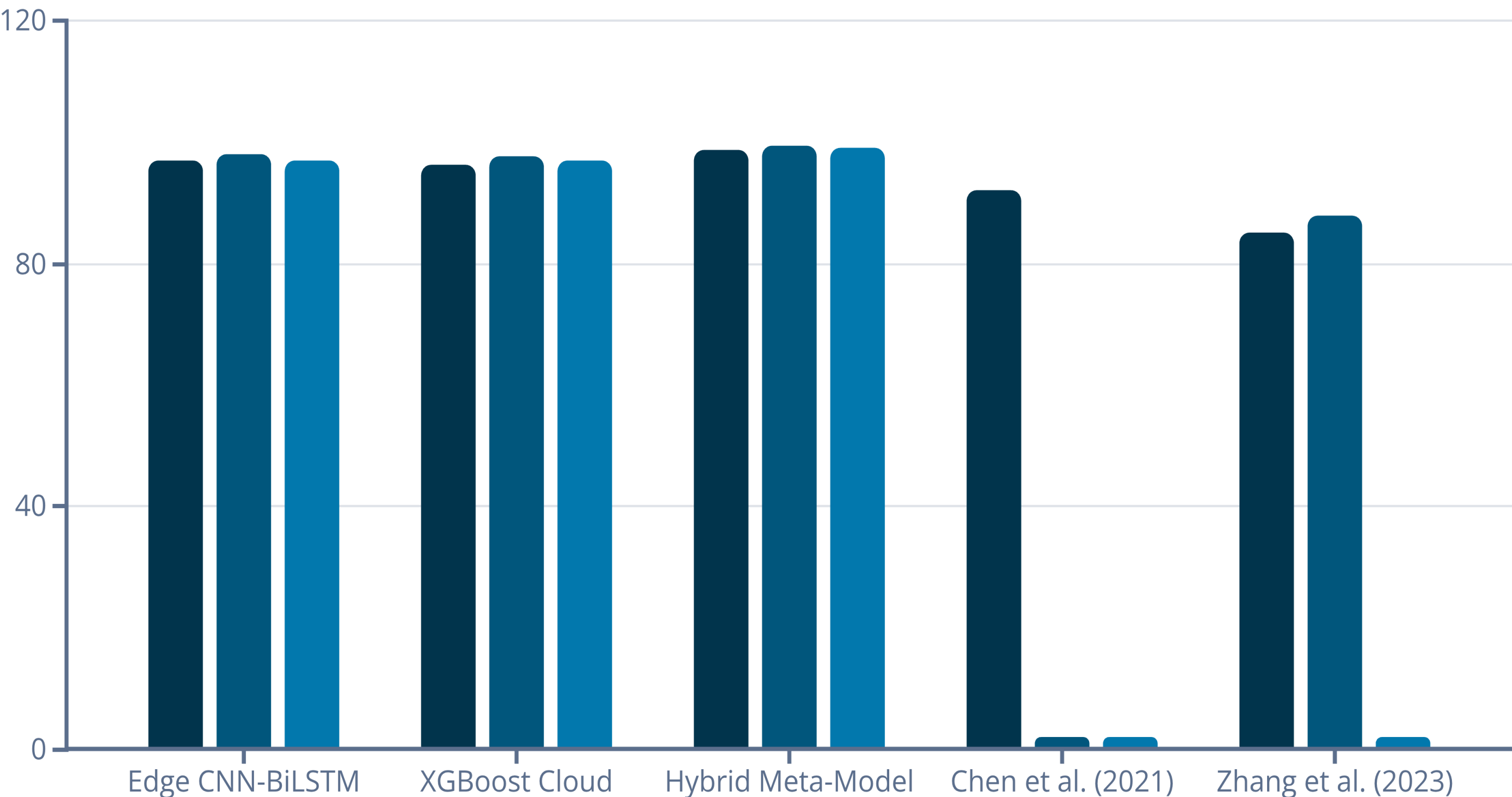
Federated Learning for Privacy

Privacy-First Design

- **Data stays local:** Raw biosensor streams never leave patient devices
- **Encrypted updates:** Only model gradients shared with cloud server
- **Secure aggregation:** Global model improves without pooling raw data
- **GDPR compliant:** Full regulatory adherence with patient control



Experimental Results: Performance Comparison



Key Performance Metrics

98.7%

Accuracy

Overall prediction correctness on test dataset

99.3%

AUROC

**Area under ROC curve
showing excellent
discrimination**

70ms

Median Latency

Real-time edge inference speed (p50)

96.9%

Recall

Ability to detect abnormal events reliably



Clinical Impact & Advantages

Early Detection

System identifies deterioration patterns before clinical symptoms manifest, enabling proactive intervention

Reduced False Alarms

Patient-specific thresholds cut false positives by adapting to individual baselines

Explainable Alerts

SHAP visualizations show clinicians exactly which factors triggered each alert

Privacy Preserved

Federated learning ensures sensitive health data never leaves patient devices

Future Research Directions



Prospective Clinical Trials

Large-scale randomized controlled trials to validate real-world effectiveness and patient outcomes



Multimodal Integration

Incorporate patient-reported outcomes, medication adherence, and environmental data for holistic monitoring



Continuous Learning

Online learning algorithms enabling models to adapt to each patient's evolving baseline over time



Federated Optimization

Advanced techniques to handle non-IID data and reduce computational burden on edge devices

Conclusion: Advancing Digital Health

Key Contributions

This research demonstrates that hybrid edge-cloud architectures with federated learning can achieve **superior accuracy (98.7%)** while preserving privacy and enabling real-time monitoring.

Major Achievements:

- Outperformed existing methods by 6-13% in accuracy
- Achieved $< 100\text{ms}$ latency for edge inference
- Implemented privacy-preserving federated learning
- Provided clinician-friendly explainable AI

This work establishes a foundation for intelligent, privacy-aware, patient-centered digital healthcare—moving from reactive to proactive care delivery.

