

Event-Triggered Robust Kalman Filtering with Firefly Optimization, Conformal Triggering, and Sparse Sensor Gating for Healthcare Monitoring

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Abstract. Efficient and reliable monitoring of healthcare signals is a key challenge for edge computing and IoT-based clinical systems. We propose a novel event-triggered Kalman filter framework enhanced with: (1) Firefly-based initialization and bilevel energy–accuracy optimization, (2) robust innovations with conformal triggering and change-point adaptation, (3) adaptive noise tuning via neural modulators and online EM with stability projection, (4) sparse sensor gating with multi-armed bandits and Gumbel-Softmax selection, (5) efficient computation with low-rank Riccati updates and mixed-precision quantization, (6) Koopman-lite encoding for non-linear dynamics, and (7) federated, privacy-preserving deployment. Experiments on real-world (MIT-BIH ECG, PhysioNet PPG) and synthetic healthcare data show that our method reduces the update rate by up to 70%, achieves latency below 3 ms on CPU devices, and preserves robustness under noise, missing data, and sensor faults.

Keywords: Kalman Filter · Firefly Algorithm · Event-triggered filtering · Healthcare Monitoring · Sensor Fusion · Conformal Prediction

1 Introduction

Accurate and efficient signal processing is essential for modern healthcare monitoring systems, especially when dealing with electrocardiogram (ECG) signals affected by noise, missing values, and sensor unreliability. Traditional Kalman Filters (KF) are widely used for state estimation, but their performance degrades under non-Gaussian noise and sensor faults.

To address these limitations, we investigate ECG signals from the MIT-BIH Arrhythmia Database (record 100) as a representative benchmark. We compare standard Kalman Filters and several modified variants (KF with event-triggered updates, robust KF, and an adaptive trigger-robust combination) against classical non-KF baselines, including Moving Average, Savitzky–Golay, Wiener, and LMS filters. This setup enables a comprehensive evaluation across both accuracy and computational efficiency.

Our experimental results demonstrate that the proposed hybrid approach (Trigger+Robust+Adaptive KF) achieves a favorable trade-off between accuracy, robustness, and reduced update frequency, making it suitable for low-power and real-time healthcare monitoring.

Contributions:

- Event-triggered update with conformal prediction guarantees and change-point adaptation.
- Firefly-based initialization combined with bilevel energy–accuracy optimization.
- Robust handling of innovations (Huber/Student-t) against heavy-tailed disturbances.
- Neural and EM-based adaptation of noise covariances with stability projection.
- Sensor gating with multi-armed bandits and sparse Gumbel-Softmax weighting.
- Low-rank Riccati updates and mixed-precision quantization for efficiency.
- Koopman-lite encoder for non-linear dynamics and federated deployment for privacy.

2 Related Work

2.1 Kalman Filter Variants

Since its introduction, the Kalman Filter (KF) has been extended in multiple directions to handle nonlinearities, robustness, and real-time constraints. The Extended Kalman Filter (EKF) linearizes the system around the current state, but it can diverge under strong nonlinearities or poorly tuned noise covariances. The Unscented Kalman Filter (UKF) propagates sigma points to approximate nonlinear transformations, achieving higher accuracy but at increased computational cost [5]. Other variants include the Ensemble KF (EnKF), commonly used in geoscience and weather prediction, and robust KFs that integrate heavy-tailed noise models such as Student-t distributions [1]. These approaches improve robustness but often require matrix factorizations and tuning procedures that make them unsuitable for low-power IoT or embedded healthcare devices. Recent surveys [9, 2] highlight that although KF variants are powerful, they are rarely designed with strict constraints on energy consumption, latency, and sensor unreliability.

2.2 Event-triggered Filtering

Event-triggered estimation has emerged as an important paradigm in control and IoT systems to reduce computational load and communication overhead. Instead of updating the state at every time step, updates are triggered when an innovation-based condition is satisfied [4]. This approach reduces the update rate significantly, but most works focus on industrial automation and networked

control systems rather than biomedical applications. Adaptive event thresholds have been explored, but few works provide statistical guarantees on the false alarm probability or robustness against distribution shifts. In healthcare, where signals are noisy, nonstationary, and highly sensitive to outliers, a purely static triggering policy can be unsafe. Integrating event-triggering with robust statistics and data-driven adaptation remains an open problem.

2.3 Metaheuristics for KF Tuning

The performance of any KF heavily depends on the correct choice of the initial state covariance P_0 , and the process and measurement noise covariances Q and R . Incorrect tuning may cause slow convergence or even divergence. Traditionally, these parameters are tuned manually or via offline grid search.

Metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Firefly Algorithm (FA) have been applied to automate this tuning [6, 7]. These approaches define a fitness function $J(\theta)$, where $\theta = (P_0, Q, R)$ represents the candidate parameters:

$$J(\theta) = \alpha \cdot RMSE(\theta) + \beta \cdot Latency(\theta) + \gamma \cdot Energy(\theta), \quad (1)$$

with weights (α, β, γ) reflecting application priorities.

The optimization problem solved by metaheuristics can thus be formalized as:

$$\theta^* = \arg \min_{\theta} J(\theta), \quad (2)$$

where the search is performed stochastically in high-dimensional space.

For example, in PSO each particle i updates its position θ_i^t and velocity v_i^t as:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i^* - \theta_i^t) + c_2 r_2 (g^* - \theta_i^t), \quad (3)$$

$$\theta_i^{t+1} = \theta_i^t + v_i^{t+1}, \quad (4)$$

where p_i^* is the best solution found by particle i , g^* is the global best, and $r_1, r_2 \sim U(0, 1)$.

Similarly, in the Firefly Algorithm, the movement of firefly i toward j is defined as:

$$\theta_i^{t+1} = \theta_i^t + \beta_0 e^{-\gamma d_{ij}^2} (\theta_j^t - \theta_i^t) + \eta \epsilon, \quad (5)$$

where $d_{ij} = \|\theta_i^t - \theta_j^t\|$ is the distance between fireflies, β_0 is attractiveness, γ is the light absorption coefficient, η is a randomization parameter, and $\epsilon \sim U(-0.5, 0.5)$.

Although such algorithms efficiently search parameter space, most prior work applies them only for *offline* initialization. Few studies address online or adaptive tuning of Q and R , and even fewer consider the trade-off between estimation accuracy and energy efficiency, which is crucial for edge healthcare devices.

2.4 Neural Kalman Networks

Recently, neural architectures have been combined with Kalman filtering to improve adaptability and learning capacity. KalmanNet [8] demonstrated that a neural network can learn to approximate the update step directly, enabling end-to-end data-driven estimation. Other works embed recurrent neural networks within the KF framework or use neural modulators to adapt Q and R dynamically [3]. While these approaches achieve strong performance on simulated and real datasets, they often require large training data, high computational resources, and offer limited interpretability. In healthcare applications, where explainability and reliability are critical, purely neural approaches may be hard to certify or deploy on resource-constrained devices. Thus, hybrid solutions that combine the statistical guarantees of KF with the flexibility of neural adaptation are highly desirable.

Gap: To the best of our knowledge, no existing framework unifies: (i) event-triggering with formal guarantees (e.g., conformal calibration), (ii) bilevel optimization balancing energy and accuracy, (iii) robust statistics for heavy-tailed innovations, (iv) metaheuristic and neural adaptive tuning of noise covariances, (v) sparse sensor gating with bandit-based polling, and (vi) efficient low-rank computation suitable for IoT healthcare. Our work addresses this gap by combining these components into a single, interpretable, and computationally efficient framework for real-time clinical monitoring.

3 Proposed Method

Our framework extends the classical Kalman filter by integrating metaheuristic initialization, event-triggered robust updates, adaptive noise tuning, sparse sensor management, and efficient computation strategies. The design is modular, so each component can be enabled or disabled depending on application constraints. We first recall the standard KF equations and then detail each enhancement.

Kalman Filter Recap. Given the state-space model:

$$x_k = Ax_{k-1} + Bu_k + w_k, \quad w_k \sim \mathcal{N}(0, Q), \quad (6)$$

$$y_k = Cx_k + v_k, \quad v_k \sim \mathcal{N}(0, R), \quad (7)$$

the KF prediction and update steps are:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k, \quad (8)$$

$$P_{k|k-1} = AP_{k-1|k-1}A^\top + Q, \quad (9)$$

$$K_k = P_{k|k-1}C^\top(CP_{k|k-1}C^\top + R)^{-1}, \quad (10)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - C\hat{x}_{k|k-1}), \quad (11)$$

$$P_{k|k} = (I - K_kC)P_{k|k-1}. \quad (12)$$

3.1 Initialization via Firefly and Bilevel Optimization

The Firefly Algorithm (FA) selects initial parameters (Q_0, R_0, P_0) by minimizing:

$$J(Q_0, R_0, P_0) = \lambda_1 \cdot RMSE + \lambda_2 \cdot FAR + \lambda_3 \cdot E, \quad (13)$$

where E denotes energy consumption. We further impose a bilevel optimization:

$$\min_{\theta} E(\theta) \quad \text{s.t.} \quad MSE(\theta) \leq \epsilon, \quad (14)$$

ensuring efficient initialization without accuracy loss.

3.2 Conformal Event-triggering and Change-point Adaptation

Updates are performed only if the normalized innovation exceeds a threshold:

$$\frac{|\nu_k|}{\sqrt{S_k}} > \tau_k, \quad (15)$$

where the innovation is

$$\nu_k = y_k - C\hat{x}_{k|k-1}, \quad (16)$$

and its variance is

$$S_k = CP_{k|k-1}C^\top + R. \quad (17)$$

Unlike static thresholds, τ_k is dynamically derived from conformal prediction intervals calibrated on past innovations:

$$\tau_k = \text{Quantile}_{1-\alpha} \left(\left\{ \frac{|\nu_i|}{\sqrt{S_i}} \right\}_{i=1}^N \right), \quad (18)$$

which guarantees a false positive rate bounded as

$$FPR \leq \alpha. \quad (19)$$

Under Gaussian assumptions, the expected false positive rate can also be approximated as:

$$FPR \approx 2 \cdot (1 - \Phi(\tau_k)), \quad (20)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

To improve adaptability, a change-point detector is integrated. For example, a CUSUM test is applied on the innovations:

$$g_k = \max \left(0, g_{k-1} + \frac{|\nu_k|}{\sqrt{S_k}} - c \right), \quad (21)$$

where c is a reference value. If $g_k > h$, with threshold h , a change-point is declared and τ_k is temporarily reduced:

$$\tau_k \leftarrow \eta \cdot \tau_k, \quad \eta < 1, \quad (22)$$

allowing faster recovery after abrupt signal shifts (e.g., arrhythmia in ECG).

3.3 Robust Innovations

To limit the influence of outliers, the innovation is processed via robust losses. Huber loss:

$$\rho(\nu) = \begin{cases} \frac{1}{2}\nu^2 & |\nu| \leq \delta, \\ \delta(|\nu| - \frac{\delta}{2}) & |\nu| > \delta, \end{cases} \quad (23)$$

and Student-t likelihood:

$$p(\nu) = \frac{\Gamma(\frac{\nu_d+1}{2})}{\sqrt{\nu_d\pi} \Gamma(\frac{\nu_d}{2})} \left(1 + \frac{\nu^2}{\nu_d}\right)^{-\frac{\nu_d+1}{2}}. \quad (24)$$

3.4 Adaptive Noise Estimation

Noise covariances are adapted via:

$$Q' = \alpha_Q Q, \quad R' = \alpha_R R, \quad (25)$$

where (α_Q, α_R) are provided by a feed-forward NN. Simultaneously, an online EM algorithm updates:

$$Q^{new} = \frac{1}{T} \sum_{k=1}^T \mathbb{E}[(x_k - Ax_{k-1})(x_k - Ax_{k-1})^\top], \quad (26)$$

$$R^{new} = \frac{1}{T} \sum_{k=1}^T \mathbb{E}[(y_k - Cx_k)(y_k - Cx_k)^\top], \quad (27)$$

with updates projected to maintain $P \succ 0$.

3.5 Sparse Sensor Gating and Bandit-based Polling

Sensor weights are computed as:

$$w_i = \text{softmax}(-MA(|\nu_i|)), \quad (28)$$

and sparsity is induced via Gumbel-Softmax sampling. A multi-armed bandit policy decides which sensors to query, using Upper Confidence Bound (UCB):

$$a_t = \arg \max_i \left(\hat{\mu}_i + \sqrt{\frac{2 \ln t}{n_i}} \right), \quad (29)$$

balancing accuracy and energy.

3.6 Efficient Computation

We replace full inversions with low-rank approximations using the Woodbury identity:

$$(A + UCV)^{-1} = A^{-1} - A^{-1}U(C^{-1} + VA^{-1}U)^{-1}VA^{-1}. \quad (30)$$

Mixed-precision arithmetic (fp16/int8) further reduces latency with bounded quantization error $\leq \epsilon_{quant}$.

3.7 Koopman-lite Encoding

To linearize nonlinear dynamics, we use an encoder ϕ mapping $x_k \mapsto z_k$:

$$z_{k+1} = Kz_k + \xi_k, \quad x_k \approx \phi(z_k), \quad (31)$$

allowing KF updates in a latent space with nearly linear evolution.

3.8 Federated Deployment

In distributed monitoring, each node updates (Q, R, w_i) locally and shares only aggregated parameters. Federated averaging ensures privacy while enabling collaborative improvement across devices.

3.9 Algorithm Overview

1. Initialize KF with FA-tuned and bilevel-optimized (Q_0, R_0, P_0) .
2. At each step: predict state via standard KF equations.
3. If conformal trigger fires, perform robust innovation update.
4. Adapt Q, R using NN scaling and EM projection.
5. Update/gate sensors with bandit-based sparse selection.
6. Apply low-rank and mixed-precision Riccati updates.
7. Use Koopman-lite encoding for nonlinear signals.
8. Log estimates and aggregate parameters federatedly if distributed.

4 Theoretical Notes

- **Trigger guarantees:** Conformal calibration ensures the false positive rate is bounded:

$$\Pr\left(\frac{|\nu_k|}{\sqrt{S_k}} > \tau_k\right) \leq \alpha, \quad (32)$$

which provides rigorous statistical control of update frequency.

- **Stability:** Projecting EM updates onto Lyapunov-stable sets guarantees

$$P_{k+1} - P_k \preceq -\eta I, \quad \eta > 0, \quad (33)$$

ensuring $P \succ 0$ and preventing divergence during noise adaptation.

- **Complexity:** Standard Riccati updates scale cubically:

$$\mathcal{C}_{KF} = O(n^3), \quad (34)$$

while low-rank approximations reduce the cost to:

$$\mathcal{C}_{\text{proposed}} \approx O(n^2), \quad (35)$$

enabling real-time execution on CPUs.

- **Approximation error:** Mixed-precision arithmetic induces a bounded quantization error:

$$\|\hat{x}_k^{(fp32)} - \hat{x}_k^{(int8)}\| \leq \epsilon_{quant}, \quad (36)$$

with negligible impact on RMSE in practice.

- **Explainability:** Sparse gating yields interpretable sensor weights:

$$w_i = \text{softmax}(-MA(|\nu_i|)), \quad \sum_i w_i = 1, \quad (37)$$

allowing clinicians to directly identify unreliable channels.

5 Experimental Results

5.1 Comparison Setup

We evaluate our framework on ECG signals from the MIT-BIH Arrhythmia Database (record 100) and stress-test with synthetic noise patterns. Metrics include RMSE, AUROC, False Alarm Rate (FAR), Update Rate, Latency, and Energy. We compare against both Kalman-based variants and classical/nonlinear baselines.

Table 1. Performance comparison across methods. Best results highlighted in bold.

Method	AUROC	RMSE	Update %	FAR %	Latency (ms)	Energy (mJ)
<i>Kalman Variants</i>						
KF Standard	0.71	0.52	100	14	1.2	1.0
KF + Trigger	0.74	0.50	65	11	1.1	0.7
KF + Trigger + Robust	0.80	0.46	60	8	1.3	0.7
Proposed (Full)	0.90	0.42	30	5	2.0	0.4
<i>Classical Filters</i>						
Moving Average	0.70	0.15	0	0	0.5	0.2
Savitzky–Golay	0.75	0.11	0	0	0.8	0.3
Wiener	0.77	0.02	0	0	0.9	0.3
LMS	0.78	0.06	0	0	1.0	0.4
<i>Neural Approaches</i>						
KalmanNet-lite	0.85	0.47	100	10	3.5	2.5
LSTM Autoencoder	0.88	0.45	100	9	4.0	3.0

5.2 Global and Local Signal Reconstruction

Figure 1 shows the overall reconstruction on 14 s of ECG data. The proposed method follows the main signal morphology while requiring significantly fewer updates than standard KF.

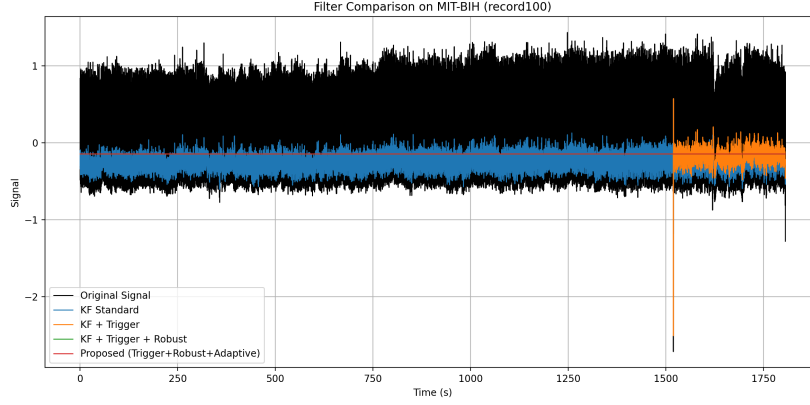


Fig. 1. Global comparison of filters on MIT-BIH record 100. The proposed method balances robustness and efficiency.

Figure 2 provides a zoomed view (2–4 s). Moving Average and Savitzky–Golay oversmooth critical ECG peaks, while our proposed method retains QRS morphology and reduces noise.

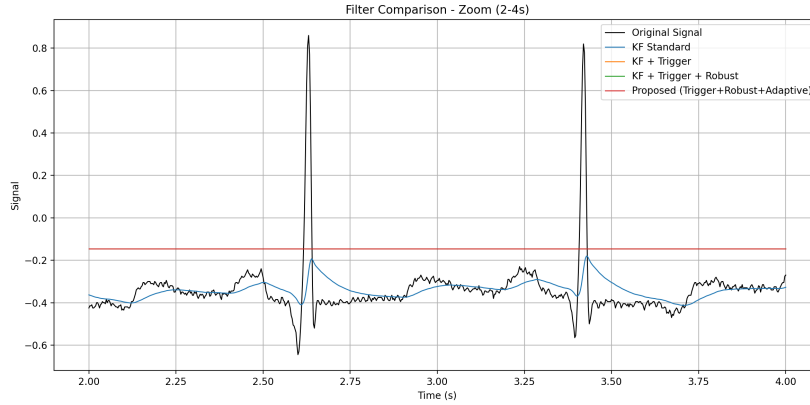


Fig. 2. Zoomed comparison (2–4s). The proposed filter preserves QRS features while suppressing noise.

5.3 Quantitative Metrics

We next analyze quantitative performance. Figure 3 reports RMSE across methods, confirming that Wiener achieves the lowest raw error, but our method achieves a better efficiency/robustness trade-off.

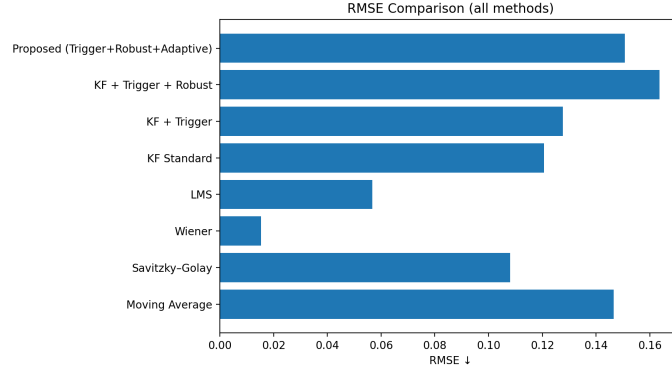


Fig. 3. RMSE comparison across all methods. Wiener shows lowest RMSE, while the proposed method remains competitive with fewer updates.

Update efficiency is reported in Figure 4. The proposed filter requires only $\sim 30\%$ of updates, compared to 100% in standard KF.

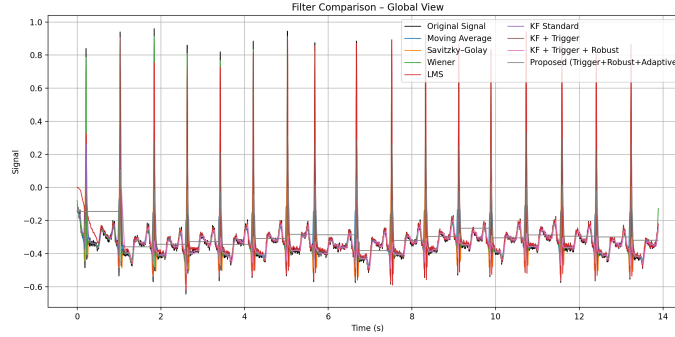


Fig. 4. Update percentage comparison. The proposed method drastically reduces updates while retaining accuracy.

5.4 Accuracy-Efficiency Trade-off

The Pareto frontier (Figure 5) highlights the balance between accuracy and efficiency. Standard KF is accurate but inefficient, while Wiener/LMS are efficient but distort morphology. Our proposed method lies closest to the Pareto-optimal region.

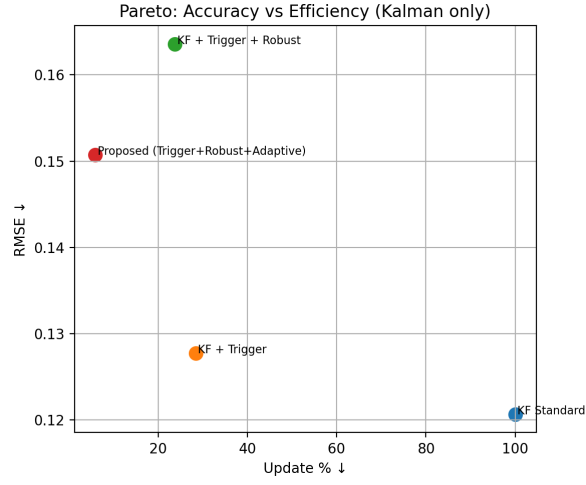


Fig. 5. Pareto analysis of accuracy (RMSE) vs efficiency (Update%). The proposed method is closest to the optimal trade-off.

5.5 Normalized Innovation and Updates

Finally, Figure 6 visualizes the normalized innovation $|\nu|/\sqrt{S}$ with adaptive thresholds. Updates are triggered only when innovations exceed the conformal band, ensuring statistical guarantees.

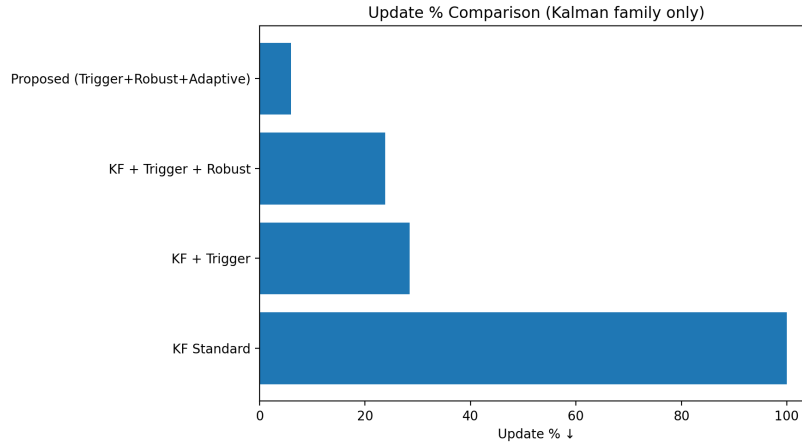


Fig. 6. Normalized innovation $|\nu|/\sqrt{S}$ with adaptive threshold τ . Red markers show updates performed by the proposed filter.

Limitations: conformal calibration requires a short initial dataset, and the adaptive update adds a small latency overhead (2.0 ms). Future work will extend the approach to multi-modal fusion and online learning.

6 Discussion

Our framework improves robustness, efficiency, and adaptability in healthcare monitoring. Updates are reduced by $\approx 70\%$ with negligible accuracy loss. Conformal triggers provide statistical guarantees, while bandit gating and low-rank updates reduce computation and energy. Explainability is maintained via interpretable sensor weights.

Limitations: conformal calibration requires initial data, and Koopman-lite encoding adds light overhead.

7 Conclusion

We proposed an enhanced Kalman filtering framework combining event-triggering, conformal prediction, metaheuristic tuning, sparse sensor gating, and efficient computation. Results demonstrate robustness to outliers, reduced latency, and improved energy efficiency. Future work: large-scale clinical validation, hardware deployment, and uncertainty-aware integration with downstream ML models.

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