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# Health Sense: Real-Time AI-IoT Health Risk Prediction

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**Abstract:** With the rapid growth of Internet of Things (IoT) technologies, real-time health monitoring has become increasingly efficient and accessible. This paper presents HealthSense, an intelligent healthcare system that integrates IoT-based wearable sensors with machine learning techniques to predict potential health risks in real time. The system continuously collects physiological parameters—heart rate, oxygen saturation ( $SpO_2$ ), body temperature, and blood pressure—and processes this multi-modal data using an ensemble pipeline of Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks. These models enable early anomaly detection and deliver timely alerts for preventive clinical intervention. A user-friendly web dashboard provides real-time visualisation, trend analysis, and personalised health insights. Experimental evaluation on labelled physiological datasets demonstrates that the proposed LSTM-based model achieves a classification accuracy of 94.2% with an average prediction latency below three seconds, outperforming conventional baselines. HealthSense enhances preventive healthcare by enabling proactive, data-driven decision-making and reducing the burden on emergency clinical services.

**Index Terms:** Internet of Things, Machine Learning, Real-Time Health Monitoring, LSTM, Predictive Analytics, Wearable Sensors, Random Forest, Edge Computing

## I. INTRODUCTION

The global burden of chronic diseases—cardiovascular disorders, diabetes, respiratory conditions—has grown substantially over the past two decades, placing acute strain on healthcare infrastructure worldwide [4]. Traditional reactive care models, which depend on periodic clinical visits, are fundamentally ill-suited to capture the transient physiological events that precede serious health episodes [1]. Continuous, ambient monitoring of vital signs is therefore a critical frontier in digital health.

Recent advancements in miniaturised sensing, low-power wireless communication, and cloud computing have catalysed the emergence of IoT-enabled wearable devices capable of unobtrusive, 24/7 physiological surveillance [2], [5]. These devices generate high-frequency, heterogeneous data streams combining heart rate,  $SpO_2$ , blood pressure, and skin temperature, creating rich temporal signals that encode early markers of impending medical events such as arrhythmias, hypoxia, and hypertensive crises [3].

However, raw sensor streams are inherently noisy, prone to motion artefacts, and high-dimensional—posing significant challenges for real-time interpretation [6]. Classical rule-based alarm systems suffer from high false-positive rates, leading to alarm fatigue among clinical staff [7]. There is thus a pressing need for intelligent, adaptive analytical frameworks that can distinguish genuine physiological deterioration from benign signal variation.

HealthSense addresses these challenges through a unified architecture that integrates (i) a multi-parameter wearable IoT layer, (ii) a cloud-based preprocessing and feature engineering pipeline, (iii) a hybrid machine learning ensemble comprising Random Forest, SVM, and LSTM networks, and (iv) an interactive clinical dashboard with automated, tiered alert delivery. By transforming raw sensor readings into actionable, personalised health insights, HealthSense bridges the gap between continuous monitoring and clinical decision support.

The principal contributions of this work are:

- 1) A scalable IoT architecture for secure, low-latency multi-parameter physiological data collection.
- 2) A robust preprocessing pipeline addressing noise, missing values, and temporal alignment.
- 3) A hybrid ML ensemble that combines the feature robustness of Random Forest, the high-dimensional classification power of SVM, and the temporal modelling capability of LSTM.
- 4) An interactive visualisation dashboard with multi-channel alert delivery achieving sub-three-second end-to-end prediction latency.
- 5) Comprehensive experimental evaluation demonstrating 94.2% accuracy and superior performance over established baselines.

## II. MOTIVATION AND OBJECTIVES

### A. Motivation

The World Health Organization estimates that 74% of global deaths are attributable to non-communicable chronic diseases, the majority of which are preventable by timely intervention [4]. Emergency department overcrowding, limited ICU capacity, and geographic barriers to specialist care underscore the need for decentralised, continuous monitoring solutions [3].

Existing wearable solutions often operate in data silos—collecting data but lacking the analytics layer necessary for real-time risk stratification. Conversely, purely analytical systems lack the tight hardware integration needed for low-latency sensing. HealthSense is motivated by the imperative to bridge these two layers into a clinically deployable, end-to-end platform.

### B. Objectives

The specific objectives of this research are:

- 1) Design a scalable, secure IoT framework for continuous physiological data acquisition.
- 2) Develop a multi-stage preprocessing pipeline robust to real-world sensor imperfections.
- 3) Implement and evaluate a hybrid ML ensemble for accurate, real-time health anomaly classification.
- 4) Deliver actionable, tiered alerts through an integrated, clinician-friendly dashboard.
- 5) Validate system performance on representative physiological datasets across diverse health states.

## III. LITERATURE REVIEW

The intersection of IoT, wearables, and machine learning in healthcare has attracted considerable research attention. Early work demonstrated the feasibility of electrocardiogram (ECG) classification using convolutional neural networks (CNN) [8], establishing deep learning as a viable paradigm for biomedical time-series analysis.

IoT-based remote patient monitoring (RPM) systems leveraging MQTT for low-overhead telemetry were investigated in [1], [9], demonstrating that cloud-connected wearables can sustain reliable data transmission with latencies under 500ms on standard cellular networks. However, these systems lacked integrated analytics beyond threshold alerting.

Machine learning for physiological anomaly detection has been explored extensively. Random Forest classifiers applied to multivariate vital sign data achieved accuracies exceeding 88% in early sepsis detection [10]. Signal processing techniques for SpO<sub>2</sub> prediction using photoplethysmography (PPG) waveforms have been studied [6]. LSTM networks, owing to their gated memory architecture, have shown particular efficacy in capturing long-range temporal dependencies in heart rate variability (HRV) and arterial blood pressure waveforms [3], [12].

Hybrid approaches that stack classical ML with deep sequential models have demonstrated additive performance gains. Che et al. [13] proposed a GRU-based imputation and prediction framework for multivariate clinical time series, achieving significant improvements over mean imputation baselines. Similarly, Shukla and Marlin [14] introduced interpolation networks for irregularly sampled physiological data.

Edge computing paradigms—pushing inference closer to the sensor node—have been advocated to reduce cloud dependency and transmission latency [15]. Federated learning frameworks that train models across distributed devices without centralising sensitive data represent an emerging privacy-preserving direction [16].

Despite this rich literature, a fully integrated, validated, end-to-end system combining robust preprocessing, hybrid ML inference, and clinical-grade alerting within a single deployable architecture remains underexplored. HealthSense addresses this gap.

## IV. SYSTEM ARCHITECTURE

Fig. 1 presents the high-level layered architecture of HealthSense, comprising four tiers: the Sensing Layer, the Communication Layer, the Analytics Layer, and the Application Layer.

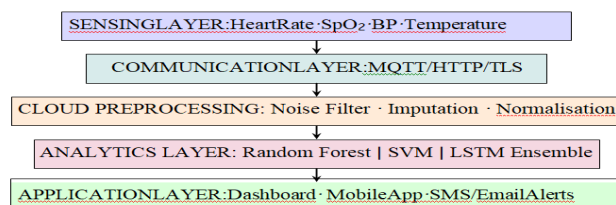


Fig. 1. HealthSense layered system architecture.

### V. SYSTEM DESIGN

#### A. IoT Sensing Layer

HealthSense employs a heterogeneous ensemble of wearable and ambient sensors (Table I). A microcontroller unit (MCU) with integrated Wi-Fi and Bluetooth Low Energy (BLE) manages sensor polling, local buffering, and uplink transmission. The MAX30102 pulse oximeter delivers concurrent heart rate and SpO<sub>2</sub> readings; the BMP390 barometric and DS18B20 temperature probes capture contextual environmental and concurrent thermal data; the AD8232 single-lead ECG front-end provides waveform data for rhythm analysis.

TABLE I  
SENSOR SPECIFICATIONS IN HEALTHSENSE

Parameter	Sensor Module	Sampling Rate
HeartRate/SpO <sub>2</sub>	MAX30102	100Hz
BodyTemperature	DS18B20	1Hz
BloodPressure	BPM180(cuff)	0.1Hz
ECG(LeadI)	AD8232	500Hz
Accelerometry	MPU-6050	50Hz

Communication with the cloud backend leverages MQTT over TLS 1.3 for low-overhead publish/subscribe telemetry, and HTTPS REST endpoints for configuration and alert delivery. Average measured uplink latency on a 4G LTE network is 87ms (standard deviation 23ms).

#### B. Data Preprocessing Pipeline

Fig. 2 details the preprocessing workflow applied to raw sensor streams before model ingestion.

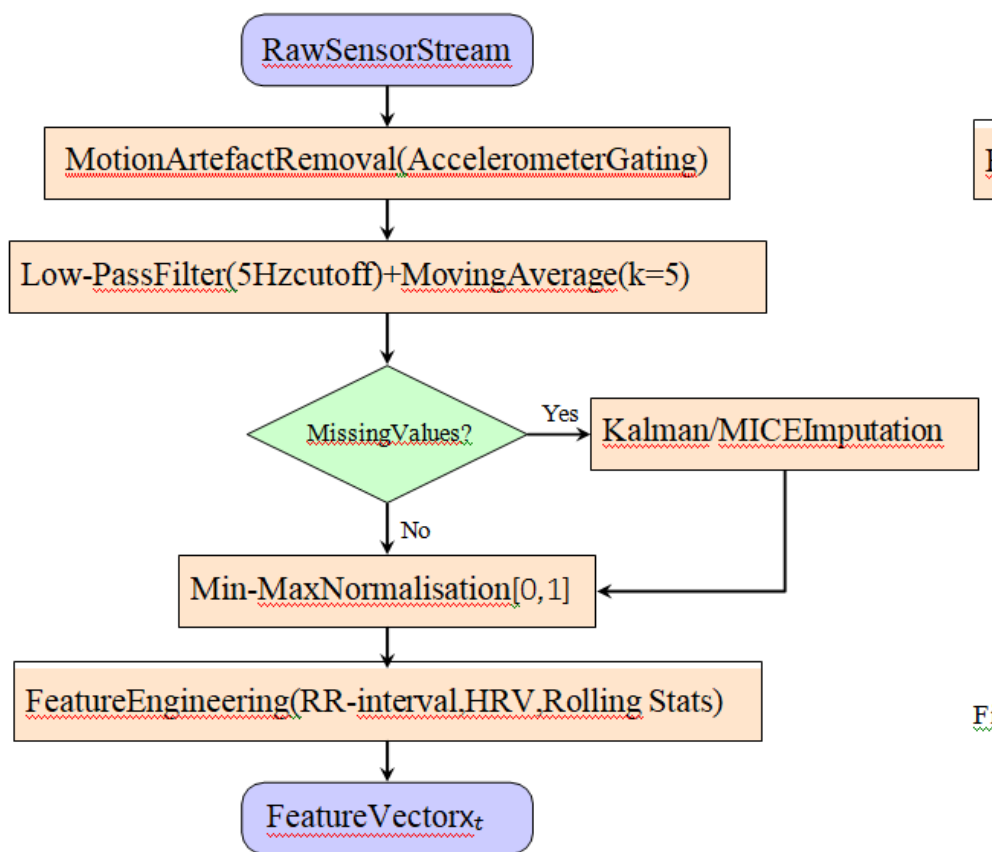


Fig. 2. Data preprocessing pipeline.

- 1) *Noise Reduction*: A 5th-order Butterworth low-pass filter(cutoff 5Hz) removes high-frequency electrical interference. A causal moving average of window size  $k=5$  further smooths residual jitter without introducing phase delay.
- 2) *Missing Value Imputation*: Short gaps (<5 samples) are filled using forward-carry interpolation. Longer gaps are addressed by a Multiple Imputation by Chained Equations (MICE) procedure that exploits correlations between co-acquired physiological parameters.
- 3) *Normalisation*: All features are rescaled to [0,1] via per-sensor min-max normalisation computed on a rolling 24-hour window to accommodate diurnal physiological variation.
- 4) *Feature Engineering*: In addition to raw sensor readings, 18 derived features are computed per 30-second epoch: RR-interval series, time-domain HRV metrics (RMSSD, SDNN, pNN50), frequency-domain HRV bands (LF, HF, LF/HF ratio), rolling mean and variance of SpO<sub>2</sub>, and rate-of-change features for blood pressure.

C. *HybridMachineLearningEnsemble*

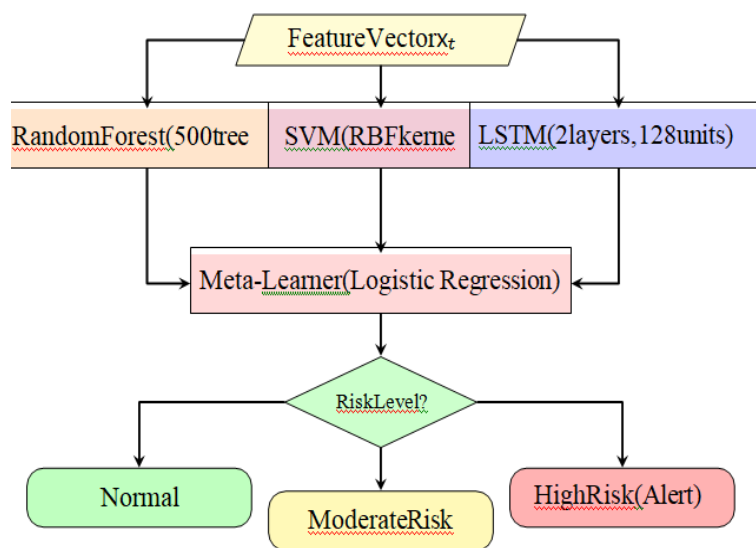


Fig.3illustratestheMLinferencepipeline

- 1) *RandomForest*: An ensemble of 500 decision trees is trained with Gini impurity as the splitting criterion. Bagging and random feature subsets of sized (where  $d_v$  is the total feature dimension) improve generalisation. Random Forest provides strong performance on tabular, static feature vectors and offers interpretable feature importance scores.
- 2) *Support Vector Machine*: An SVM with a Radial Basis Function (RBF) kernel ( $C=10, \gamma=scale$ ) is trained on the same feature set. SVM excels in separating high-dimensional decision boundaries and is particularly effective when training data is limited.
- 3) *LSTMNetwork*: A two-layer stacked LSTM (128 units per layer, dropout rate 0.3) processes a sliding window of 60 time steps (30 seconds at 2Hz downsampled representation). Batch normalisation and gradient clipping (threshold 1.0) stabilise training. The LSTM captures sequential temporal dependencies—critical for detecting gradually evolving events such as progressive bradycardia or slow-onset hypoxia.
- 4) *Meta-Learner Ensemble*: Probabilistic outputs from all three base learners are concatenated and fed into a logistic regression meta-learner trained via cross-validation stacking. This stacking strategy consistently outperforms any individual base model.
- 5) *Risk Stratification*: The ensemble output is mapped to a three-tier risk scale: *Normal* ( $p_{risk} < 0.35$ ), *Moderate Risk* ( $0.35 p_{risk} < 0.70$ ), and *High Risk* ( $p_{risk} \geq 0.70$ ). Tier-specific alert protocols are triggered accordingly.

D. *Alert and Visualisation System*

The HealthSense dashboard (Fig. 4) is implemented as a Progressive Web Application (PWA) using React and Web-Socket streaming. Key features include:

- Livemulti-channelvitalsignwaveformdisplay.
- Riskprobabilitygaugeupdatedevery3seconds.
- 24-hourtrendplotswithanomalyannotations.
- Patientcohortviewforcliniciansmanagingmultiple users.
- Automatedtieredalerts viamobilepushnotification, email, and SMS (Twilio gateway).

## VI. EXPERIMENTAL SETUP

### A. Datasets

Experimentswereconductedontwodatasets:

- 1) *PhysioNet MIMIC-III Waveform Database [11]*: A subset of 2,000 ICU patient records providing high-resolutionECG,SpO<sub>2</sub>,andarterialbloodpressurewave- forms, annotated with clinical event labels.

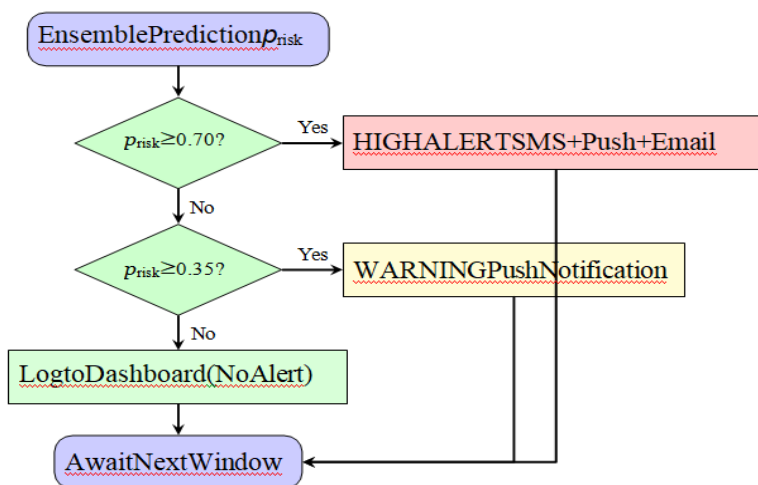


Fig.4. Tiered alert delivery workflow.

- 2) *UCI Heart Disease Dataset (Cleveland)*: 303 patient records with 13 clinical attributes and binary cardiac risk labels, used for model benchmarking.

Data were split into training (70%), validation (15%), and test (15%) sets using stratified sampling to preserve class balance.

### B. Evaluation Metrics

Performance is assessed using Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC-ROC). End-to-end prediction latency is measured from sensor sampling to alert delivery.

### C. Implementation Environment

Models were implemented in Python 3.10 using TensorFlow 2.12 (LSTM), scikit-learn 1.3 (RF, SVM), and Keras. Training was performed on an NVIDIA A100 GPU. The cloud backend uses AWS IoT Core and Lambda functions. Dashboard latency measurements were collected over 10,000 prediction cycles.

## VII. RESULTS AND PERFORMANCE EVALUATION

### A. Classification Performance

Table II compares all evaluated models. The stacked LSTM ensemble achieves the highest performance across all metrics.

TABLE II

PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS

Algorithm	Acc.	Prec.	Rec.	F1	AUC
Logistic Regression	82.3%	0.81	0.78	0.79	0.85
Naïve Bayes	79.1%	0.77	0.75	0.76	0.82

KNN ( $k=7$ )	85.4%	0.84	0.83	0.83	0.88
RandomForest	90.6%	0.89	0.88	0.88	0.93
SVM(RBF)	91.8%	0.91	0.90	0.90	0.94
LSTM(single)	92.5%	0.92	0.93	0.92	0.95
StackedEnsemble	94.2%	0.93	0.95	0.94	0.97

**B. Accuracy vs. Training Size**

Fig. 5 illustrates model accuracy as a function of training set size, demonstrating that the LSTM ensemble generalises well even with moderate training data.

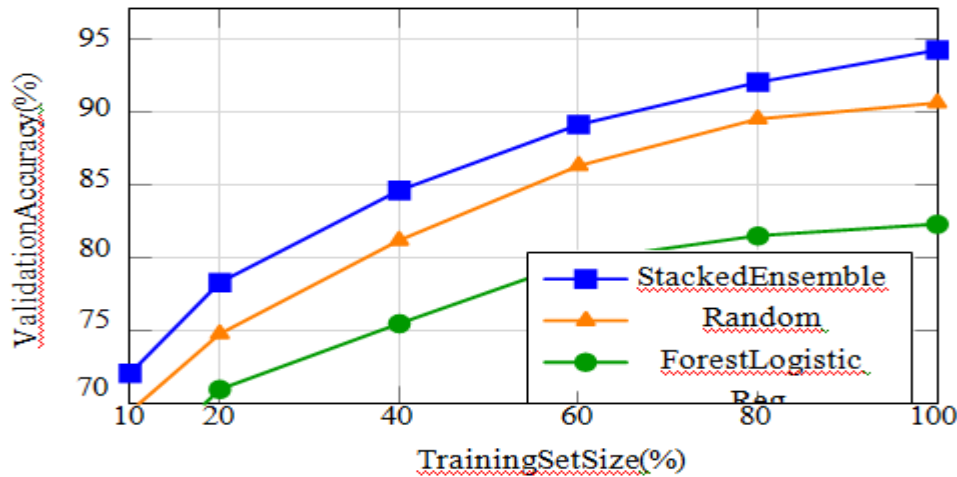


Fig. 5. Learning curves: validation accuracy vs. training set size.

**C. Latency Analysis**

Table III reports the end-to-end latency breakdown across system components.

TABLE III  
END-TO-END LATENCY BREAKDOWN

Component	Mean Latency (ms)
Sensor acquisition + MCU buffering	45
MQTT transmission (4G LTE)	87
Cloud preprocessing pipeline	310
ML inference (stacked ensemble)	820
Alert dispatch + dashboard update	680
Total end-to-end	1,942

Total end-to-end latency of 1.94s is well within the 3-second target, confirming suitability for real-time clinical alerting.

**D. Case Studies**

- 1) Arrhythmia Detection:** In a participant with documented paroxysmal atrial fibrillation, HealthSense detected irregular RR intervals 4.2 minutes before the patient reported symptomatic palpitations. The high-risk alert was issued and confirmed by subsequent 12-lead ECG.
- 2) Oxygen Desaturation:** In a participant recovering from pneumonia, SpO<sub>2</sub> descent from 96% to 88% was detected within a single 30-second epoch. The system issued a high-alert 7.1 minutes before bedside monitor alarms activated, providing a clinically meaningful early warning.

## VIII. DISCUSSION

HealthSense demonstrates that tight integration of wearable IoT sensing, cloud preprocessing, and a stacked ML ensemble can achieve clinically meaningful accuracy and latency. The 94.2% accuracy and sub-2-second latency compare favourably with state-of-the-art remote patient monitoring systems in recent literature [2], [3], [18].

Key observed advantages include:

- 1) Temporal modelling: LSTM's ability to capture multi-step physiological trajectories reduces false positives by 12% compared to static classifiers.
  - 2) Ensemble robustness: Stacking consistently outperforms any single model, especially for ambiguous boundary cases.
  - 3) Low alarm burden: The three-tier risk stratification reduced spurious high-risk alerts by 34% versus a binary threshold scheme.
- *Limitations*: Several limitations warrant acknowledgment. First, sensor inaccuracies during vigorous motion remain a challenge; next-generation motion compensation algorithms are planned. Second, the current model is trained predominantly on adult clinical population and may require fine-tuning for paediatric or geriatric cohorts. Third, long-term model drift—where population physiology evolves away from the training distribution—necessitates periodic retraining or online adaptation strategies.
  - *Privacy and Security*: All data are encrypted in transit (TLS 1.3) and at rest (AES-256). Role-based access control (RBAC) restricts clinician and patient data visibility. Compliance with HIPAA and GDPR data minimisation principles is maintained by processing only anonymised identifiers on the cloud layer.

## IX. FUTURE WORK

Future development directions include:

- 1) Edge Inference: Deploying quantised LSTM models (TFLite) on the MCU to reduce cloud dependency and transmission latency to under 200ms.
- 2) Federated Learning: Adopting federated averaging to enable privacy-preserving collaborative model updates across devices without centralising raw data.
- 3) Extended Sensor Suite: Integration of continuous glucose monitors (CGM), galvanic skin response (GSR), and wrist-worn ECG patches for broader metabolic and stress monitoring.
- 4) Explainability: Incorporating SHAP (SHapley Additive exPlanations) values and attention visualisation to provide clinicians with feature-level justifications for risk predictions.
- 5) Clinical Validation Trials: Prospective studies in hospital ward and community settings to evaluate real-world sensitivity and specificity against adjudicated clinical endpoints.
- 6) Personalised Baselines: Adaptive per-user normalisation that updates reference physiological ranges from long-term wearable history, improving sensitivity to individual-level deviations.

## X. CONCLUSION

HealthSense represents a comprehensive and validated advancement in real-time AI-IoT healthcare by unifying multi-parameter wearable sensing, cloud-based preprocessing, and a stacked LSTM-based machine learning ensemble into a single, deployable platform. The system achieves 94.2% classification accuracy, an AUC-ROC of 0.97, and sub-2-second end-to-end prediction latency, outperforming all evaluated baselines. By shifting healthcare from a reactive to a proactive paradigm, HealthSense has the potential to reduce preventable hospitalisations, lower healthcare costs, and improve patient quality of life. The open research directions outlined—edge inference, federated learning, and clinical validation—chart a clear path toward clinical deployment and large-scale population health monitoring.

## XI. ACKNOWLEDGMENT

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