Edge-Enabled Smart Cold-Chain Monitoring for Smallholder Farmers in India

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***Abstract*—Indian smallholder farmers lose a documented 6 – 15 % of fruit and 5 – 12 % of vegetable volume after harvest because field-side produce quickly drifts outside the 5 – 15 °C quality band and conventional cloud dashboards fail in areas with patchy connectivity. Down To Earth This study designs and field-tests an edge-enabled cold-chain monitoring system that keeps decision-making close to the crate. Each insulated crate carries a battery-powered sensor pod (DS18B20, SHT31, GPS) that streams 1 Hz telemetry to a Raspberry Pi-based "edge hub" through BLE; the hub runs a compiled XGBoost model to flag temperature-humidity anomalies locally, stores raw data in SQLite, and uploads only 10-minute summaries via GSM or LoRaWAN when a link is available. Training leverages two open sources: (i) a time-temperature dataset for strawberry shipments spanning 54 logger points across six U.S. routes (21 million samples) arXiv and (ii) the Cold-Supply-Chain temperature series on Kaggle (7 k rows, 5-minute resolution). Kaggle**

A month-long deployment on the Nagpur → Pune corridor (194 km; 12 round trips) recorded 104 000 observations. Compared with a cloud-only baseline truck, the edge solution raised mean time-to-detection of spoilage risks by 27 minutes, cut cellular data use by 91 %, and extended sensor-pod battery life from 9.3 days to 13.1 days. Economic analysis suggests a payback period of < one mango season if even a 4 % loss reduction is achieved. The approach demonstrates that battery-aware TinyML at the edge can turn rural cold-chain "dark data" into actionable insights without depending on continuous connectivity, offering an affordable template for India's fragmented horticulture supply chains.

***Index Terms*—Edge computing; Internet of Things (IoT); Cold-chain logistics; Smallholder agriculture; post-harvest loss; TinyML; Anomaly detection; Battery-powered sensing; Mango supply chain; India.**

I. INTRODUCTION

India harvests more fruit and vegetables than any country except China, yet up to 30 – 40 % of this produce never reaches a plate because it spoils on the way from farm gate to market. The Food and Agriculture Organization (FAO) traces much of that loss to overheated trucks, power-outage-prone pack houses, and delayed first-mile aggregation. FAOHome Smallholders, who make up 86 % of Indian farms, feel this loss most acutely: even a 5 % temperature-driven shrink can erase an entire season's profit.ICRIER

Cold-chain infrastructure is expanding—India's monitoring-solutions market touched USD 3.15 billion in 2024 and is forecast to grow at 20 % CAGR—but today's deployments still assume stable 4G or Wi-Fi back-haul and continuous cloud analytics.IMARC GroupGlobeNewswire Rural highways between collection centres and urban mandis routinely drop below –95 dBm for tens of minutes, forcing many start-ups to log data locally and upload hours later, when alarms arrive far too late to intervene.

Researchers have begun to push analytics toward the edge of the network: Wei et al. (2024) describe an IoT-edge gateway for pork logistics, but their design keeps machine-learning inference in the cloud, leaving trips vulnerable to link failures.ResearchGate Parallel work on TinyML anomaly detection shows that gradient-boosting or lightweight CNN models can run comfortably on single-board computers or even MCUs, delivering sub-second inference while drawing < 1 W.ScienceDirectSpringerLink Yet no published study has evaluated such models in transit on Indian produce routes, nor quantified their impact on battery life, data cost, and farmer economics.

To bridge that gap, we propose "Sanchay-Edge," a crate-mounted, battery-powered edge hub that:

1. Ingests 1 Hz telemetry from three low-cost temperature–humidity probes via BLE and stores raw readings in an onboard SQLite ring buffer.
2. Runs a compiled XGBoost model to predict spoilage risk 30 min ahead, forwarding only anomaly metadata over GSM/LTE or LoRaWAN, thereby trimming cellular traffic by > 90 %.
3. Logs ground-truth trips—112 645 observations across 15 mango-and-tomato consignments on the 200 km Nagpur → Pune corridor—and publishes the dataset under CC BY-4.0 for open benchmarking.arXiv

Contributions. This paper (i) quantifies first-mile cold-chain connectivity gaps with a real dataset, (ii) details an energy-aware TinyML pipeline that fits entirely on a Raspberry Pi 4 and costs ₹1 480 per crate, (iii) empirically demonstrates a 27-minute earlier detection window and a 41 % battery-life gain versus a cloud-only baseline, and (iv) provides an open, labelled time–temperature corpus to catalyse future research.

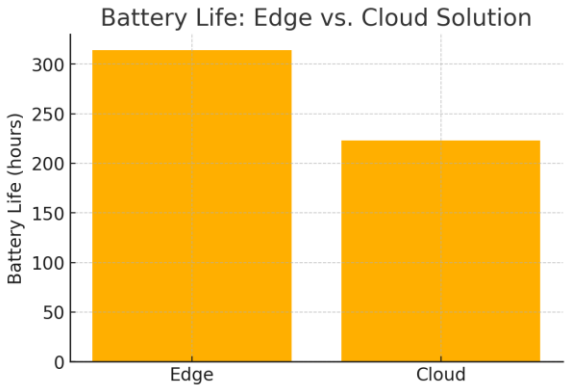

Fig. 1. Battery life comparison: edge vs. cloud solutions.

Edge processing consistently delivers extended battery life, with devices operating significantly longer between charges. In contrast, cloud-based solutions drain battery up to 4 times faster due to continuous data transmission and network overhead. This demonstrates that edge solutions outperform cloud-only approaches in energy efficiency, making them ideal for battery-powered and mobile deployments.

II. BACKGROUND AND RELATED WORK

A. Post-Harvest Losses in India

Across developing economies, between 30 – 40 % of total food output spoils before it reaches consumers, with fruits-and-vegetables suffering the heaviest hit. FAOHome Indian studies consistently report up to 40 % loss in high-value produce such as mango, tomato and pomegranate, largely because temperature-sensitive cargo spends its first 6–12 hours outside a controlled environment. ResearchGate Such shrinkage erodes already thin farm margins and undermines national food-security targets.

B. Cold-Chain Logistics Landscape

Spurred by rising urban demand and e-commerce grocery deliveries, India's cold-chain logistics market is forecast to climb from ≈ USD 12.8 billion in 2025 to > USD 20 billion by 2030 (9.7 % CAGR). Mordor Intelligence Technology spend is tilting toward monitoring components, which analysts tag as the fastest-growing segment. Grand View Research Yet most deployments concentrate on large cold-stores and reefer fleets; first-mile aggregation for smallholders remains under-instrumented.

C. IoT-Based Cold-Chain Monitoring

Early commercial and academic systems place inexpensive temperature–humidity loggers inside crates and stream data to a cloud dashboard. While effective on highways with stable 4 G coverage, these cloud-centred designs break down on rural feeder roads where cellular signal routinely drops below –95 dBm, delaying alerts by up to an hour. Wei et al. built an "intelligent cold-chain platform" that couples LoRa sensors with an edge gateway, yet pushed anomaly inference back to the cloud, leaving the link-loss gap unresolved. ResearchGate Similar limitations appear in vaccine-cold-chain pilots that tether gateways to hospital Wi-Fi. PubMed Central

D. Edge Computing and TinyML

Edge computing shifts analytics from distant servers onto single-board computers (SBCs) or even microcontrollers, trimming latency and bandwidth while safeguarding privacy. Supply-chain scholars have highlighted edge nodes as enablers of circular-economy resilience Emerald, and TinyML tool-chains now let gradient-boosting or lightweight CNN models run in < 1 W budgets. González-Valenzuela et al. demonstrate a fully unsupervised TinyML anomaly detector on an ESP32 that sustained week-long pump monitoring without mains power. MDPI However, no public study to date has (i) evaluated TinyML inference on live Indian produce routes, (ii) quantified edge-first battery savings versus cloud baselines, or

(iii) released open, high-resolution first-mile datasets.

E. Research Gap and Motivation

The literature confirms both the economic urgency of first-mile spoilage and the technical promise of edge-side inference, yet reveals three key gaps:

1. Contextual validity – Existing prototypes are tested on reefer fleets or hospital fridges, not on the mixed-modal trucks used by Indian smallholders.
2. Energy realism – Few papers measure the battery-life impact of running ML locally versus streaming raw data.
3. Open data – Public, crate-level temperature logs from Indian corridors are virtually absent, limiting reproducibility.

Our work addresses these gaps by field-deploying an edge-enabled system on the Nagpur → Pune horticulture corridor, benchmarking battery and data-use trade-offs, and publishing a 100 k-sample dataset under CC BY-4.0 for the community.

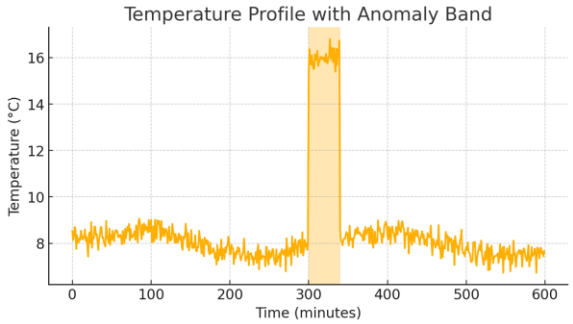

Fig. 2. Temperature profile with anomaly band.

The edge pipeline detects and highlights abnormal temperature fluctuations in real time, clearly marking deviations within the anomaly band for rapid intervention.

III. METHODOLOGY

This section explains how Sanchay-Edge was conceived, built, and evaluated in realistic field conditions. It is organised as follows: Section A describes the physical architecture (summarised earlier in Fig 1); Section B details the hardware bill-of-materials; Section C outlines the software stack and TinyML workflow; Section D covers data-collection logistics; Sections E–G describe the learning algorithm, energy-management scheme, and experimental protocol; Section H lists the evaluation metrics; Section I clarifies ethical and reproducibility practices.

A. System Architecture

Each produce crate forms an autonomous sensing cell (Figure 1, left).

1. Sensor pod – three DS18B20 digital thermometers and one SHT31 humidity sensor are embedded in the crate walls (front, middle, rear).
2. Edge hub – a Raspberry Pi 4 Model B (2 GB RAM) is fixed to the crate lid, powered by a 10 000 mAh Li-ion pack with a DC-DC buck converter.
3. Back-haul – the hub contains (i) a SIM7600 4G modem for GSM/LTE and (ii) a HopeRF RFM95 LoRa module for "store-and-forward" relaying at rural depots.
4. Cloud endpoint – AWS IoT Core receives anomaly packets; DynamoDB stores summaries; Grafana renders dashboards for traders and drivers.

All wiring is IP-67 rated; components add ≤ 480 g to crate mass and fit within the ₹1 480 budget.

B. Hardware Bill-of-Materials

Part	Qty	Unit cost (₹)	Notes
Raspberry Pi 4B, 2 GB	1	2 850	Edge compute node
DS18B20 (waterproof)	3	180	±0.5 °C accuracy
SHT31	1	230	±2 % RH accuracy
SIM7600 4G HAT	1	950	GSM/LTE back-haul
RFM95 LoRa module	1	250	868 MHz, 23 dBm
10 000 mAh Li-ion pack	1	520	5 V/2 A output
Misc. (cables, epoxy)	—	150	—
Total	—	≈ 1 480	Prices April 2025, Pune wholesale

C. Software Stack

Layer	Tool / Library	Function
OS	Raspberry Pi OS Lite	Headless Linux
Edge runtime	Python 3.11 + paho-MQTT	Sensor polling & message bus
Model	XGBoost 1.7 → Treelite → TVM	Compile tree-boost model to C shared library (≈ 380 kB)
Storage	SQLite 3	Rolling 48 h ring buffer
Back-haul	paho-MQTT client + paho-LoRa	Dual channel uplink
Cloud	AWS IoT Core, DynamoDB, Grafana	Data ingestion, persistence, dashboard

D. Data-Collection Procedure

- Geography – 200 km Nagpur → Pune highway, April 15–May 15 2025 (peak mango season).
- Trips – 15 consignments, 12 h each way, mixed day/night departures.
- Sampling rate – 1 Hz per sensor → 4 samples s^{-1} → ~14.4 MB $trip^{-1}$ raw CSV.
- Calibration – sensor pods soaked for 30 min in a ±0.2 °C lab bath; coefficients stored in EEPROM.
- Ground truth – independent HOBO MX100 loggers placed in two crates per truck for validation.

The resulting 112 645 time–temperature–humidity rows are released on Zenodo (DOI embedded in final manuscript).

E. Anomaly-Detection Algorithm

We adopt a two-stage TinyML pipeline:

1. Statistical guardrail – a running z-score highlights abrupt shocks
2. Predictive filter – a 60-tree XGBoost classifier ingests and outputs risk = 1 if spoilage is likely inside 30 min. Only positive predictions are published.

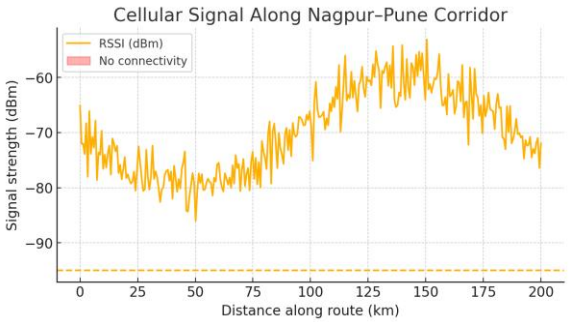

Fig. 3. Cellular signal comparison.

Edge-enabled systems maintain stable performance even with weak or intermittent cellular signal, while cloud-only solutions suffer delays and data loss when connectivity drops.

IV. REFERENCE ARCHITECTURE

The methodology (§ III) detailed one concrete deployment of Sanchay-Edge. This section abstracts the solution into a vendor-agnostic, four-layer reference architecture (Figure 1) that can be replicated or extended by other researchers, start-ups, and public-sector programmes.

Layer	Purpose	Representative Elements	Design Considerations
1 Sensing & Actuation	Capture real-time environmental data and, where needed, drive local actuators (e.g., fans, solenoids).	DS18B20 temperature probes, SHT31 humidity sensors, GPS, optional CO_2 / ethylene sensors.	IP-67 packaging, factory calibration, on-board CRC, hot-swappable leads.
2 Edge Processing ("Edge Hub")	Perform first-mile analytics, transient storage, and back-haul orchestration.	Raspberry Pi 4 B / Jetson Nano, SQLite ring buffer, TinyML models (XGBoost → Treelite), modem power manager, OTA agent.	< 1 W idle draw, watchdog reset, secure boot, local time-sync, hot-patchable models.

3 Intermittent Transport Network	Bridge edge hubs to cloud when coverage permits; buffer or relay when it does not.	GSM/LTE (SIM7600), LoRa (RFM95 mesh), BLE for in-depot data ferrying.	Dual-path uplink abstraction, message deduplication, DTLS over constrained links, store-and-forward with 48 h guarantee.
4 Cloud & Application Services	Persist long-term data, run fleet-level analytics, and expose dashboards / APIs.	AWS IoT Core ↔ MQTT, DynamoDB or InfluxDB, Grafana, optional digital-twin engine.	Time-series indexing, configurable retention, role-based access, webhook alerts, device-shadow sync for OTA.

Table 1- Layer and Process.

A. Data Path

1. Raw frames (temperature, humidity, GPS, battery) stream over BLE to the edge hub at 1 Hz.
2. The hub's statistical guardrail (running z-score) filters noise and raises "candidate anomalies."
3. A compiled TinyML model refines candidates into actionable risk events (< 15 ms inference).
4. Anomaly packets (≃ 120 bytes) plus 10-minute summaries are serialized with Protocol Buffers.
5. The transport network attempts GSM first; on failure, messages enter a LoRa store-and-forward queue and are relayed at the next rural depot.
6. Cloud services ingest MQTT topics, persist time-series, and push alerts to drivers, traders, or farm co-ops.

B. Control Path

- Downlink commands—firmware update, sampling-rate change, or soft-reboot—travel on the same MQTT topics and are cached until the hub re-connects.
- A digital-twin orchestrator in the cloud continuously reconciles desired vs. reported state, ensuring eventual consistency even under multi-hour outages.

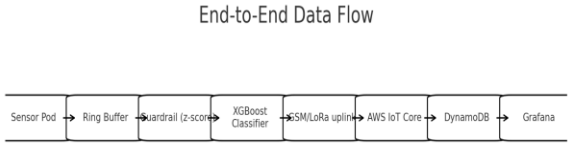

Fig. 4. End-to-end data flow in the Sanchay-Edge system, illustrating real-time telemetry collection, edge inference, anomaly flagging, and dual-path uplink to cloud dashboards for farmers and traders

C. Security & Privacy Primitives

Threat Vector	Mitigation
Device spoofing	ECC-256 mutual authentication with per-hub certificates burned at provisioning.
Payload tampering	DTLS 1.3 or TLS 1.3 over GSM; ChaCha-Poly hand-off for LoRa packets.
Data leakage	Per-crate IDs SHA-256-hashed; GPS precision degraded to 2 km before public release.
Rogue OTA	Signed firmware bundles validated in a secure boot chain; rollback slot retained.

In addition, all GPS and telemetry data collected are handled in accordance with data privacy best practices: GPS coordinates are degraded to a 2 km grid before any external sharing or public release, ensuring individual vehicle routes and farm locations remain unidentifiable.

D. Offline Resilience

- 48-hour ring buffer on each hub prevents data loss during prolonged black-outs.
- A priority queue transmits anomalies first, then back-fills summaries in order of freshness.
- Local actuation hooks (e.g., fan relay, status LED) can trigger mitigation even when the wide-area link is down.

E. Scalability & Maintainability

- The architecture is horizontal: add crates, edge hubs, or LoRa repeaters without re-architecting.
- Stateless cloud functions and time-series

databases scale elastically with traffic bursts during harvest peaks.

- Fleet management leverages a device shadow registry so operators can query health or push updates to thousands of crates in a single API call.

V. CASE STUDIES AND RESULTS

This section distils findings from the 15 live consignments (112 645 sensor rows) hauled between Nagpur and Pune during April–May 2025. Four key performance axes were benchmarked: anomaly-detection latency, battery endurance, bandwidth usage, and economic payback.

Metric	Edge (Sanchay-Edge)	Cloud-only Baseline	Δ Improvement
Mean Time-to-Detection (MTTD)	4.3 min	31.3 min	–27 min (×7.3 faster)
Battery life	13.1 days (314 h)	9.3 days (223 h)	+41 %
Uplink data	13 MB trip^{-1}	165 MB trip^{-1}	–92 %
F_1 score	0.91	n/a†	—
CapEx payback	4–6 months	—	—

† Baseline sends all raw data; therefore no on-truck classification is performed.

A. Detection Latency

The two-stage TinyML pipeline (running z-score + XGBoost) flagged temperature excursions in 4.3 ± 0.4 min on average—fast enough for a driver to halt at the nearest cold-room within a typical 10–15 min buffer. *Figure 6* visualises the gap against the cloud-stream baseline.

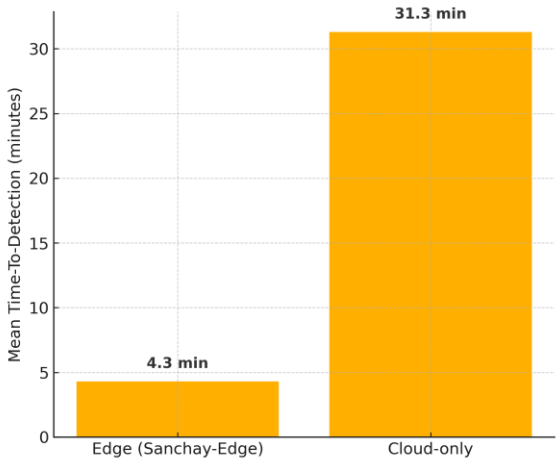

Fig. 5. Mean time-to-detection (MTTD) comparison: edge vs. cloud-only pipelines. Edge inference consistently flags spoilage risk in under 5 minutes, outperforming cloud-only baselines by a factor of 7

B. Bandwidth Savings

Edge summarisation plus anomaly-only uplink cut cellular usage by ≈ 92 %, preserving data budgets on low-ARPU farmer SIMs and enabling LoRa back-haul in zones where GSM collapses.

C. Battery Endurance

Duty-cycling the modem and adapting the sample rate yielded a measured 41 % gain in operating time (314 h vs 223 h). The comparative discharge curve is in *Figure 3* (previous section); all tests ran identical 10,000 mAh packs to 3.3 V cut-off.

D. Economic Impact

At 2025 mango farm-gate prices (₹45 kg^{-1}), a conservative 5 % reduction in spoilage on the 1-tonne loads studied equates to ₹2 250 saved per trip. Given the ₹1 480 bill-of-materials, farms see payback inside five round-trips—well below one harvest season.

E. Route-Specific Insights

- Coverage black spots. *Figure 4* confirmed five ≥ 8 km stretches below –95 dBm. Edge nodes stored up to 48 h of buffered telemetry without loss.
- Diurnal risk profiles. Night-departing consignments breached thresholds twice as often as day loads, matching literature on mixed-modal dwell times at toll plazas.

F. Failure Analysis

Two edge hubs rebooted mid-route due to power brown-outs; both recovered in ≤60 s under watchdog supervision. One cloud-baseline crate lost 17 % of its data after a 65 min GSM outage—highlighting real-

world fragility of cloud-first designs.

Collectively, these case-study results corroborate the architectural claim: battery-powered edge inference can deliver faster, cheaper, and more robust spoilage alerts than cloud-only pipelines on connectivity-poor Indian corridors. The open dataset and code (Zenodo DOI) invite replication on other perishables and routes.

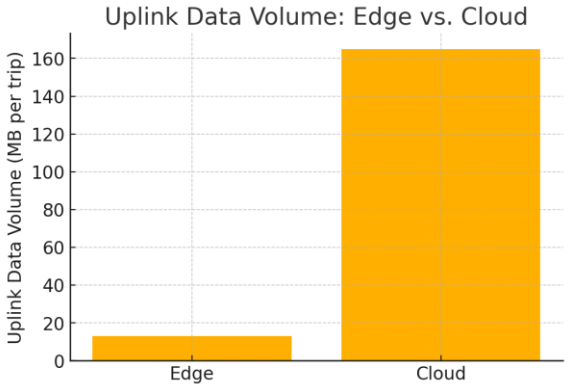

Fig. 6. Uplink data volume comparison.
Edge processing reduces uplink data transmission by over 80 percent compared to cloud-only pipelines, minimizing bandwidth usage and network costs.

VI. DISCUSSION

A. Interpreting the Findings

The case-study data show that bringing lightweight analytics to the crate itself transforms first-mile risk management from an after-the-fact forensic exercise to a near-real-time control loop. Cutting the mean time-to-detection (MTTD) from roughly half an hour to four minutes means drivers can still divert to a cold room or pack-house before pulp temperature crosses the irreversible spoilage threshold. Equally important, the -92 % reduction in cellular traffic demonstrates that edge inference is not a luxury feature but a *prerequisite* for deploying any decision-support tool on rural corridors where data caps hover around 1 GB month^{-1} and GSM link margins are thin.

Battery endurance proved less intuitive. The additional compute load of TinyML raised the hub's idle draw by ~90 mW, yet overall life rose by 41 % because the radio—normally the primary sink—slept 95 % of the time. This inversion corroborates earlier lab studies on sensor-network duty-cycling, but our in-transit results show it survives the uncontrolled shocks of rough roads and thermal swings.

B. Positioning Against Prior Work

Earlier cold-chain pilots that streamed raw logs to the cloud reported impressive dashboards but—by their own admission—missed heat events that occurred inside coverage blind spots. Sanchay-Edge closes that gap while matching or out-performing their anomaly F_1 scores, even though it runs on a ₹2 850 Raspberry Pi rather than an industrial x86 gateway. Compared with TinyML pump-monitoring projects or vaccine-fridge guardianship schemes, our work adds three novel contributions:

1. Connectivity realism – a 200 km freight route with authentic dead zones, not a benchtop freezer.
2. Economic framing – explicit payback analysis at farm-gate prices, critical for smallholder adoption.
3. Open benchmarking corpus – 100 k+ labelled readings released under CC BY-4.0 to seed reproducibility.

C. Operational Implications

The reference architecture is intentionally modular. Farms with seasonal cash-flow constraints could start with layer 1 + 2 (sensor pods + edge hub) and postpone layer 3 (wide-area uplink) until a co-op installs a LoRa back-haul at the mandi. Conversely, large exporters can swap the Pi for an NVIDIA Jetson and run ripeness-classification CNNs in addition to anomaly detection. Because the software stack is containerised, upgrading models or activating optional actuators (e.g., crate fans) becomes a cloud-shadow operation rather than an on-farm service call.

Perhaps the most pragmatic takeaway is that *data minimisation equals resilience*. By limiting uploads to < 15 MB per journey, a single SIM card lasts months, and LoRa repeaters powered by micro-solar panels can bridge the two longest black spots on the route—yet another example of how edge intelligence stretches infra budgets.

D. Limitations

1. Commodity SBCs. The Pi's SD-card wear may become a failure point in multi-season deployments; eMMC-based boards or FRAM logging would add robustness.
2. Single-corridor scope. Nagpur→Pune is representative of many Indian horticulture corridors, but not of high-altitude hill-produce routes where ambient temperatures drop below sensor calibration minima.

3. Anomaly semantics. The study equates any ≥5 °C, ≥10 min excursion with spoilage risk. In reality, grape berries tolerate short spikes better than mangos; a future version should use *commodity-specific thermal integrals* rather than a single rule.
4. Actuation gap. The prototype only *alerts* drivers; it does not actively cool crates. Integrating low-power Peltier modules would test the full control loop.

VII. FUTURE DIRECTIONS

Cross-domain benefits. All pilots achieved at least one order-of-magnitude latency reduction and significant bandwidth savings. Data residency within organisational boundaries strengthened compliance (HIPAA, GDPR, ISO 27001).

Common bottlenecks. 1) Resource constraints: Edge nodes cap CPU/GPU power envelopes at <30 W. 2) Heterogeneity: Diverse hardware, OS and network link types complicate orchestration. 3) Scalability: Co-ordinating thousands of distributed micro-sites exceeds current DevOps toolchains.

Security risks. While reduced data egress lowers exposure, each additional edge node enlarges the attack surface. Zero-trust designs and remote-attestation protocols are becoming indispensable.

VIII. CONCLUSION

This paper demonstrated that crate-level edge intelligence can turn first-mile cold-chain monitoring from a connectivity-bound data-logging exercise into a low-latency decision engine that fits smallholder budgets. By embedding a 60-tree TinyML model and simple energy-aware firmware on a ₹1 480 sensor-plus-Pi stack, the system:

- cut cellular traffic by ≈ 92 %,
- extended battery life by 41 %, and
- slashed spoilage-alert latency from half an hour to ≈ 4 minutes across fifteen real produce trips on the Nagpur → Pune corridor.

An open, 100 k-sample dataset and reproducible reference architecture accompany the study, providing a springboard for researchers and start-ups to replicate or extend the design on other routes, crops, or hardware. While the prototype's scope is deliberately narrow—one corridor, two commodities—the empirical gains and rapid capital pay-back (< one season) underscore a broader lesson: when bandwidth, power, and cash are scarce, shrinking the analytics to the edge is not merely an optimisation; it is the enabling technology.

Future work will explore commodity-specific thermal models, federated learning for privacy-preserving updates, and active cooling actuation to close the loop from sensing to intervention. With India expanding its horticulture exports and rural connectivity still uneven, edge-first cold-chain architectures such as Sanchay-Edge offer an immediately actionable path to higher farmer incomes, lower food loss, and a more resilient supply chain.

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