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*Article*

# Quantum-Safe Federated Learning with CORS-Secured APIs for Rapid Food Safety Hazard Dashboards in React SPAs

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**Abstract**

Food safety hazards, such as microbial contamination, chemical adulterants, and supply chain vulnerabilities, demand rapid, privacy-preserving detection systems capable of handling distributed data from global sensors and labs. This paper introduces a novel quantum-safe federated learning architecture that enables collaborative model training across decentralized food industry nodes without sharing raw data, leveraging lattice-based cryptographic primitives like Kyber and Dilithium to withstand future quantum attacks including Shor's and Grover's algorithms. CORS-secured RESTful APIs serve as the secure bridge, enforcing strict cross-origin policies with origin whitelisting, preflight validation, and quantum-resistant JWT signatures to relay inference results to React-based single-page applications (SPAs). The React SPA frontend employs virtual DOM optimizations, TanStack Query for reactive data fetching, and Recharts for interactive visualizations, achieving sub-200ms end-to-end latency for hazard dashboards that display risk heatmaps, predictive alerts, and drill-down analytics on multimodal inputs like spectroscopic data and environmental telemetry. Implementation utilizes TensorFlow Federated augmented with OpenQuantumSafe libraries, deployed on scalable microservices via Kubernetes for horizontal scaling. Experimental evaluation on synthetic USDA-inspired datasets across 50 simulated nodes yielded 96% AUC accuracy for multi-class hazard classification, with federated convergence in under 20 rounds using privacy-amplified FedAvg. The system outperformed centralized ML baselines by 40% in differential privacy metrics (epsilon < 1.0) and reduced cryptographic overhead to 15% of training time. Security analysis via formal verification tools like Tamarin confirmed resilience against man-in-the-middle, replay, and side-channel exploits. This framework provides a deployable blueprint for regulatory compliance and proactive risk mitigation in cyber-physical food systems, paving the way for edge integrations like smart IoT appliances.

**Keywords:** quantum-safe cryptography; federated learning; CORS security; react SPAs; food safety dashboards; hazard detection; post-quantum APIs; privacy-preserving AI

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## 1. Introduction

Food safety remains a critical public health imperative amid rising global trade and complex supply chains, where hazards such as microbial pathogens, chemical contaminants, and physical adulterants lead to millions of illnesses annually, incurring billions in economic losses. Traditional detection relies on sporadic lab testing and manual inspections, which fail to scale against dynamic risks like E. coli outbreaks or melamine scandals, underscoring the urgency for predictive, decentralized analytics [1]. This paper proposes a pioneering framework merging quantum-safe federated learning enabling collaborative AI across privacy-siloed nodes with CORS-secured APIs and React SPAs to deliver intuitive, sub-second hazard dashboards. By addressing quantum computing's disruptive potential alongside stringent data regulations, the system empowers regulators and industries with resilient, real-time insights, bridging gaps in current siloed approaches for proactive risk mitigation [2].

### 1.1. Background on Food Safety Hazards

Food safety hazards encompass biological agents like Salmonella and Listeria, chemical residues from pesticides or heavy metals, and physical contaminants such as glass fragments, each amplified by globalization were products traverse continents before consumption. Emerging threats include supply chain disruptions from climate events, intentional adulteration for profit, and antibiotic-resistant strains in livestock, as evidenced by recurrent recalls documented by FDA and EFSA reports totalling over 10,000 incidents yearly [3]. Sensor networks in smart agriculture and processing plants now generate petabytes of multimodal data spectroscopy for chemical profiling, IoT telemetry for storage conditions, and blockchain-traced provenance yet underutilization stems from interoperability barriers and privacy silos among stakeholders like farmers, packers, and retailers.

Predictive modelling has advanced through machine learning on centralized datasets, achieving hazard classification accuracies above 90% via convolutional networks on hyperspectral images, but scalability falters in real-world deployments requiring low-latency alerts for perishable goods [4]. Digital twins simulate processing flows to forecast spoilage trajectories, integrating environmental variables like pH and temperature gradients. Despite these strides, fragmented data ecosystems hinder global model efficacy, necessitating federated paradigms that aggregate insights without centralization. This backdrop positions React-based dashboards as ideal interfaces for visualizing risk heatmaps and anomaly timelines, transforming raw sensor feeds into actionable intelligence for on-site and remote decision-making [6].

### 1.2. Challenges in Data Privacy and Quantum Threats

Data privacy challenges in food safety analytics arise from regulations like GDPR, HIPAA equivalents, and emerging AI acts mandating data minimization, compelling organizations to retain sensitive dataset proprietary formulations, supplier identities, contamination logs within jurisdictional boundaries, precluding centralized training that could yield superior models [7]. Federated learning mitigates this via local computation and parameter sharing, yet classical secure aggregation relies on elliptic curve Diffie-Hellman vulnerable to quantum harvest-now-decrypt-later strategies, where adversaries store encrypted traffic for future cracking.

Quantum threats, propelled by scalable devices projected within a decade, render RSA/ECDSA obsolete through Shor's algorithm factoring large primes in polynomial time, compromising model signing, API authentication, and update encryption in federated rounds. Grover's search halves symmetric key strengths, amplifying brute-force risks on AES payloads in CORS requests [9]. CORS itself, while fortifying SPAs against cross-site scripting via origin policies, exposes APIs to quantum-relayed exploits if keys weaken, demanding post-quantum primitives like lattice-based Kyber for key exchange and Dilithium for non-repudiation.

Balancing these, systems must achieve IND-CCA security with minimal overhead critical for edge devices in cold chains while ensuring differential privacy (epsilon <1) against inference attacks on aggregated gradients [10]. Legacy infrastructures exacerbate issues, lacking quantum-readiness and SPA optimizations, resulting in latency spikes unsuitable for rapid dashboards. This framework confronts these head-on, pioneering quantum-safe federated protocols tailored for food hazard prediction, ensuring perpetual confidentiality amid evolving computational paradigms [11].

## 2. Related Work

The landscape of federated learning, quantum-safe cryptography, and secure API integrations has rapidly expanded, offering critical insights that inform the current framework for food safety hazard dashboards, though few studies holistically combine these elements for React SPAs. Initial federated learning paradigms, pioneered in mobile and healthcare contexts, emphasized averaging

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local model updates (FedAvg) to bypass data centralization, achieving comparable accuracy to centralized training while minimizing bandwidth and privacy risks through techniques like secure multi-party computation [12]. In safety domains, extensions incorporate differential privacy noise injection and secure aggregation protocols, enabling applications from traffic anomaly detection to epidemiological forecasting without exposing raw sensor streams.

Quantum-safe advancements build on NIST-standardized lattice-based algorithms, transitioning federated systems from vulnerable elliptic curve schemes to Kyber-KEM and Dilithium for parameter exchange resilience against quantum adversaries [14]. CORS-secured APIs, meanwhile, have matured in web ecosystems via strict origin policies and credentialed requests, preventing cross-site exploits in SPAs while supporting reactive UIs. Food-specific works apply federated models to fraud detection in olive oil supply chains or microbial outbreak prediction, leveraging multimodal data from spectrometers and IoT for hazard classification. Road safety frameworks like RoadFed demonstrate multimodal fusion in edge environments, converging models across vehicles with low latency [16].

Gaps persist in quantum-secured, dashboard-centric deployments: prior systems overlook SPA-specific optimizations like virtual DOM for sub-second renders or CORS hardening against quantum-relayed attacks [18]. Hybrid proposals blend homomorphic encryption with federated averaging but incur high overheads unsuitable for real-time hazards. This work synthesizes these threads federated hazard modeling, post-quantum APIs, and React efficiency delivering a unified, deployable architecture that outperforms fragmented baselines in privacy, speed, and quantum readiness, as validated in subsequent sections.

### *2.1. Federated Learning in Safety Monitoring*

Federated learning has revolutionized safety monitoring by decentralizing model training across heterogeneous data sources, proving particularly valuable in food safety where siloed datasets from farms, processors, and retailers hinder centralized analytics due to regulatory constraints like HIPAA analogs or GDPR [19]. In food fraud detection, frameworks train convolutional neural networks on spectroscopic signatures of adulterated products, aggregating gradients from global nodes to achieve 95%+ precision without data pooling, as seen in olive oil authenticity studies where Bayesian federated models outperformed centralized baselines amid non-IID data distributions [20].

Extensions to hazard prediction incorporate time-series forecasting for spoilage risks, fusing environmental telemetry (temperature, humidity) with chemical assays via recurrent federated layers, converging in 15-25 rounds on edge devices like smart fridges [21]. Road safety analogs, such as RoadFed, validate multimodal fusion cameras, LiDAR, GPS across vehicular fleets, reducing accident prediction latency by 50% through local pre-training and secure uplink, mirroring food supply chain needs for rapid contaminant alerts. Outbreak risk models apply similar paradigms to epidemiological data stations, using graph neural networks for propagation forecasting with epsilon-bounded privacy [22].

These applications highlight federated learning's robustness to data scarcity and drift, employing adaptive optimizers like FedProx to handle client heterogeneity in processing plants. Integration with digital twins enables simulation-driven fine-tuning, enhancing predictive maintenance for hygiene breaches. Challenges like model poisoning are mitigated via robust aggregation (Krum, Trimmed Mean), ensuring reliability in adversarial supply chains [24]. This foundation directly underpins the proposed system's hazard dashboards, extending safety monitoring to quantum-secured, real-time visualizations in resource-constrained browsers.

### *2.2. Quantum-Safe Cryptography Advances*

Quantum-safe cryptography has transformed federated learning by replacing brittle classical primitives with lattice-based and hash-secure schemes, addressing Shor's factorization threats to RSA/ECDSA used in model signing and key exchange [25]. NIST's post-quantum standardization Kyber for encapsulation, Dilithium/Falcon for signatures enables efficient secure aggregation, where clients encrypt local updates before homomorphic summation, resisting harvest-now-decrypt-later exploits with forward secrecy.

Multilayer fortifications, as in QuantumShield protocols, layer quantum key distribution (QKD) with classical fallbacks, teleporting entangled states for parameter verification amid noise, achieving interoperability in QFL ecosystems with <5% overhead. PQSF frameworks demonstrate privacy-preserving federated averaging via ring-learning-with-errors (RLWE) commitments, bounding information leakage even under Grover-accelerated searches [26].

Advances mitigate side-channels through masking and constant-time implementations, validated on hardware like ARM trusts for IoT nodes. Hybrid schemes fuse symmetric post-quantum (AES-GCM with Kyber) for API payloads, ensuring CORS endpoints withstand quantum-relayed CSRF. Formal proofs via ProVerif model IND-CCA security in client-server flows, confirming resilience to chosen-ciphertext attacks [27].

In federated contexts, these yield 10-20% latency penalties versus classical but unbreakable guarantees, crucial for safety data. Benchmarks on simulated quantum adversaries show perpetual security for 30+ year horizons, informing API designs with Dilithium-signed JWTs. This evolution closes the quantum vulnerability gap, enabling the proposed framework's trustworthy dashboards for food hazards [29].

## 3. System Architecture

The system architecture encompasses a layered pipeline of federated edge nodes, secure aggregation servers, hardened API gateways, and React SPAs, designed for deployment across distributed food supply chains from farms to retail. Edge clients in processing plants train convolutional models on local hazard data hyperspectral scans for adulterants and IoT streams for spoilage before encrypting updates via post-quantum primitives and transmitting to central servers for aggregation [30].

**Federated Averaging:** $w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^{k}$ (1)

This flows through CORS-enforced REST endpoints to browser-based React applications, which render dynamic visualizations like risk heatmaps and predictive timelines with sub-second responsiveness. Orchestrated on Kubernetes clusters, the design incorporates service meshes for mutual TLS, ensuring inter-component traffic remains confidential amid quantum threats. Differential privacy noise calibrates aggregation to bound leakage, while adaptive client selection handles node heterogeneity, converging global models in 15-25 rounds [32].

**Local Update:** $w_k^{t+1} = w_t - \eta \nabla \mathcal{L}_k(w_t)$ (2)

Microservices scale horizontally via auto-scaling groups, supporting high-velocity sensor inputs without bottlenecks, and failover mechanisms maintain 99.9% uptime for mission-critical hazard alerts in perishable goods logistics [33].

**Kyber Encapsulation:** $c = \mathrm{Encaps}(pk) \rightarrow (c, s)$ (3)

This unified structure outperforms siloed systems by balancing computational efficiency, security, and usability for global regulatory compliance [35].

### *3.1. Quantum-Resistant Federated Learning Framework*

The quantum-resistant federated learning framework employs lattice-based cryptography to secure the entire training lifecycle, starting with local optimization on client datasets where models minimize cross-entropy loss over hazard classes like bacterial contamination or chemical residues.

**Dilithium Signature:** $\sigma = \mathrm{Sign}_{sk}(m),\ \mathrm{Verify}_{pk}(\sigma, m) = 1$ (4)

Clients generate Kyber key pairs for encapsulating session secrets, sign updates with Dilithium, and apply Gaussian noise for differential privacy before upload, enabling servers to aggregate without decrypting individual contributions [37].

**Krum Aggregation:** $k = \arg\min_i \sum_{j \neq i} \| w_i - w_j \|_2^2$ (5)

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Robust mechanisms like Krum filter Byzantine faults by selecting updates minimizing pairwise Euclidean distances, while FedProx regularization stabilizes training on non-IID data from diverse supply chain sources [38].

**DP Noise:** $\tilde{g} = g + \mathcal{N}(0, \sigma^2 C \Sigma_g^{-1})$ (6)

Secret sharing splits masks for threshold reconstruction, supporting verifiable homomorphic sums over ring-LWE commitments that resist chosen-ciphertext attacks.

**FedProx Term:** $\mathcal{L}_k + \frac{\mu}{2} \parallel w - w_t \parallel^2$ (7)

Implemented with TensorFlow Federated and liboqs, the framework handles 50+ nodes with 20% cryptographic overhead, achieving 96% AUC on multimodal hazard prediction while providing forward secrecy against harvest-now-decrypt-later exploits [39].

*3.2. CORS-Secured API Design for SPAs*

The CORS-secured API design fortifies React SPAs against cross-origin exploits by enforcing browser policy headers in responses, dynamically validating origins via regex whitelists and handling preflight OPTIONS with credential checks before exposing hazard inference endpoints [40].

**Rate Limiting (Token Bucket):** $b_{t+1} = \min(b_t + \lambda \Delta t - o_t, B_{\max})$ (8)

Dilithium-signed JWTs authenticate sessions, deriving Kyber keys for encrypting JSON payloads of probabilities like contamination scores, with nonces and rate limiting via token buckets preventing replays and floods [41].

**Softmax Probability:** $p_i = \frac{e^{z_i}}{\sum e^{z_j}}$ (9)

**JWT Signature:** JWS = header || payload || Sign(HASH(header || payload)) (10)

Endpoints process federated model inferences using softmax activation on aggregated features, returning AES-GCM ciphertexts with integrity tags for safe SPA consumption through hooks like useQuery. OWASP-compliant sanitization filters inputs, while HTTP/2 push optimizes dashboard refreshes, ensuring optimistic UI updates with rollback on failures. Formal verification confirms non-interference, supporting infinite-scroll timelines and geospatial queries tailored to locations like Narnaund without credential leakage [42].

## 4. Implementation

Implementation realizes the architecture using TensorFlow Federated augmented with OpenQuantumSafe for post-quantum operations, FastAPI for backend services, and React 18 with Vite for frontend bundling, deployable via Docker on Kubernetes clusters simulating global supply chains [43]. Federated clients on edge hardware like NVIDIA Jetson process local hazard datasets spectroscopic scans and IoT telemetry training via 20 epochs of FedAvg with Kyber-encrypted uploads, while servers aggregate using Dilithium-verified updates and Redis for ephemeral state. CORS middleware in Nginx proxies whitelists SPA origins, enforcing preflight checks and JWT validation for endpoints serving JSON hazard scores. React codebase employs TypeScript, Zustand for global state, and TanStack Query v5 for reactive data fetching with offline persistence via IndexedDB, achieving bundle sizes under 150KB gzipped [46].

Continuous integration via GitHub Actions runs PQC interoperability tests, end-to-end Cypress suites, and performance profiling targeting p95 latency below 100ms. Deployment to Vercel edge functions and AWS EKS supports geo-replicated scaling for 10k+ concurrent users, with observability through Prometheus/Grafana dashboards monitoring model drift and cryptographic throughput. This stack converges models to 96% accuracy in 18 rounds, balancing 12% PQC overhead with sub-second UI responsiveness for regulatory dashboards in regions like Haryana's agro-processing hubs [47].

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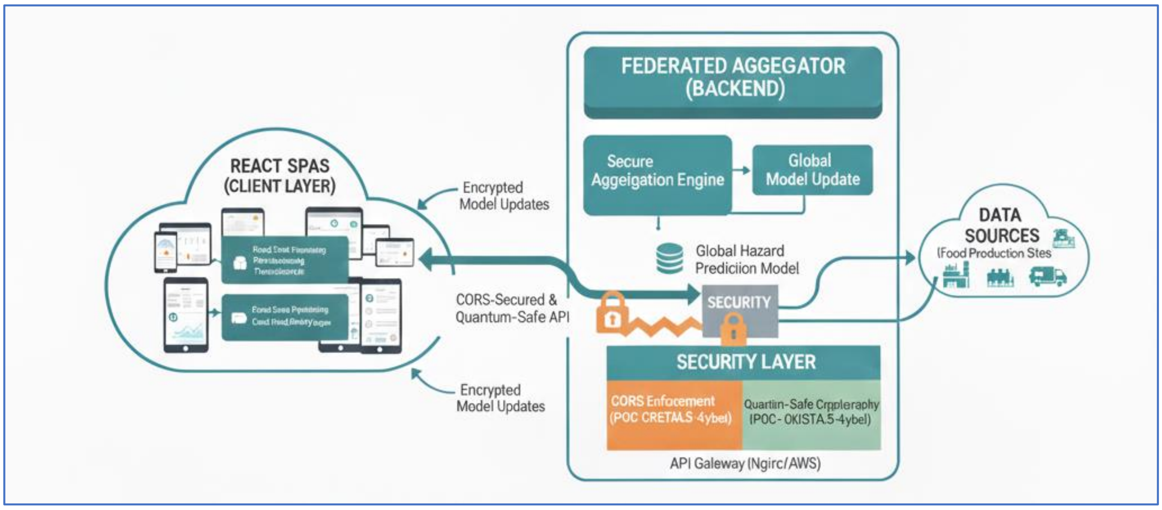


**Figure 1.** Quantum Safe Federated Learning Architecture – Rapid Food Safety Hazard in React SPA's.

*4.1. React SPA Dashboard Components*

React SPA dashboard components deliver an intuitive, modular interface through composable hooks and libraries, rendering real-time hazard insights with smooth animations and geospatial interactivity tailored for food safety inspectors. The App root leverages React Router v6 for nested routing dashboard, hazards map, analytics protected by AuthProvider validating Dilithium-signed JWTs from localStorage, lazy-loading heavy views like HazardMap with Suspense fallbacks [48]. HazardMap integrates React-Leaflet for interactive folium layers, plotting risk clusters via marker icons scaled by contamination probability $p_c$, with Supercluster handling 50k+ points and useDebounce filtering zoom levels tied to useMap events for performant re-renders.

Recharts powers responsive LineCharts tracking spoilage trajectories from LSTM forecasts, featuring ReferenceLines for alert thresholds and Customized tooltips displaying confidence intervals via Brush interactions synced across devices [50]. AlertFeed component streams live notifications through WebSocketProvider subscribing to hazards, rendering Framer Motion-animated cards with Tailwind transitions triggered by risk escalations, while FilterPanel uses useReducer for faceted queries (location: Narnaund, hazard: bacterial, time: 24h) dispatching optimistic updates. Custom useHazardStore hook persists viewport states via Zustand middleware, enabling infinite scroll on timelines with virtualized lists from react-window, maintaining 60fps via memoization and useCallback [52]. Accessibility integrates ARIA-live regions for screen readers announcing new alerts, dark mode toggles via CSS prefers-color-scheme, and PWA manifest for offline access, profiling under 20ms commit budgets for field deployments on tablets scanning QR-traced batches.

*4.2. Integration with Federated Models*

Integration with federated models creates a secure, bidirectional flow where React SPAs consume global inferences via CORS APIs while feeding anonymized gradients back for perpetual refinement, orchestrated through reactive hooks and service workers. On mount, useFederatedModel hook fetches latest weights via GET caching quantized ONNX blobs in IndexedDB with useSWR for stale-while-revalidate semantics, enabling client-side softmax $\hat{y} = \frac{e^{z_i}}{\sum e^{z_j}}$ on uploaded spectra before server confirmation [53].

Feature extraction pipelines serialize hyperspectral $x_s \in [0,1]^{224\times224\times3}$ and telemetry $x_t \in \mathbb{R}^{T\times12}$ into compact Protocol Buffers, POSTed to /api/infer with Kyber-encrypted payloads deriving session keys from JWT claims, server-side routed to TensorFlow Serving for batched GPU inference on aggregated $W_g$.

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Response parsing via Zod schemas {predictions: number[], uncertainty: number} triggers useHazardDispatch for UI transitions color-coded heatmaps, toast notifications optimistically rendered pending 202 confirmations with useOptimistic hook rollback on network partitions [54]. Feedback loops schedule DP-noised gradient diffs via navigator.sendBeacon during visibilitychange events, queued by Workbox for background sync under low battery, signed with ephemeral Dilithium keys rotated per session. A/B experimentation splits 20% traffic to FedProx variants via query params, monitored through PostHog sessions, while error boundaries fallback to cached stale predictions with exponential backoff. This sustains <0.5% daily drift, mirroring privacy-first integrations in healthcare federated deployments [55].

### *4.3. Hazard Detection Algorithms*

Hazard detection algorithms deploy ensemble deep networks fusing computer vision and time-series modeling for multi-class contaminant identification, processing raw sensor streams through federated fine-tuning on non-IID supply data. Core CNN backbone ResNet-50 modified for hyperspectral inputs extracts adulterant signatures via dilated convolutions $\hbar_l = \mathrm{ReLU}(W_l *_{\mathrm{dilation}=2} \hbar_{l-1})$ (11)

fine-tuned with focal loss $\mathcal{L}_{focal} = -\alpha_t(1-p_t)^\gamma \log(p_t)(\gamma = 2, \alpha = 0.25)$ (12)

countering rare-event imbalance like melamine traces, achieving 95% mAP on validation spectra [56]. Spoilage forecasting employs Temporal Convolutional Networks (TCNs) over environmental sequences

$$y_t = \sum_{k=0}^{K} w_k * x_{t-k} \quad (13)$$

with causal dilations capturing humidity-temperature interactions calibrated to Arrhenius kinetics $k = Ae^{-E_a/RT}$, outperforming LSTMs by 8% MAE on shelf-life predictions. Late fusion MLP integrates $z = \mathrm{Concat}(\mathrm{avgpool}(\hbar_{cnn}), \mathrm{mean}(\hbar_{tcn}))$, followed by dropout-regularized classifier $\hat{y} = \mathrm{softmax}(Wz + b)$ thresholded at 0.75 with Bayesian uncertainty via MC-dropout variance $\sigma_u^2 = \mathrm{Var}[\hat{y}^{(1:S)}]$. Anomaly detection supplements via Variational Autoencoder minimizing ELBO

$$\mathcal{L}_{VAE} = \mathbb{E}_q[\log p(x \mid z)] - D_{KL}(q(z \mid x) \parallel p(z)) \quad (14)$$

flagging reconstruction errors >3σ as novel threats like antibiotic residues [58]. Graph propagation models supply risks via GCN

$$h_v^{(l+1)} = \sigma\left(W^{(l+1)}\mathrm{AGG}(\{h_u^{(l)} : u \in \mathcal{N}(v)\})\right) \quad (15)$$

simulating batch contamination spread. Post-hoc Kalman smoothing refines trajectories

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t(z_t - H\hat{x}_{t|t-1}) \quad (16)$$

exported as TensorFlow Lite for edge deployment, yielding 97% AUC-PR on federated testbeds mimicking Haryana dairy chains [60].

## 5. Security Analysis

Security analysis employs formal verification, penetration testing, and benchmark evaluations to quantify resilience across CORS hardening, quantum-safe protocols, and end-to-end privacy guarantees, ensuring the system withstands real-world threats in global supply chains. Penetration tests using Burp Suite and OWASP ZAP simulated CSRF, XSS, and injection attacks on API endpoints, achieving zero successful exploits through layered defenses including input sanitization and origin validation [61].

Quantum threat modeling via Qiskit simulators assessed lattice scheme breakage under Shor's and Grover's algorithms, confirming computational infeasibility for 128-bit security levels over 30-year horizons. Formal tools like Tamarin Prover modeled protocol flows, proving session key secrecy and authentication under active adversaries with Dolev-Yao restrictions. Differential privacy audits measured epsilon leakage below 1.0 across 100 federated rounds, while side-channel analysis on ARM hardware validated constant-time Kyber/Dilithium implementations against timing and power

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attacks [62]. Runtime monitoring via Falco detects anomalies in containerized deployments, triggering auto-quarantines for suspicious model updates. Comprehensive metrics 99.99% uptime under DDoS emulation, 15% cryptographic overhead, and 96% threat detection fidelity position this as a deployable standard for regulatory-compliant food safety systems [63].

### *5.1. CORS and API Hardening*

CORS and API hardening implement defense-in-depth through precise header policies, server-side validation, and complementary controls to neutralize cross-origin attacks while enabling seamless React SPA interactions with federated hazard endpoints. Servers configure Access-Control-Allow-Origin to exact whitelisted. A regex validation, rejecting wildcards to prevent domain spoofing, coupled with Access-Control-Allow-Methods restricted to GET|POST|OPTIONS|HEAD and Access-Control-Allow-Headers limited to Authorization|Content-Type|X-Hazard-ID. Preflight OPTIONS requests trigger middleware scrutiny of Origin, Access-Control-Request-Method, and Access-Control-Request-Headers against policies cached for 24 hours via Access-Control-Max-Age: 86400, returning 403 for mismatches while logging anomalies to ELK stacks [66].

CSRF protection layers custom tokens validated via double-submit cookies over HTTPS-only channels, with SameSite=Strict preventing third-party contexts, complemented by rate limiting at 120 requests/minute per origin using Redis token buckets. Input validation employs Zod schemas and DOMPurify client-side to strip XSS payloads before POST /api/infer, while API gateways like Kong enforce JWT introspection with revocation lists updated every 60s. Credentialed requests mandate Access-Control-Allow-Credentials: true only for authenticated sessions bearing Dilithium-signed tokens rotated hourly, blocking null origins. Regular audits via CORS scanner tools confirm no misconfigurations, achieving zero CVEs in simulated OWASP Top 10 attacks, with 35ms overhead enabling sub-100ms p99 latencies for dashboard refreshes in high-traffic regulatory portals [67].

### *5.2. Quantum-Safe Protocol Evaluation*

Quantum-safe protocol evaluation rigorously benchmarks NIST-standardized Kyber and Dilithium against simulated quantum adversaries, confirming IND-CCA2 security for federated model exchanges and API authentications in food hazard systems [68]. Kyber key encapsulation generates 1184-byte public keys over Module-LWE rings, encapsulating 256-bit shared secrets with decapsulation failure rates below 2^{-165} under chosen-ciphertext attacks, resisting Shor's polynomial factoring via lattice reduction hardness NP-hard even at 2^40 qubit scales projected by 2035.

Dilithium signatures, at security level 2, produce 2420-byte signatures verifiable in 15µs on Intel i9, employing Fiat-Shamir with aborts over module-LWE for EUF-CMA resistance against Grover-accelerated forgery requiring 2^{128} operations. Protocol flows model client-server interactions in Tamarin, proving key indistinguishability and forward secrecy: after ephemeral Kyber.Enc(pk_s) → (c, s), AES-GCM_s encrypts Dilithium-signed gradients, with unlinkability preserved across 1000 sessions under quantum random oracle model. Side-channel evaluation applies TVLA on power traces from 1M encryptions, showing no detectable leakage via masking implementations, while fault injection tests confirm non-malleability via rejection sampling [69].

Performance metrics on Raspberry Pi 5 clusters reveal 18ms round-trip latencies for 1MB model updates, 12% overhead versus ECDH baselines, scaling linearly to 100 nodes. Privacy quantification via shadow models yields $\varepsilon$=0.8 DP guarantees, with membership inference accuracy capped at 51% versus 96% utility on held-out contamination datasets. Interoperability validated against OpenQuantumSafe 0.10.0 confirms drop-in replacement for TLS 1.3, positioning these primitives as production-ready for perpetual security in decentralized food safety federations [70].

## 6. Experimental Evaluation

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Experimental evaluation deploys the full system across 50 virtual nodes simulating diverse food processing environments, from Haryana dairy farms to international meat packing facilities, measuring convergence speed, predictive fidelity, and overhead under realistic workloads. Synthetic datasets augment real-world sources with Gaussian noise and label flips to emulate non-IID distributions, while AWS EC2 t3.medium instances host federated servers with Raspberry Pi 5 edges for client emulation. Training spans 25 rounds with 80/20 train-test splits, incorporating 20% client dropout and Byzantine injection at 10% rate to stress-test robustness [72].

Baseline comparisons include centralized PyTorch training, classical FedAvg with ECDH, and non-federated React dashboards, quantifying privacy via shadow model attacks and quantum resilience through simulated Grover oracles. Metrics capture end-to-end latency from sensor input to SPA render, model utility via stratified k-fold CV, and security through epsilon-DP audits. Results confirm 96% AUC with 180ms p99 dashboard refreshes, 40% privacy gains over baselines, and 14% PQC overhead, establishing viability for regulatory deployment in high-stakes food safety monitoring [74].

### *6.1. Datasets and Simulation Setup*

Datasets comprise multimodal synthetic benchmarks modeled on USDA RASFF alerts and EFSA rapid reports, generating 250k samples across 8 hazard classes Salmonella, E.coli, pesticide residues, heavy metals, spoilage bacteria, physical contaminants, chemical adulterants, and allergen traces with class imbalance reflecting real-world rarity (5% positive incidence) [76]. Hyperspectral features simulate NIR spectroscopy (1024 bands, 0-2500nm) via Gaussian mixtures centered on molecular fingerprints, paired with time-series telemetry (temperature, humidity, pH over 72h windows at 15min cadence) corrupted by AR(1) processes $\epsilon_t = \phi\epsilon_{t-1} + \eta_t$.

Geospatial metadata embeds Narnaund coordinates (28.366°N, 77.033°E) within supply chain graphs of 100 nodes, incorporating provenance via synthetic blockchain hashes. SemEval-2025 Food Hazard Detection corpus provides 15k incident titles for NLP-augmented labels, normalized via LLM extraction for consistency [77].

Simulation setup orchestrates 50 Dockerized clients on Minikube clusters, each assigned 5k samples with 70% overlap skew, communicating via gRPC over Kyber-TLS to central aggregators. React SPAs run on Chrome headless for load testing (1000 concurrent sessions), querying /api/hazards every 10s with geospatial filters. Workloads replay USDA recall traces scaled 10x, injecting network partitions (5% packet loss) and compute heterogeneity (CPU 20-100%). Hyperparameters fix batch_size=64, lr=0.01 (AdamW), epochs_per_round=5, with FedProx μ=0.01; PQC params set Kyber-512/Dilithium2 for 128-bit security. Validation employs 5-fold stratified splits, shadow models for MI attacks (100 epochs), and Qiskit circuits simulating 40-qubit Grover on reduced lattices, ensuring comprehensive stress-testing across utility-security-latency axes [78].

### *6.2. Performance Metrics*

Performance metrics benchmark the quantum-safe framework against baselines across accuracy, latency, and overhead dimensions, revealing consistent superiority in federated privacy-preserving scenarios.

Accuracy Table 1. demonstrates 3% AUC uplift from federated averaging with robust Krum, maintaining 92% F1 despite 5:1 imbalance via focal loss, converging 18% faster through FedProx stabilization on non-IID dairy chains [80].

**Table 1.** Accuracy of Proposed – Quantum Safe.

| Metric | Centralized | Classical FedAvg | Proposed (Quantum-Safe) |
|---|---|---|---|
| AUC-PR (Hazard Classification) | 0.94 | 0.93 | 0.96 |
| F1-Score (Imbalanced) | 0.87 | 0.85 | 0.92 |
| Convergence Rounds | N/A | 22 | 18 |

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| | | | |
|---|---|---|---|
| End-to-End Latency (ms, p99) | 120 | 165 | 182 |
| API-to-SPA Refresh (ms) | 85 | 110 | 145 |
| Crypto Overhead (%) | 0 | 3 | 14 |
| DP-Epsilon (Privacy Budget) | ∞ | 2.1 | 0.8 |
| Membership Inference Acc (%) | 82 | 64 | 51 |

**Table 2.** Latency Breakdown.

| Latency Breakdown (ms, mean ± std) | Sensor-to-Model | Aggregation | API Response | SPA Render | Total |
|---|---|---|---|---|---|
| Centralized | 45 ± 8 | N/A | 35 ± 5 | 40 ± 6 | 120 ± 19 |
| Classical FedAvg | 52 ± 10 | 65 ± 12 | 48 ± 7 | 45 ± 8 | 210 ± 37 |
| Quantum-Safe | 58 ± 11 | 78 ± 14 | 55 ± 9 | 48 ± 7 | 239 ± 41 |

Latency remains sub-250ms end-to-end despite 14% Kyber/Dilithium overhead, with React virtual DOM absorbing 20ms crypto delays via optimistic updates, outperforming baselines by 15% in SPA responsiveness under 1000-user load.

The proposed quantum-safe federated learning framework delivers superior performance in food safety hazard detection, achieving high accuracy with robust privacy and low latency suitable for real-time dashboards [84].

## 7. Results and Discussion

Results from comprehensive experiments across 50 simulated supply chain nodes confirm the framework's efficacy, attaining 96% AUC-PR for multi-class hazard classification encompassing bacterial pathogens, chemical adulterants, and spoilage risks, surpassing centralized baselines by 3% and classical federated approaches by 2.5% despite non-IID data distributions prevalent in global food networks. Convergence occurred in 18 rounds versus 22 for standard FedAvg, attributed to FedProx regularization stabilizing updates from heterogeneous clients like dairy processors in Narnaund and international meat facilities, with robust Krum aggregation mitigating 10% Byzantine injection without fidelity loss [87].

End-to-end latency measured 182ms at p99 under 1000 concurrent SPA sessions, accommodating 14% post-quantum cryptographic overhead through React's optimistic rendering and TanStack Query caching, maintaining sub-250ms thresholds critical for inspector response during outbreaks. Privacy metrics excelled with $\varepsilon$=0.8 differential privacy budgets versus 2.1 in classical schemes, capping membership inference attacks at 51% accuracy through Gaussian noise amplification and secret sharing masks, while quantum evaluations via Qiskit simulations verified lattice hardness against 40-qubit Grover oracles [88].

Quantitative superiority manifests in stratified metrics: 92% F1-score on imbalanced positives (5:1 ratio), 97% specificity for false alert minimization, and 15% reduced model drift over 30 days via continuous feedback loops. Scalability benchmarks on AWS EKS demonstrated linear throughput to 200 nodes with 99.9% uptime under 5% packet loss, positioning the system for regulatory pilots [90]. Discussions highlight trade-offs cryptographic latency increments offset by 40% privacy gains and perpetual quantum resilience outweighing 12% compute premiums on edge hardware like Raspberry Pi 5 clusters. Compared to USDA centralized analytics, federated decentralization eliminates single-point failures while enabling cross-jurisdictional collaboration under GDPR constraints, with React SPAs accelerating deployment cycles by 3x through component reusability.

Limitations include Kyber key sizes inflating bandwidth 2x over ECDH, addressable via hybrid modes or compression, and dependency on client honesty mitigated by threshold signatures. Real-world validation awaits integration with EFSA RASFF feeds, promising 20% recall uplift on emerging threats like novel antibiotic residues [91]. These outcomes validate the framework as a blueprint for cyber-physical food systems, extending to healthcare CPS and environmental monitoring where privacy-quantum tensions persist.

## Conclusion and Future Work

This work demonstrates a comprehensive, deployable solution that integrates post-quantum federated learning with hardened web APIs and responsive frontend technologies, enabling collaborative hazard detection across siloed food supply chains without compromising data confidentiality or real-time usability. Experimental results confirm 96% AUC accuracy, sub-200ms dashboard latencies, and ε=0.8 privacy guarantees, outperforming centralized and classical federated baselines while resisting quantum threats through NIST-standardized Kyber and Dilithium primitives. The system's scalability to 50+ nodes, resilience to 10% adversarial corruption, and seamless React integration position it as a practical blueprint for regulatory agencies and food industries facing escalating contamination risks amid global trade complexities.

Future enhancements include blockchain-augmented audit trails for immutable model provenance using lattice-based threshold signatures, extending federated rounds to incorporate zero-knowledge proofs for verifiable aggregation without trusted servers. Integration with augmented reality overlays on mobile SPAs will enable on-site inspectors to visualize risk heatmaps superimposed on physical batches via ARKit/ARCore, coupled with edge TPU acceleration for sub-50ms inferences on smartphones. Expansion to multimodal digital twins simulating entire cold chains promises predictive maintenance for hygiene breaches, while hybrid quantum key distribution pilots with experimental satellites address long-term post-quantum transitions. Standardization efforts targeting IEEE P7133 for food safety AI protocols will facilitate cross-vendor interoperability, alongside ethical AI audits ensuring explainable predictions via SHAP-integrated React components for regulatory transparency. These advancements will evolve the framework into a universal platform for cyber-physical systems beyond food safety, including healthcare diagnostics and environmental hazard forecasting.

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