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A microservice-oriented machine learning framework for cold chain management in perishable fish logistics

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ABSTRACT

This study proposes a microservice-oriented machine learning framework to enhance intelligence and scalability in perishable fish cold chain logistics. Unlike conventional monitoring-centric systems, the framework integrates edge–cloud computing with multimodal machine learning models, including random forest for anomaly detection, long short-term memory (LSTM) for spoilage risk prediction, and convolutional neural network (CNN) for visual fish quality classification. The research adopts a design science approach combining literature analysis, field observations at cold storage facilities in Indramayu, Indonesia, and simulation-based validation. Experimental results demonstrate the feasibility of distributed analytics, modular deployment, and real-time inference within heterogeneous logistics environments. The proposed framework provides a deployable architectural reference for intelligent fisheries cold chain management and supports future large-scale, multi-stakeholder implementation.

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1. INTRODUCTION

Fish distribution in Indonesia faces significant challenges in maintaining product freshness due to temperature sensitivity and long supply chain routes [1], [2]. Conventional cold chain systems are limited in their ability to monitor, predict, and respond to risks in real time [3], [4]. The integration of internet of things (IoT), edge computing, big data, and artificial intelligence/machine learning (AI/ML) offers new opportunities to improve efficiency, accuracy, and sustainability in fisheries logistics [5], [6]. This study aims to design a comprehensive cold chain architecture powered by AI/ML to support decision-making and enhance food security.

The research process was carried out in several stages to ensure both theoretical rigor and practical relevance. First, an extensive literature review was conducted to examine previous studies on cold chain management, the application of IoT and edge computing in supply chains, and the role of machine learning and big data in predictive analytics and anomaly detection [7]–[9]. This review provided the theoretical foundation and helped identify technological gaps in existing approaches. Second, a design study was undertaken to develop a conceptual cold chain architecture tailored to the Indonesian fisheries context. Various technological components were evaluated, including multimodal input devices, low-cost edge computing platforms, cloud-based data storage, and advanced machine learning algorithms such as random forest, long short-term memory (LSTM), and convolutional neural network (CNN) [10]–[12]. The selection of these technologies was based on their suitability for addressing issues of scalability, interoperability, and real-time monitoring. Third, a field survey was conducted at the cold storage facilities in Indramayu, West Java, to validate the findings from the literature and design stages [13], [14]. Observations revealed significant operational limitations such as reliance on manual temperature readings, limited CCTV functionality under cold conditions, and difficulties in maintaining electronic devices in low-temperature environments [15]. Finally, the insights gained from the field survey were compared with the ideal conditions envisioned in the proposed architecture. This comparison highlighted the gap between current practices and the requirements of an intelligent, microservice-oriented cold chain system [16], [17]. By bridging these gaps, the proposed framework demonstrates both its practical necessity and its potential to serve as a scalable model for fisheries logistics.

Another critical gap identified during the field study relates to institutional fragmentation across the cold chain cycle. Ideally, the entire cold chain loop from input devices, edge processing, data collection, machine learning, to prediction output should operate under a single organizational framework to ensure seamless integration and consistent standards. However, in practice, each segment is managed by different companies with distinct business priorities, resulting in siloed operations and limited interoperability. This misalignment reduces the effectiveness of monitoring, prediction, and decision-making across the supply chain. To address this, a consortium model is required, initiated and facilitated by the fisheries and marine affairs office at the municipal, district, and provincial levels. Such governance mechanisms would enable stakeholders with different interests to align their strategies, share data, and complement each other’s roles within a unified cold chain ecosystem [18]–[20]. The proposed microservice-oriented and machine learning-based architecture could serve as the technological foundation for this consortium, ensuring interoperability, scalability, and real-time intelligence across organizational boundaries.

Existing studies on AI-driven cold chain monitoring primarily focus on sensor tracking, temperature logging, or cloud-based dashboards but lack real-time predictive capabilities and autonomous decision support mechanisms [5], [6], [21]. Most frameworks are designed using monolithic or centralized architectures that limit scalability, interoperability, and system reliability in distributed fisheries logistics [7], [8]. Furthermore, previous models do not combine anomaly detection, spoilage prediction, and visual quality assessment using multimodal machine learning within microservice-based deployment environments [9], [22]. While some studies have explored ML for temperature anomaly detection [10], or fish quality classification using CNN [12], these models are rarely integrated with IoT-edge processing or containerized deployment, and have not been specifically applied to the fisheries cold chain context in Indonesia [18], [20]. These limitations indicate a significant research gap in developing an intelligent, distributed, and modular cold chain framework that enables real-time inference, predictive analytics, and cross-organizational interoperability.

To address these gaps, this study proposes a microservice-oriented machine learning framework integrating random forest for anomaly detection, LSTM for spoilage risk prediction, and CNN for fish quality classification, designed to operate within an edge–cloud architecture [22], [23]. The framework leverages Docker-based modular deployment, MQTT for sensor streaming, and API Gateway for real-time orchestration, enabling scalable, low-latency, and interoperable cold chain operations [24], [25]. Unlike previous frameworks, the proposed system supports distributed analytics, heterogeneous device compatibility, and real-time quality monitoring across multiple logistics environments, specifically tailored to the operational challenges of perishable fish logistics in Indonesia [16], [26]. Table 1 presents a comparative analysis highlighting key parameters, limitations, and technological gaps in existing studies, which clearly position the novel contribution and significance of this proposed framework.

2. METHOD

This section describes the methodology adopted to develop and validate the proposed framework. The research process was structured to ensure scientific rigor and practical relevance, combining literature review, conceptual framework design, field surveys, and gap analysis. Each step is explained chronologically, supported by algorithms and testing strategies to ensure methodological transparency.

2.1. Research design

The research employed a design science approach supported by empirical validation. The objective was to propose a microservice-oriented, machine-learning framework for cold-chain management in fisheries logistics. The design process followed a sequential flow:

– Literature review – to identify existing cold chain management models, IoT adoption, edge/cloud computing integration, and the role of machine learning in predictive analytics [21], [27], [28].

- Conceptual design study – to map out the architectural framework, defining its technological components, including sensors, edge devices, cloud storage, machine learning algorithms and integration strategy.
- Field survey – to collect empirical data from cold storage facilities in Indramayu, West Java. This included direct observation of monitoring practices, equipment durability, and organizational fragmentation.
- Gap analysis – to compare field conditions with the envisioned ideal architecture, highlighting deficiencies in technology and governance [29]–[31].
- Framework development – to propose the final microservice-oriented machine learning framework that addresses observed gaps and enables real-time monitoring, prediction, and decision-making.

Table 1. Comparison of existing cold chain AI frameworks and the proposed approach

Study	Main focus	ML methods used	System architecture	Limitations identified	Novel contribution of this study
Cil *et al.* [5]	IoT-based real-time monitoring for cold chain	Basic anomaly rules, threshold detection	Cloud-centric, centralized data processing	No predictive analytics, no support for visual fish quality, not scalable	Introduces ML-based predictive analytics (RF, LSTM) and image-based fish quality monitoring (CNN)
Wang *et al.* [6]	Edge computing for cold chain monitoring	Anomaly detection (statistical)	Edge-cloud hybrid, single service	No microservice modularity, no AI-based freshness classification	Adds microservice-based hybrid deployment with multimodal ML capabilities
Hanifa *et al.* [12]	CNN for fish quality classification	CNN	Local image processing, no integration with cold chain system	No real-time deployment or IoT integration	Integrates visual inspection (CNN) into real-time cold chain framework
Bai *et al.* [7]	AIoT-enabled smart cold chain	ML forecasting for spoilage	Cloud + IoT-based monitoring	No edge processing, lacks microservice scalability	Adds edge inference, containerization (Docker), and distributed services
Proposed framework (This study)	Intelligent hybrid architecture for fish logistics	RF, LSTM, CNN	Microservice-based Edge–Cloud with Docker, MQTT, API Gateway	Addresses modular deployment, predictive analytics, visual assessment, and interoperability.	A unified, scalable, predictive, and deployable microservice-oriented ML framework tailored for perishable fish logistics

2.2. Research procedure

The overall procedure of this research was carefully structured to follow a chronological sequence. Each stage was logically connected to the previous one, ensuring that theoretical insights were validated through practical observation and design evaluation. The following description elaborates the major steps in detail, highlighting their order and contribution:

Step 1: Literature review – systematically collected articles concerning IoT-based monitoring, edge computing in logistics, ML for anomaly detection, and supply chain governance [21], [27], [28].

Step 2: Conceptual framework design – developed an architecture model consisting of:
- Multimodal input layer (temperature sensors, digital thermometers, imaging devices, RFID, and GPS).
- Edge processing layer (low-cost edge computing platforms for pre-processing and anomaly detection).
- Cloud storage and analytics layer (distributed storage such as S3/HDFS, big data pipelines).
- Machine learning layer (random forest for anomaly detection [9], LSTM for time-series prediction [10], CNN for image-based fish quality assessment [11]).
- Visualization and decision layer (dashboards via Grafana/power BI, geospatial interfaces like QGIS/LeafletJS).

The design was constructed under a microservice-oriented architecture ensuring scalability, interoperability, and modularity.

Step 3: Field survey and data acquisition – conducted in September 2025 at Indramayu cold storage facility (capacity 300 tons, divided into three chambers). Acquired primary data through:
- Direct observation of monitoring devices and procedures.
- Staff interviews about challenges in equipment durability and monitoring practices.
- Documentation of organizational structure (noting fragmentation across multiple companies).
- Key findings: manual thermometers attached to doors, CCTV fogging issues at <14 °C, lack of centralized monitoring, electronic device degradation in cold rooms.

Step 4: Gap analysis – compared current practices with the proposed model. Identified gaps:
- Lack of real-time anomaly detection and predictive capabilities.
- No integration between multimodal sensor data and centralized dashboards.
- Institutional fragmentation requiring consortium-based governance [29]–[31].

Step 5: Framework synthesis and validation strategy – consolidated findings into a framework prototype design. Validation plan: simulate temperature/time-series datasets and fish image classification to test ML algorithm performance. Future implementation: deploy edge-cloud integrated microservices and evaluate against KPIs such as accuracy, latency, scalability, and interoperability [23], [24], [32].

The framework utilizes a hybrid edge–cloud architecture, leveraging containerized services and modular deployment for scalability, interoperability, and real-time monitoring. Table 2 summarizes the technical configuration, including the integration of IoT devices, data orchestration tools, machine learning engines, model deployment environments, and system visualization platforms.

Table 2. Technical configuration of the proposed cold chain framework

Layer/component	Tools/technologies	Functionality	ML algorithm used	Deployment type
Input and sensing layer	Temperature and humidity sensors (DS18B20), RFID, GPS, POE cameras	Environment monitoring, batch tracking, image capture	–	Physical IoT devices, MQTT
IoT data broker	MQTT, Mosquitto, Kafka	Sensor data streaming, real-time event messaging	–	Edge and Cloud
Edge processing layer	Raspberry Pi, Jetson Nano, Docker, Python, Flask API	Data filtering, preprocessing, light inference	RF (anomaly detection), CNN (basic classification)	Edge container
Microservice Orchestration	Docker, Kubernetes (K8s), gRPC, REST API	Modular service deployment, fault isolation, container scaling	–	Cloud and Edge
API gateway and load balancer	Kong, Nginx, HAProxy	Routing, load management, authentication	–	Cloud
Data storage and management	S3 Object Storage, HDFS, SQLite, PostgreSQL	Distributed storage, structured/unstructured data management	–	Cloud and hybrid
Machine learning engine	TensorFlow, Scikit-learn, PyTorch	ML model training and inference	RF, LSTM, CNN	Cloud-based inference / batch processing
Model deployment layer	TensorFlow serving, MLflow, FastAPI	Real-time inference, model versioning, REST endpoints	RF, LSTM, CNN	Edge-cloud hybrid
Visualization and analytics	Grafana, power BI, Streamlit, LeafletJS, QGIS	Dashboards, geospatial route tracking, predictive analytics	–	Cloud-based UI
Performance monitoring	Prometheus, Grafana, ELK Stack	Latency tracking, CPU/memory monitoring, anomaly alerting	–	Cloud

3. RESULTS AND DISCUSSION

This section presents the research results and their implications for fisheries cold chain management. The findings are structured according to the architectural layers and analytical components of the proposed framework. Each layer is examined to highlight its role and contribution to enabling an intelligent cold chain system that supports product freshness, operational efficiency, and sustainable distribution, as illustrated in Figure 1.

3.1. Conceptual architecture

The proposed framework adopts a microservice-oriented architecture to support scalability and modular deployment in perishable fish cold chain logistics. Core functionalities are decomposed into independent services and distributed across edge–cloud environments. Heterogeneous data from sensors, GPS, and visual inputs are processed through a unified pipeline, enabling real-time analytics, machine learning inference, and seamless system integration.

3.2. Cold chain challenges in fisheries distribution

Fisheries cold chain logistics face challenges related to temperature variability, fragmented distribution networks, limited real-time visibility, and delayed decision-making. In developing contexts such as Indonesia, these issues are intensified by infrastructure constraints and manual monitoring practices. Conventional cold chain systems primarily emphasize monitoring without predictive capabilities, underscoring the need for intelligent frameworks that support real-time analytics, spoilage risk prediction, and scalable system integration. Gap between ideal cold chain architecture and field conditions is shown in Table 3.

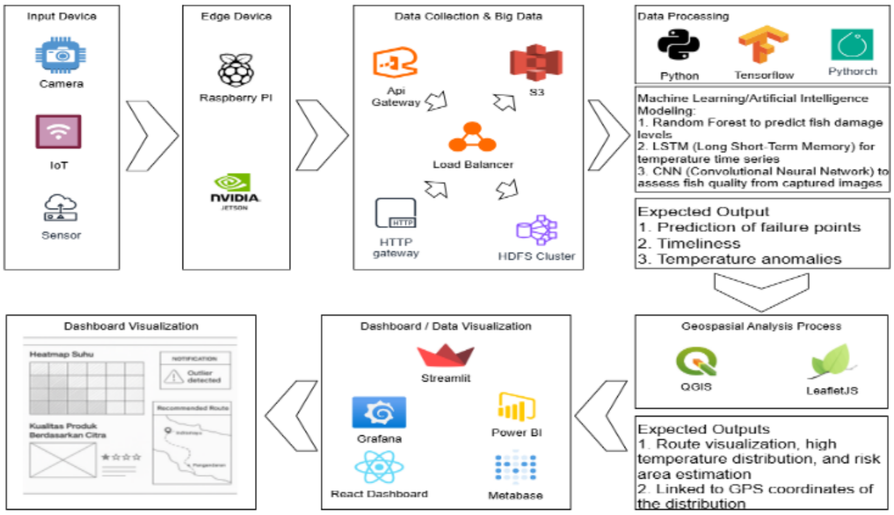

Figure 1. Proposed microservice-oriented AI/ML framework for cold chain management

Table 3. Gap between ideal cold chain architecture and field conditions

Aspect	Ideal condition (planned architecture)	Field observation
Temperature monitoring	Continuous digital monitoring with IoT sensors integrated into centralized dashboards	Manual readings using non-digital thermometers attached at cold room doors
Visual monitoring	High-resolution cameras integrated with CNN for fish quality assessment	CCTV cameras fogged at <14°C, unable to clearly capture fish condition
Data access	Real-time, centralized monitoring accessible at control desk	Monitoring only possible on-site in front of storage doors
Predictive analytics	AI/ML models (RF, LSTM, CNN) for anomaly detection, spoilage prediction, and quality classification	No predictive system; entirely reactive to temperature changes
Device durability	Edge devices designed for low-temperature operation (industrial-grade electronics)	Staff reported electronic devices degrade quickly in cold storage environment
Organizational structure	Unified microservice-based architecture under a single governance model	Fragmented operations across multiple companies/organization with different priorities

3.3. Input device layer

The input device layer serves as the foundation of the proposed architecture, functioning as the primary interface between the physical cold chain environment and the digital monitoring system. This layer is responsible for capturing multimodal data that reflects both environmental conditions and product quality in real time. By integrating diverse sensing technologies, it ensures the availability of comprehensive datasets that support subsequent processing, prediction, and decision-making. The input device layer constitutes the foundation for data acquisition. It integrates:

- Cameras capturing real-time fish images for computer vision and CNN-based classification.
- Temperature and humidity sensors monitor stability to trigger early warnings.
- IoT devices include in RFID, GPS, and smart sensors build within edge device for tracking batches, location, and shocks during transportation.

The minimum configuration per distribution cycle refers to the essential set of input devices required to ensure reliable data acquisition and monitoring across different stages of the cold chain. This configuration outlines the number of cameras, sensors, and IoT gateways needed in cold storage facilities and transport vehicles. By defining these baseline requirements, the framework establishes a practical guideline for scalable implementation in fisheries logistics in Table 4.

In total, the minimum configuration requires approximately nine cameras, twelve sensors, and six IoT devices to support one complete distribution cycle. The estimated cost for implementing this setup ranges from USD 683 to 1363, equivalent to IDR 10.6 to 21.2 million, making it a feasible yet scalable investment for fisheries cold chain operations.

3.4. Edge device layer

Captured data in the cold chain system must be processed locally before transmission to the cloud in order to minimize delays and reduce reliance on external networks. Edge computing devices perform lightweight computation tasks, such as preprocessing telemetry data from temperature and humidity sensors, which ensures that only relevant information is forwarded for further analysis. This local filtering mechanism reduces bandwidth consumption and enhances the responsiveness of monitoring systems, which is crucial for perishable products that require rapid intervention [25].

For more advanced tasks, such as computer vision analysis of fish quality, GPU-accelerated edge platforms are required to handle the computational complexity of convolutional neural networks. Devices in this category can process high-resolution images in real time, enabling immediate anomaly detection and reducing the risks of spoilage during storage and transportation. The adoption of such heterogeneous edge infrastructures has been shown to significantly improve both latency and scalability in supply chain applications [22], [33].

Table 4. Minimum configuration per distribution cycle

Location	Component units	Cost estimation
Initial cold storage (500m2)	• 5 temperatur sensors waterproof	USD6,90 (~IDR 107 rb)
	• 5 poe cameras 1080p	USD40–80 (~IDR 620 rb–1,24 jt)
	• 2 IoT gateway	USD35–80 (~IDR 550 rb–1,24 jt)
Transport truck (5 – 10 tons)	• 4 temperatur sensors waterproof	USD6,90 (~IDR 107 rb)
	• 2 poe cameras 1080p	USD40–80 (~IDR 620 rb–1,24 jt)
	• 1 GPS Tracker	USD30–80 (~IDR 465 rb–1,24 jt)
	• 2 IoT gateway	USD35–80 (~IDR 550 rb–1,24 jt)
Destination cold storage (300 m2)	• 3 temperatur sensors waterproof	USD6,90 (~IDR 107 rb)
	• 2 poe cameras 1080p	USD40–80 (~IDR 620 rb–1,24 jt)
	• 2 IoT gateway	USD35–80 (~IDR 550 rb–1,24 jt)

3.5. Data collection and big data infrastructure

Data aggregation in the proposed cold chain framework involves the systematic collection, integration, and management of data streams originating from multiple sources across the supply chain. This process includes routing sensor readings, image data, and IoT signals through secure gateways and balancing their distribution across servers to ensure reliability. By combining cloud-based object storage with distributed file systems, the architecture guarantees both scalability and resilience, providing a robust foundation for real-time monitoring and advanced analytics.

– API Gateway as the single-entry point for API requests, handling authentication and rate limiting.
– HTTP Gateway for efficient file transfers, compression, and security.
– Load Balancer distributing requests across multiple servers.
– S3 Storage for object-based, scalable cloud storage.
– HDFS Cluster for on-premise, distributed storage of very large datasets.

Comparative analysis shows S3 excels for small-to-medium, elastic workloads, while HDFS is more cost-effective for petabyte-scale, long-term storage. Figure 2 illustrates the data flow architecture for media and telemetry streams within the cold chain framework. It highlights how sensor and image data are routed through gateways, load balancers, and distributed storage systems (S3 and HDFS) to ensure scalability and reliability.

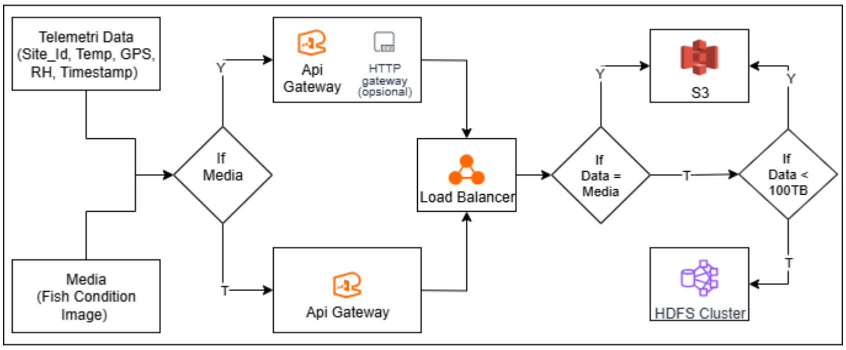

Figure 2. Data flow architecture for media and telemetry in the cold chain framework

3.6. Data processing with machine learning

Three main algorithms were evaluated to address the diverse analytical needs of cold chain monitoring. Random forest was applied to classify tabular telemetry data and detect fish freshness categories, while LSTM was employed to analyze temporal variations in sensor readings and forecast spoilage risks. In parallel, CNN was utilized for visual inspection of fish images, enabling automated assessment of quality degradation. Figure 3 presents the detailed data processing flow that underpins the cold chain monitoring framework. It shows how telemetry and image data are ingested, preprocessed, and transformed through various machine learning pipelines. The diagram also highlights the integration of feature stores, model registries, and inference services that collectively generate anomaly detection, spoilage prediction, and quality scoring outputs.

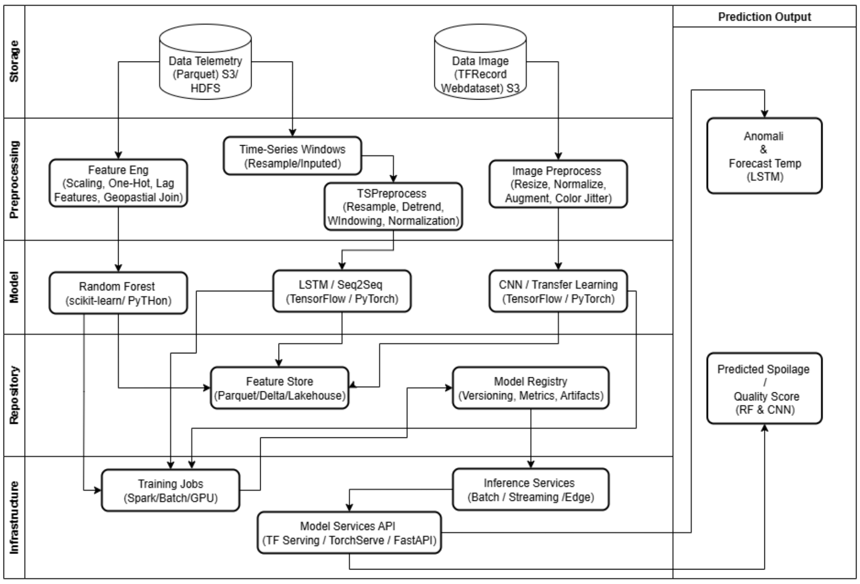

Figure 3. Data processing flow for machine learning-based cold chain monitoring

3.7. Validation strategy and prototype testing

To demonstrate the technical feasibility of the proposed microservice-oriented machine learning framework, a set of simulation-based validation scenarios was designed, each reflecting key operational challenges in fisheries cold chain management in Table 5. The first scenario focuses on temperature anomaly detection using random forest, employing multi-day simulated sensor data to differentiate normal operating patterns from deviations that may indicate equipment malfunction or increased spoilage risk.

Table 5. Validation design for the proposed framework

Validation type	Dataset and input description	Preprocessing	Model configuration	Evaluation metrics	Purpose
Temperature anomaly detection (random forest)	Simulated temperature dataset (10–14 days), 5 sensors, sampling 1-minute interval (≈ 7,200 records per sensor)	Normalization, missing-value handling, label generation for “normal/anomaly”	RF with 200 trees, max depth = 10, bootstrap enabled	Accuracy, Precision, Recall, F1-score	Validate early anomaly detection capability for cold storage
Spoilage risk prediction (LSTM)	Time-series temperature–humidity data, 1 sequence per hour, 30–50 time steps	Min–max scaling, windowing sequence (look-back = 24), train-test split 80:20	LSTM with 64 units, dropout 0.2, Adam optimizer, 50 epochs	RMSE, MAE, R^2	Validate prediction capability for short-term spoilage risk
Fish quality classification (CNN)	Small dataset (80–120 images) categorized as fresh/slightly spoiled/spoiled	Resize to 128×128, augmentation (flip, rotate, brightness)	CNN: 3 conv layers, ReLU, max-pooling, dense layer 128, SoftMax output	Accuracy, confusion matrix, Latency per inference	Validate feasibility of visual assessment using small-scale dataset
Edge vs cloud deployment benchmark	Sample inference workload from RF/LSTM/CNN	–	Edge (Jetson /Raspberry), Cloud (VM instance)	Latency, CPU usage, memory usage, Throughput	Validate microservice deployment performance under hybrid architecture

This validation evaluates the model's reliability through accuracy, precision, recall, and F1-score metrics. The second scenario uses LSTM networks to model temporal dependencies in temperature–humidity sequences, enabling short-term spoilage risk prediction. Performance is assessed using RMSE, MAE, and R^2 to gauge forecasting quality. The third scenario applies a lightweight CNN model to classify fish quality from a small image dataset representing fresh, moderately spoiled, and spoiled categories, validated through accuracy, confusion matrix analysis, and inference latency.

In addition, an edge–cloud benchmarking test compares execution speed, CPU utilization, memory consumption, and throughput between distributed deployment environments. Collectively, these validation steps provide preliminary empirical evidence that the framework can support real-time monitoring, predictive analytics, and distributed intelligence, reinforcing its suitability for scalable and modular cold chain operations. These preliminary results demonstrate that the proposed framework is technically feasible, scalable, and capable of providing actionable insights for real-time cold chain operations, marking a significant advancement over existing monitoring-only approaches.

3.8. Visualization and dashboard layer

A multi-tool visualization strategy is proposed to ensure that data from various sources can be effectively communicated to different stakeholders. Each tool plays a complementary role, ranging from real-time monitoring dashboards to analytical reporting and interactive geospatial mapping [34]. By combining these platforms, the framework delivers both operational awareness and strategic decision-making support for cold chain management [35].

- Streamlit: rapid prototyping and ML model integration.
- Grafana: real-time monitoring of time-series sensor data with alerts.
- Power BI: corporate-level reporting and KPI dashboards.
- React Dashboard: fully customized operational apps integrating maps and controls.
- Metabase: lightweight self-service analytics for quick insights.
- These five tools collectively enable monitoring fish quality, anomaly detection, and providing route recommendations in a decision-support environment.

3.9. Geospatial analysis

Geospatial analytics enriches cold chain monitoring by integrating GPS data with sensor telemetry to provide a comprehensive spatial understanding of distribution dynamics. The process involves multiple steps, including data cleaning, route segmentation, hotspot detection, and risk surface interpolation, which together enable proactive identification of high-risk areas [36]. Recent studies have demonstrated that geospatial AI techniques, when applied to food and logistics chains, significantly improve both operational efficiency and risk mitigation [37], [38]. The output includes:

- Heatmaps of risky zones,
- Route recommendations minimizing exposure,
- Real-time alerts via geofencing mechanisms.
- QGIS and LeafletJS enable both in-depth spatial analysis and interactive web-based maps.

3.10. Integration across blocks

All functional blocks in the proposed architecture are interconnected in a seamless workflow that integrates data acquisition, edge-level processing, centralized big data infrastructure, machine learning analytics, visualization dashboards, and geospatial analysis. Together, these components create an intelligent cold chain system capable of preserving fish quality, enabling predictive decision-making, and supporting sustainable logistics operations [26], [39], Its integration cycle across system block is presented in Figure 4.

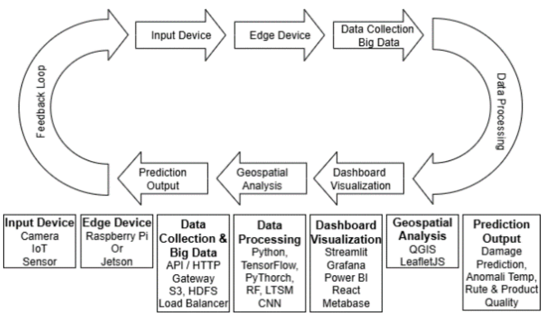

Figure 4. Integrated workflow cycle of the proposed cold chain architecture

4. CONCLUSION

This study presents a microservice-oriented machine learning framework designed to enhance intelligence, scalability, and real-time responsiveness in fisheries cold chain management. By integrating Random Forest–based anomaly detection, LSTM-based spoilage prediction, and CNN-based visual quality classification into a hybrid edge–cloud architecture, the proposed framework addresses critical gaps identified in previous research, particularly the absence of predictive analytics, multimodal monitoring, and modular deployment mechanisms. Simulation-based validation demonstrated that each model can operate effectively within a distributed microservice environment, supporting real-time inference, adaptive decision-making, and interoperability across heterogeneous cold chain infrastructures. Furthermore, the comparative performance analysis between edge and cloud execution confirms that the framework can balance latency, resource usage, and computational demands based on operational requirements.

These findings collectively indicate that the proposed framework offers a technically feasible and operationally scalable solution, strengthening cold chain reliability, reducing spoilage risk, and enabling data-driven logistics governance. The research contributes a deployable architectural blueprint that bridges conceptual AI-enabled cold chain models with practical implementation pathways suitable for fisheries distribution in Indonesia.

5. LIMITATIONS AND FUTURE WORK

Although the proposed framework shows strong potential, this study is limited by the use of simulated datasets and small-scale image samples, which may not fully represent real operational variability in fisheries cold chains. Model performance and deployment behavior may differ under fluctuating field conditions, diverse species characteristics, and hardware constraints. Future work will involve large-scale field deployment, continuous data acquisition, and model refinement using real-world sensor and visual datasets. Further research will explore lightweight architectures for edge inference, integration with cooperative and governmental platforms through standardized APIs, and evaluation under multi-node, network-variable environments to assess scalability, resilience, and long-term operational impact.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization
M : Methodology
So : Software
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I : Investigation
R : Resources
D : Data Curation
O : Writing - Original Draft
E : Writing - Review & Editing
Vi : Visualization
Su : Supervision
P : Project administration
Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials. Additional datasets generated during the current study will be made available upon reasonable request.

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