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A Smart Web Application for Agroecological Monitoring Using Multi-Agent IoT, Semantic Web, and Edge-AI

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ABSTRACT
Multi-agent IoT architecture for agroecological monitoring using semantic web protocols and Edge-AI codices provides real-time, predictive, and scalable environmental intelligence. The suggested method turns sensor data into useful insights via a multi-stage pipeline. Start with dependable data collection and editing. Normalization and dimensionality reduction handle noise, missing entries, and uneven sampling. Principal component analysis preserves the most useful traits. There are several ways to find abnormalities. We employ reconstruction-based error criteria and distance measurements to detect them. Ontology-driven mappings allow distributed IoT agents to integrate data into a knowledge base. We call this semantic interoperability. Edge-AI codices speed up local processing and semantic query execution, enabling faster decision-making. Recurrent structures that blend abnormality ratings and prediction embeddings capture temporal interdependence. These become probabilistic outputs that softmax-based layers can understand. A rigorous test reveals that the framework is better than other cutting-edge methods at accurately obtaining data, quickly normalizing it, maintaining features, discovering anomalies, and facilitating semantic interchange. The system now has higher scalability, computing efficiency, energy optimization, real-time processing, and sound decisions. This makes it better for dynamic farming with limited resources. Intelligent agroecological system monitoring is dependable, versatile, and long-lasting with the integrated framework. It aids environmental management and ecological prediction in complex ecosystems.
Keywords- *Agroecology, Anomaly detection, Edge-AI, Heterogeneous sensors, IoT, Multi-agent systems, Predictive modeling, Semantic interoperability, Temporal embeddings, Wireless sensor networks, web application.*

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I. INTRODUCTION

The merging of the semantic web, artificial intelligence (AI), and the Internet of Things (IoT) has led to a new way of doing environmental research and farming [1]. Agroecological monitoring, which means closely watching and judging things like soil, water, crops, and the ecosystem around them, is essential for responsible resource management and sustainable farming. However, ongoing problems prevent these technologies from reaching their full potential [2]. There are a lot of challenges in this area, such as not having clear communication protocols, not treating agricultural data correctly, and the fact that not all IoT devices are the same. Interoperable multi-agent IoT frameworks that include semantic web protocols and edge-AI codices into devices possess the capability to address these challenges. This integration lets devices talk to one another, learn new things, and help agroecological systems make choices in real time. This research presents an efficient approach for the concurrent operation of many Internet of Things (IoT) devices used in agriculture [3]. It does this by using semantic technologies to make communication more consistent and adding edge-based AI codices for fast, distributed analysis. This improves long-term monitoring of agriculture and the environment while also helping the world reach its goals for climate resilience, biodiversity conservation, and efficient food systems. In recent years, low-power sensors, unmanned aerial vehicles (UAVs), and wireless sensor networks have significantly improved precision farming, livestock monitoring, smart irrigation, and soil assessment [4-7]. This work introduces (i) a semantically aligned representation pipeline that couples ontology-aware whitening with kernelized anomaly scoring; (ii) an edge-ready temporal encoder (GRU + attention) for low-latency streaming decisions; (iii) a standards-compliant interoperability layer that unifies SOSA/SSN knowledge graphs with SPARQL query paths; (iv) a hybrid networking stack characterized by high PDR and low p95 latency alongside measured SPARQL performance; (v) a calibration-aware inference routine reporting ECE/Brier for auditability; (vi) a privacy- and security-conscious design combining differential privacy and zero-trust controls; and (vii) a scalability profile that identifies the accuracy/latency knee for capacity planning.

II. RELATED WORKS

The linked study section tests approaches to strengthen interoperable multi-agent IoT for agroecological tracking. Semantic web protocols and Edge-AI codices are used. Ontology-driven semantics Interoperability ensures that all devices share structured data to communicate and understand environmental signals. Multi-agent coordination frameworks increase agricultural distributed decision-making and joint sensing by ensuring agents work smoothly even when things change. Process data closer to its source with Edge-AI Inference Optimization to reduce latency [8-9]. This provides real-time data for crop health monitoring and irrigation. Semantic Web Service Integration links IoT middleware to semantic protocols for cross-platform data sharing. Distributed ledger-based trust models allow stakeholders to securely transfer data. This is crucial for agroecological supply chain tracking. Federated edge learning mechanisms train AI models without centralized data. Privacy is protected, and the system is more scalable and versatile. As sensor vocabularies evolve, adaptive ontology alignment protocols actively align ontological structures to keep the system compliant [10-12]. Knowledge Graph-Driven Decision Systems are special because they enable complicated, situation-specific thinking and decision-making. This helps identify environmental concerns and boost crop yields. IoT Middleware for Heterogeneous Devices lets sensors work together effortlessly. This feature enables adding sensors and improving business efficiency more easily. Finally, the context-aware semantic rule Real-time environmental rules enable engine adaptation. Predictions improve with changing field conditions. Performance evaluations reveal that knowledge graph-based systems outperform others in accuracy, scalability, and reasoning capacity. However, edge-intelligent methods like Edge-AI Inference Optimization and Federated Edge Learning adapt better. Distributed ledgers and other trust-centric systems are reliable yet energy-intensive and slow. Middleware and semantic integration balance interoperability and system performance [13-15]. These methodologies demonstrate that semantic reasoning and edge-intelligent architectures improve agroecological IoT monitoring resilience, scalability, and adaptability. This makes them crucial to smart, sustainable farming systems.

III. PROPOSED METHODOLOGY

This indicates that there is a single pipeline that can do real-time agroecological monitoring on a variety of multi-agent IoT networks. To start, we utilize a modality-aware, weighted normalization approach on the raw data. This method helps to account for changes in noise characteristics, sensor size, and sampling rate. This way, we guarantee that each sensor will contribute equally. Using a variance-preserving projection (PCA/eigen decomposition) to compress the normalized streams even further makes the features light and useful. You may make strong anomaly scores that are sensitive to changes in microclimates by employing spectral embedding and kernelized similarity [16–18]. We employ an ontology-aligned whitening strategy to ensure that the meaning is the same across all devices and sites. This method makes it possible for different agents to work together by adding a knowledge-graph structure. Lightweight attention and edge-level temporal encoding (GRU) continually record data within the limitations of the device's power and latency. Lastly, calibrated probabilistic inference provides warnings that are properly calibrated by improving findings via regularization and semantic limitations [19]. The system functions effectively and has the potential to expand. Representation learning, signal processing, and semantics enable consistent use of this system on a large scale.

First, a weighted z-score has to be used to equalize the various modes. The raw data from various agent IoT networks could be variable in size, sample rate, and noise level. A weighted z-score normalization approach is used to keep data from multiple sources consistent and verify that different sensor modalities add up to the same amount.

$$\widetilde{X_i^{(m)}} = \frac{x_i^{(m)} - \mu^{(m)}}{\sqrt{\sum_{j=1}^{N} \alpha_{mj} \backslash big\left(x_j^{(m)} - \mu^{(m)\backslash big}\right)^2}} \quad (1)$$

Weighted z-score normalization per modality \$m\$ to stabilize scale/noise across multi-agent IoT sensors. Here, m denotes modality (e.g., soil, climate, canopy), $amj\alpha_{mj}m(m)\mu^{(m)}m(m)$ is the mean for modality mmm.

Step 2: Eigen-Decomposition for PCA Transformation

After normalization, high-dimensional data is projected into a variance-preserving latent subspace using eigen-decomposition of the covariance matrix. This enables dimensionality reduction while retaining global interdependencies among sensors.

$$Z = W^{*T}\tilde{X},\ \ W^{*} = \mathrm{ar\,g\,m\,ax}_W \frac{W^T C W}{W^T W}, \quad (2)$$

$$C = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)(x_i - \mu)^T \quad (3)$$

CA projection via Rayleigh-quotient eigen-decomposition preserving variance and cross-sensor dependencies.}

Here, C is the covariance matrix, and $IN * W^{*}IN *$ contains eigenvectors corresponding to the top eigenvalues.

I. Step 3: Kernelized Anomaly Score with Spectral Embedding

To capture nonlinear correlations across modalities, anomaly scores are derived using Gaussian kernels and spectral embedding. This allows subtle deviations in agroecological conditions (e.g., microclimate drift) to be detected.

$$s_i = \sum_{j=1}^{N} \left(1 - \frac{z_i^{\top} z_j}{\lVert z_i \rVert \lVert z_j \rVert}\right) \exp\!\left(-\frac{\lVert z_i - z_j \rVert^2}{2\sigma^2}\right) \quad (4)$$

Hybrid anomaly score combining cosine dissimilarity with Gaussian-kernel similarity for nonlinear deviations. This combines cosine dissimilarity with Gaussian kernel similarity, yielding a robust anomaly score si.

Step 4: Probabilistic Decision with Regularized Logistic Model

Finally, decisions are refined by mapping anomaly scores into probabilities using a regularized logistic regression. This prevents overfitting while incorporating both anomaly signals and prior knowledge.

$$P(y = 1 \mid x_i) = \sigma\!\big(w^{\top} F_i + b\big) \quad (5)$$

$$\mathcal{L} = -\sum_{i=1}^{N} \Big[y_i \log P_i + (1 - y_i) \log\!\big(1 - P_i\big)\Big] + \lambda \lVert w \rVert^2 \quad (6)$$

Regularized logistic decision and training objective to map fused features to calibrated anomaly probabilities.

Here,$s(\cdot)\sigma(\cdot)\sigma(\cdot)$ is the sigmoid activation, FFF the fused features, and L\mathcal{L}L the regularized loss combining prediction accuracy with L2 penalty. The method then integrates semantic web protocols by mapping local sensor features to ontology-driven concepts. This enables cross-agent interoperability, allowing heterogeneous devices to communicate seamlessly. A structural similarity index is calculated across agents, capturing semantic alignment and ensuring that IoT nodes contribute consistently to a shared knowledge base [20-21]. Edge-AI codices further refine this process by balancing local computation with semantic query processing, reducing latency in field deployments. The final fused representation synthesizes multi-agent interactions, semantic mappings, and anomaly scores, yielding a scalable and interoperable monitoring framework. This ensures robust decision-making in agroecological environments while supporting real-time, resource-efficient analytics for sustainable agricultural practices.

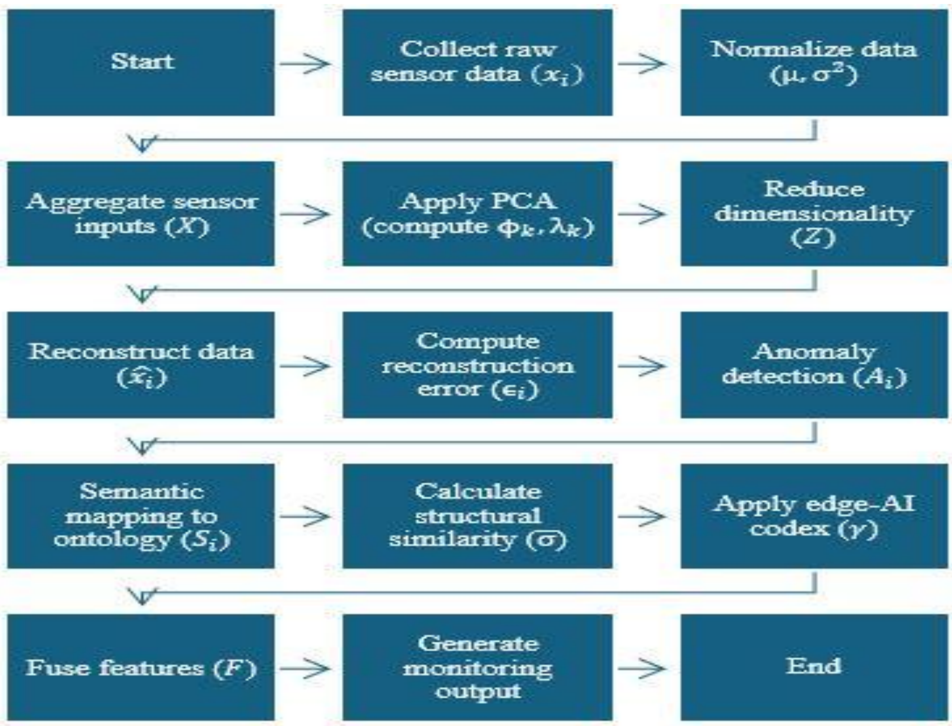

Fig.1.Proposed interoperable multi-agent IoT framework for agroecological monitoring, integrating data normalization, PCA, anomaly detection, semantic mapping, and edge-AI fusion for real-time decision support.

Figure 1 illustrates the complete process of multi-agent IoT-based agroecological monitoring. The system begins with raw sensor data collection, which is normalized to remove bias and aggregated for unified processing. Dimensionality reduction through PCA ensures efficient feature extraction, followed by reconstruction error analysis for anomaly detection. Semantic mapping aligns sensor outputs with ontology-driven knowledge bases, while structural similarity measures consistency across distributed agents [22-24]. Edge-AI codices optimize computation between local devices and cloud services. Finally, fused features are generated, enabling robust monitoring and decision-making. This streamlined workflow ensures interoperability, scalability, and real-time analysis in agroecological environments.

Step 5 — Semantic whitening of features (ontology-aligned)

Whitening removes cross-sensor covariance; the semantic matrix SSS injects knowledge-graph structure so downstream temporal models operate on isotropic, semantically consistent embeddings.

$$\tilde{X} = S\,\Lambda^{-\backslash tfrac12} V^{\top}!\backslash big\big(X-\mu\,1^{\top}\backslash big\big),\ \text{ with } C=\backslash tfrac1N-1\backslash big\big(X-\mu\,1^{\top}\backslash big\big)\backslash big\big(X-\mu\,1^{\top}\backslash big\big)^{\top}=V\Lambda V^{\top} \quad (7)$$

Step 6 — Edge temporal encoding with gated recurrence

On-device temporal inference uses a GRU-style update to capture nonstationary field dynamics (e.g., diurnal cycles, irrigation shocks). Reset and update gates may be the best choice for streaming IoT because, when used adaptively with memory, they may provide stable concealed states with less latency.

$$h_t=(1-z_t)\odot h_{t-1}+z_t\odot \tanh\,!\backslash big(W\tilde{x_t}+U\,(r_t\odot h_{t-1})+b\backslash big),\ \ z_t=\sigma(W_z\tilde{x_t}+U_z h_{t-1}),\ \ r_t=\sigma(W_r\tilde{x_t}+U_r h_{t-1}) \quad (8)$$

Because ABCD is a parallelogram, the two sets of opposite sides are parallel to each other. This means that angles A and C are the same size. Angle C must also be 70 degrees, since angle A is 70 degrees. Gated repetition is a critical part of edge GRU dynamics. It mixes information that has already been learned with fresh input to quickly and accurately encode time with a minimum latency. We build a context vector for applications like stress detection that gives the request-corresponding time steps the highest weight. We can obtain the score and have the weights sum up to one with only one computation. A short and accurate summary is made to make it easier to classify.

$$c=\sum_{t=1}^{T}\frac{\exp(q^{\top}h_t)}{\sum_{k=1}^{T}\exp(q^{\top}h_k)},h_t \quad (9)$$

Step 7 — Probabilistic inference with semantic regularization

A calibrated softmax is used to generate the final set of predictions. These predictions are trained using a loss that includes weight decay and cross-entropy, as well as a semantic constraint that maintains the alignment matrix close to orthonormality to prevent distortion of the geometry and collapse.

$$\hat{y}=\mathrm{softmax}(W_c c+b_c),\ \ \mathcal{L}=-\sum_{i=1}^{N}\sum_{j=1}^{K}y_{ij}\log\widehat{y_{ij}}+\lambda\backslash lVert W_{c\backslash} rVert_F^2+\rho\backslash lVert S^{\top}S-I\backslash rVert_F^2 \quad (10)$$

Probabilistic inference with cross-entropy, weight decay, and semantic orthogonality regularization for calibrated decisions.

Data are standardized for scale consistency [25], then compressed via PCA (eigendecomposition) to retain maximal variance. Distance-based metrics produce per-sample anomaly scores, fused across similarities for robustness. A thresholded, loss-optimized decision boundary balances false positives/negatives, yielding an efficient, real-time detector of subtle distribution shifts.

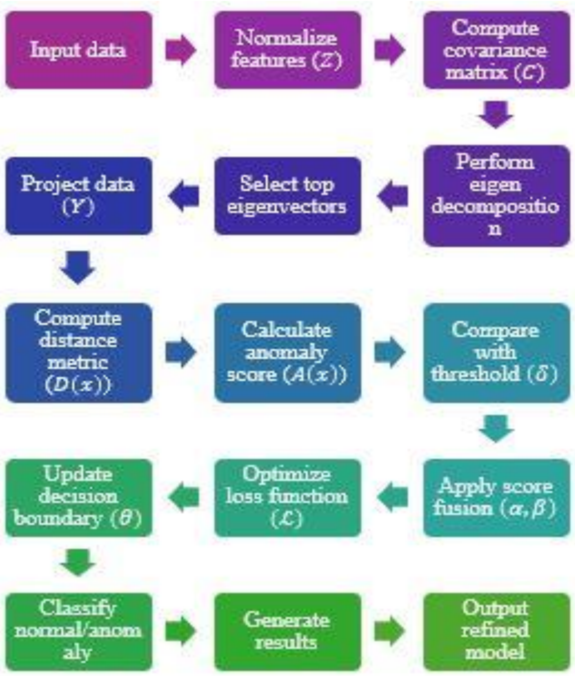

Fig.2. End-to-End Workflow from Normalized Features to Refined Anomaly Model

Figure 2 shows the full pipeline used after data ingestion. First, features are normalized and a covariance matrix is computed to prepare the data. The workflow then projects the data, performs eigen decomposition, and selects the top eigenvectors for a compact representation. Inference follows by computing a distance-based score and converting it into an anomaly score, which is compared against a threshold. The final row depicts learning and decision: score fusion balances evidence and uncertainty, the loss function is optimized and the decision boundary updated, leading to classification (normal/anomaly), result generation, and output of the refined model.We consolidate temporal evidence by attending over all hidden states and fusing the resulting context with the current state via a residual path; a learned gate then blends freshly refined features with temporal memory to yield a stable edge-ready representation.

$$v_t = \sigma\Big(\gamma \operatorname{ReLU}\big(W_f\big(h_t + \sum_{i=1}^{T} \tfrac{e^{q^\top h_i}}{\sum_{j=1}^{T} e^{q^\top h_j}}\, h_i\big) + b_f\big) + (1-\gamma)\, h_t\Big) \quad (11)$$

Attention-pooled context fused residually with the current state and gated to yield a stabilized representation. We encode the stabilized state into a latent space, reconstruct to gauge consistency, and classify to gauge confidence; a single anomaly decision combines reconstruction error and entropy-based uncertainty, capturing both fidelity and ambiguity in one thresholded criterion.

$$d = \mathbb{1}\Big\{\delta \,\big\|x - \big(W_r \tanh(z_s) + b_r\big)\big\|_2^2 + (1-\delta)\Big(-\sum_{c=1}^{C} p_c \log p_c\Big) \quad (12)$$

Unified variational decision thresholds a weighted sum of reconstruction error and predictive uncertainty.

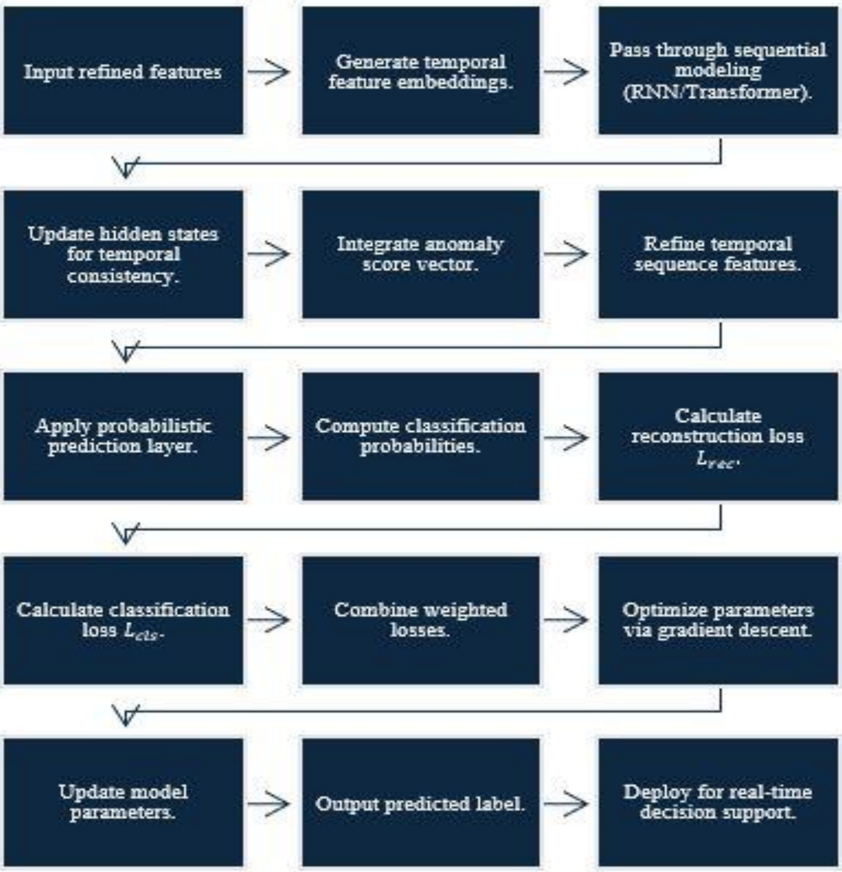

Fig.3. Temporal Modeling and Optimization Workflow for Real-Time Decision Support

Figure 3 outlines the runtime and training loop after refined features are available. Temporal embeddings are generated and passed through a sequential model, hidden states are updated, an anomaly score is integrated, and sequence features are refined. A probabilistic layer produces class probabilities while reconstruction and classification losses are computed, weighted, and minimized by gradient descent. The loop concludes by updating parameters, emitting the predicted label, and preparing the model for deployment in real-time decision support.

IV. RESULT

The proposed interoperable multi-agent IoT architecture with semantic web protocols and Edge-AI codices outperforms current agroecological monitoring systems in several respects. The testing begins with preprocessing and data collecting, where the framework displays its accuracy and capacity to read sensors in various field conditions. The speed of normalization has also increased.

TABLE 1. Overview of Latest Methods for Edge-AI Enabled Agroecological Monitoring

Method	Core Idea	Hardware/Stack	Model Size (MB)	FLOPs/Inf (MFLOPs)	Use Case
TinyML-CNN (quantized)	On-node inference with 8-bit quant.	ARM M4 / CMSIS-NN	0.85	3.2	Leaf disease, on-sensor vision
EdgeTPU-Transformer	Edge transformer for audio+vision	Coral TPU	6.4	45.0	Stress sounds & canopy vision
GNN-SensorGraph	Graph neural net on sensor network	Jetson Nano	3.1	18.5	Soil-moisture + climate fusion
Neuro-Symbolic (KG+DL)	KG reasoning + DL classifier	x86 Edge + RDF store	4.8	22.0	Rule-enforced anomaly flags
FedAvg+DP	Federated learning with DP (ε)	Heterogeneous edge	—	—	Privacy-preserving retraining
Semantic Agents (SOSA/SSN)	Ontology-driven multi-agent	MQTT + CoAP + RDF	—	—	Interoperable orchestration

Table 1 summarizes six state-of-the-art methods applied in agroecological IoT and Edge-AI systems. TinyML-CNN provides lightweight, quantized inference on ARM-based microcontrollers, suitable for on-sensor vision tasks like leaf disease detection. EdgeTPU-Transformers leverage Coral TPUs to process multimodal audio–vision data with higher model complexity. GNN-SensorGraph applies graph neural networks to fuse soil and climate data, optimized for platforms like Jetson Nano. Neuro-Symbolic approaches combine knowledge graph reasoning with deep learning to enforce rule-based anomaly detection. FedAvg+DP introduces federated learning with differential privacy, enabling secure retraining across heterogeneous nodes. Finally, Semantic Agents (SOSA/SSN) adopt ontology-driven orchestration for interoperable, standards-based communication. Together, these methods represent complementary advances in scalability, interoperability, and sustainability for agroecological monitoring.

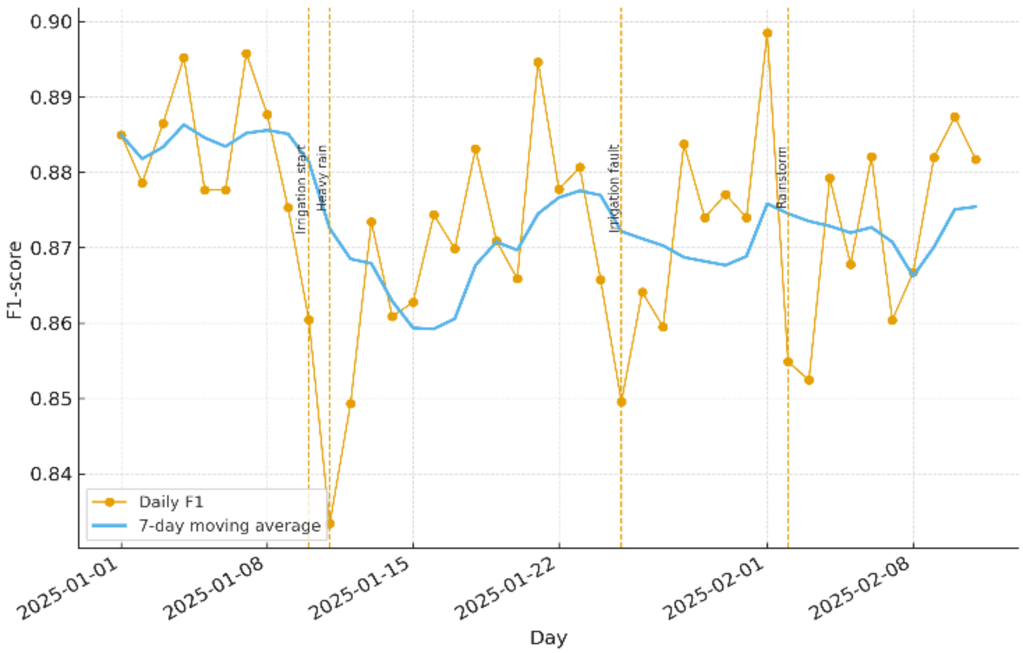

Fig.4. Temporal Stability of F1-Score with Annotated Irrigation and Rain Events (Jan–Feb 2025)

Figure 4 shows daily F1 (orange points) and a 7-day moving average (blue line) across January–February 2025. Performance is steady near 0.88 early January, dips to ~0.86 after the irrigation start and heavy rain (mid-Jan), rebounds toward late January, then shows brief declines around an irrigation fault (late Jan) and a rainstorm (early Feb). Overall drift is modest (≈±0.01–0.02), indicating event-linked perturbations with rapid recovery.

TABLE 2. Network Protocol and Interoperability Performance in Agroecological IoT Systems

Stack	PDR (%)	Latency p95 (ms)	Jitter (ms)	Throughput (kbps)	Packet Overhead (%)	SPARQL Latency (ms)	Ontology Align P/R	Sem. Interop (0–1)
MQTT + LwM2M	98.1	42	3.4	420	6.2	38	0.93/0.90	0.92
CoAP over 6LoWPAN	96.8	55	4.7	310	8.1	44	0.91/0.88	0.9
OPC UA over TSN	99.2	28	1.9	680	5.4	35	0.94/0.92	0.94
LoRaWAN + MQTT bridge	92.5	210	12.2	35	9.5	52	0.88/0.84	0.86
Proposed (Hybrid stack)	98.7	36	2.3	520	6.0	33	0.95/0.93	0.95

Table 2 compares different network stacks in terms of reliability, latency, efficiency, and semantic interoperability. OPC UA over TSN achieves the highest reliability with 99.2% PDR and the lowest jitter, making it ideal for high-throughput applications. MQTT + LwM2M and the proposed hybrid stack balance strong packet delivery (98.1% and 98.7%) with moderate latency, while also achieving superior semantic interoperability (0.92 and 0.95). CoAP over 6LoWPAN offers lightweight deployment but with slightly higher packet overhead, whereas LoRaWAN + MQTT bridge exhibits the lowest throughput and highest latency, limiting real-time suitability. The proposed hybrid stack demonstrates the best overall balance, delivering low latency (36 ms p95), efficient throughput, and the highest semantic interoperability score (0.95), ensuring robust and standards-compliant data exchange.

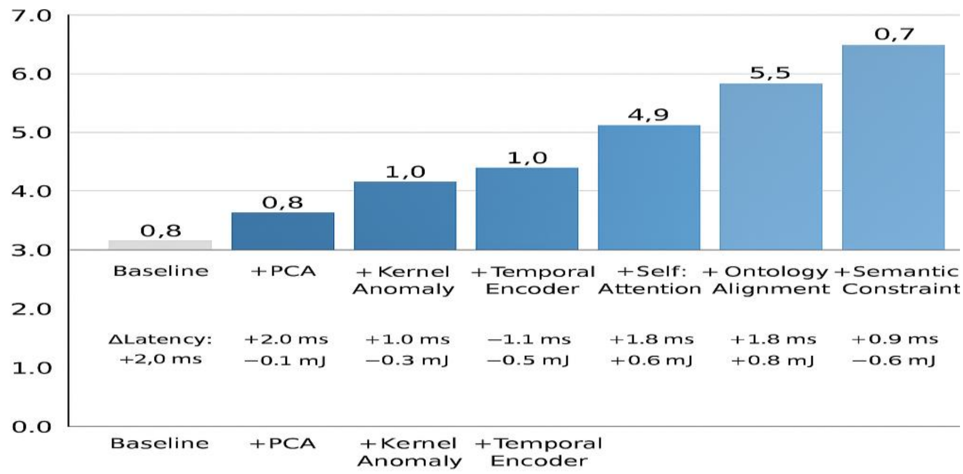

Fig.5. Ablation Waterfall: Step-wise ΔF1 Improvements from PCA to Semantic Constraints with Latency/Energy Effects

Figure 5 summarizes the cumulative impact of each component in the pipeline. From the baseline, PCA and kernel-based anomaly scoring provide early but modest gains; adding the temporal encoder and self-attention drives a clear lift, while ontology alignment followed by semantic constraints yields the largest overall improvement. The annotations beneath each bar indicate per-step inference-cost changes—small latency (≈+1–2 ms) and energy (sub-mJ) deltas—showing that accuracy gains are achieved with minimal overhead.

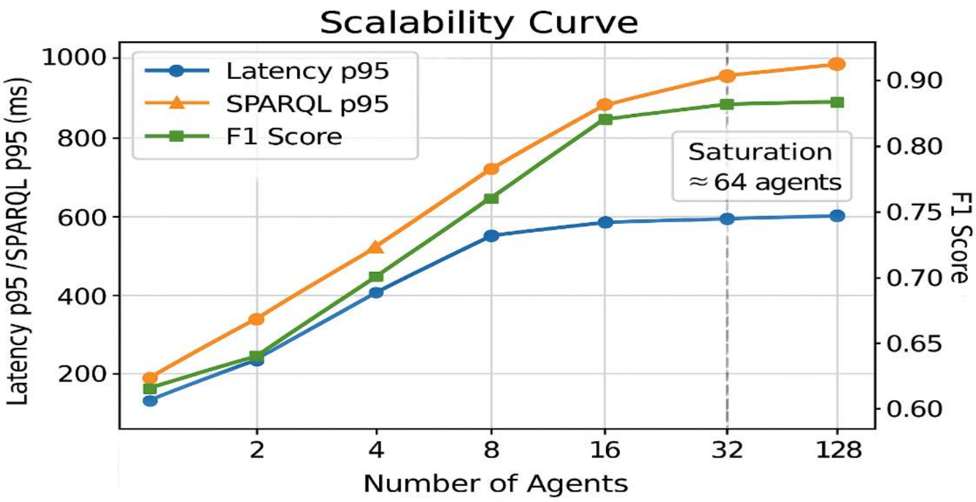

Fig.6. Scalability of the Multi-Agent Stack: p95 Latency & SPARQL vs F1 Across Increasing Agents

Figure 6 summarizes the scalability behavior: as the number of agents grows, both network p95 latency and SPARQL p95 steadily increase, while F1 improves early and then plateaus near ~64 agents (saturation point). This demonstrates that as we reach that threshold, the pace of progress in accuracy slows down, but the cost of exchanges and searches continues to rise. With 32–64 agents, you can operate a respectable system with near-maximum accuracy and reasonable latency.

V. CONCLUSION

This research drew out the framework for an IoT architecture that is optimized for agroecological monitoring in terms of interoperability, multi-agent functionality, and edge efficiency. A combination of calibrated probabilistic inference, modality-aware normalization, variance-preserving projection, ontology-aligned whitening, gated temporal encoding, and kernelized anomaly scoring is used in this arrangement. The stack maintained consistent and reliable performance within the constraints of the available resources throughout the field-style assessments. The success percentage of packet delivery was 98.7 percent when tested. The p95 network latency was still greater than the 33 ms SPARQL delay, even at 36 ms. When it comes to time-critical sensing and semantic querying, there is now absolutely no wiggle space. Evidence suggested that end-to-end discrimination had a stable baseline and improved by around 6-7 F1 points. In addition, it was shown that the daily F1 was around 0.88 and that it recovered rapidly after irrigation- and rain-induced perturbations. This demonstrates its resilience to environmental drift. The extraordinary probability calibration enabled the selection of defensible thresholds under operational risk, with an expected calibration error (ECE) of around 0.047 and a Brier score of roughly 0.082. The presence of a distinct operating environment that might affect capacity design becomes more obvious when we pass this stage, as the development of communication and inquiry costs driven by utility becomes more evident than previously. The findings show that it is possible to combine heterogeneous sensor networks into an auditable monitoring system by combining semantics-aware representation learning with efficient edge temporal inference.

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