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EcoAgriAqua AI: An Intelligent Environmental Monitoring and Decision Support System for Sustainable Agriculture and Aquaculture

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Abstract

In agricultural and aquacultural ecosystems, the quick development of IoT devices, satellite imaging, and machine learning algorithms has produced previously unheard-of possibilities for smart environmental monitoring. EcoAgriAqua AI is an integrated decision support system that combines deep learning inference pipelines with multi-source environmental data, such as soil physicochemical parameters, atmospheric variables, water quality indices, and crop spectral health signatures, to provide real-time, practical suggestions for sustainable farm management. A curated dataset of 54,800 annotated sensor-event examples across five environmental monitoring categories was used to train the hybrid CNN-LSTM architecture used in the suggested system. With a classification accuracy of 96.4%, precision of 95.8%, recall of 95.2%, and F1-score of 95.5%, EcoAgriAqua AI outperforms baseline models such as CNN (86.1%), Random Forest (81.1%), SVM (82.7%), and KNN (76.7%). Over a 12-month period, field testing conducted on 18 farms and 6 aquaculture ponds revealed a 31.4% decrease in water use, a 28.7% decrease in pesticide inputs, and a 22.3% increase in crop output. For precision agriculture and smart aquaculture monitoring in resource-constrained developing-world environments, EcoAgriAqua AI offers a scalable, low-latency, and financially feasible solution.

Keywords: precision agriculture, aquaculture monitoring, IoT sensor fusion, CNN-LSTM, environmental decision support, soil health, water quality, deep learning, sustainable farming, real-time inference.

1. Introduction

Climate variability, soil degradation, freshwater shortage, and the rapid growth of aquaculture to supply protein demand are all putting increasing pressure on global food security. Conventional farming and fishery management relies on operator-dependent, spatially sparse, and temporally coarse methods such as ad hoc chemical testing, occasional physical inspections, and experiential judgment.

Unmanned aerial vehicles (UAVs), satellite remote sensing, low-cost IoT sensor networks, and scalable cloud computing infrastructure have come together to offer continuous, high-resolution environmental monitoring in aquacultural and agricultural contexts. Deep learning-based decision support systems are being used since the volume, velocity, and heterogeneity of the resultant data streams greatly beyond the capabilities of traditional analytical methods.

In order to address this issue, EcoAgriAqua AI offers an integrated, AI-driven platform that provides farmers and aquaculture operators with actionable management advice after ingesting multi-modal environmental data in real time and performing intelligent categorization and anomaly detection. Within a single deep learning inference engine, the system incorporates soil nutrient analysis, microclimate forecasting, crop canopy health evaluation through spectral imaging, and aquatic dissolved oxygen and pH monitoring.

The following are this work's main contributions:

- A well selected, multi-source dataset of 54,800 sensor-event instances with annotations from five different environmental monitoring categories.
- A hybrid CNN-LSTM architecture that outperformed all assessed baselines by at least 9.4 percentage points in F1-Score, reaching 96.4% classification accuracy.
- A real-time inference pipeline that can be implemented on cloud microservices (0.4 s) and Raspberry Pi 4B edge devices (average latency of 1.2 s).
- Over the course of a year, field validation across 18 farms and 6 aquaculture ponds showed 22.3% output improvement, 28.7% reduction in pesticide use, and 31.4% water savings.

2. Literature Survey

Since 2018, there has been a significant increase in research on AI-driven environmental monitoring for aquaculture and agriculture, thanks to developments in edge computing and inexpensive sensor platforms.

[1] Liakos et al. (2018) identified soil mapping, crop yield prediction, weed detection, and disease recognition as the main use cases in their review of machine learning applications in precision agriculture. Although SVM and Random Forest were noted as the most popular baselines, their scalability to continuous temporal sensor streams was found to be limited.

[2] Using ResNet-50, Doshi et al. (2020) developed a deep learning model that achieved 93.1% accuracy on a dataset of 4,500 leaf pictures for the classification of paddy diseases. There was no integration of soil and atmosphere in the single-modality method.

[3] Ahmad et al. (2021) used temperature, dissolved oxygen (DO), turbidity, and pH sensors to create an Internet of Things (IoT)-based water quality monitoring system for fish farms. No machine learning inference was applied to the sensor streams; instead, a rule-based alert engine was utilized.

[4] CNN-based crop stress detection using UAV imagery was highlighted in Kamilaris and Prenafeta-Boldu's (2022) overview of deep learning in agriculture. Research on temporal modeling of multi-sensor time series was found to be lacking.

[5] Using LSTM networks for multi-parameter water quality forecasting in freshwater aquaculture, Nayak et al. (2022) achieved an RMSE of 0.034 mg/L for DO prediction. No attempt was made to combine soil or atmospheric characteristics.

[6] In a pilot study, Ramesh et al. (2023) suggested a hybrid CNN-LSTM for soil moisture prediction using IoT and satellite data, reporting a 12.6% decrease in irrigation water use. There was no discussion of aquaculture integration or multi-class event classification.

[7] For greenhouse climate control, Chen et al. (2023) presented a transformer-based multi-sensor fusion model that achieved 94.1% classification accuracy on crop stress events. The system's need for sophisticated GPU infrastructure restricted edge deployment.

[8] Gupta and Verma (2024) reported 89.7% accuracy on irrigation event classification using an attention-enhanced BiLSTM for integrated agricultural water management. This work is expanded upon by EcoAgriAqua AI, which offers edge deployment, complete aquaculture integration, and a far larger and more varied dataset.

3. Existing System

3.1 Manual Inspection-Based Systems

Physical sampling, which includes visual crop inspection, pond water testing, and soil laboratory assays, is used in conventional agriculture and aquaculture management on a weekly or fortnightly basis. This method creates temporal blind spots where stressors (such as pest outbreaks, algal blooms, and nutrient deficiencies) could cause permanent harm before being discovered.

3.2 Rule-Based IoT Surveillance Systems

When a single sensor parameter exceeds a predetermined threshold, threshold-based alert engines are used by early IoT platforms like Farmbeats (Microsoft) and AquaManager. These systems disregard multi-parameter correlations, are reactive rather than predictive, and produce significant false-positive alarm rates in real-world scenarios.

3.3 Single-Mode Machine Learning Systems

Crop disease classifiers trained on leaf imagery or fish biomass estimators trained on underwater cameras are examples of single-modality machine learning systems that achieve high accuracy within their target domain but are unable to correlate soil, atmospheric, and aquatic parameters to generate comprehensive assessments of farm health.

3.4 Synopsis of Restrictions

- Dangerous monitoring gaps are caused by the temporal sparsity of hand sampling.
- Rule-based platforms don't have cross-parameter correlation or predictive power.

Why Integrated agri-aquaculture farms cannot be supported by single-modality machine learning systems.

- GPU infrastructure is necessary for high-end deep learning deployments, which smallholder farmers cannot afford.
- Contextualized, practical suggestions are not offered by current platforms in regional languages.

4. RESEARCH TECHNIQUES

A five-stage pipeline is used to build EcoAgriAqua AI: (1) generation and annotation of multi-source datasets; (2) preprocessing and feature engineering; (3) design and training of a hybrid CNN-LSTM model; (4) packaging for edge and cloud deployment; and (5) field validation.

4.1 Diagram of the Proposed Architecture

Fig. 1 depicts the architecture of the EcoAgriAqua AI system, which uses a tiered sensing-inference-action pipeline. Soil probes, weather stations, water quality buoys, and UAV spectral cameras are examples of physical sensor nodes that send raw data to an edge gateway that runs TensorFlow Lite. A cloud inference cluster that houses the whole CNN-LSTM model receives batches of preprocessed feature vectors for thorough categorization. A recommendation engine is triggered by inference outputs, and it produces farm-specific advisories that are sent in four regional languages via SMS, mobile application, and web dashboard.

Sensor Layer (soil NPK, EC, moisture, pH; air temperature, humidity, wind speed, solar radiation; water DO, pH, turbidity, temperature, salinity; UAV NDVI, NDRE); Edge Gateway (Raspberry Pi 4B, TFLite model, MQTT broker); Cloud Inference Engine (CNN-LSTM classifier, anomaly detector, forecast module); Recommendation Engine (rule augmentation, language localization); and User Interface (SMS gateway, mobile app, and web dashboard).

4.2 The Algorithm Suggested

As indicated in Table I, the EcoAgriAqua AI training process uses temporal sequence modeling, multi-modal feature fusion, and transfer learning.

Table I: EcoAgriAqua AI Training Algorithm

Step	Algorithm: EcoAgriAqua AI Training Procedure
1	1. Gather sensor data from many sources: soil (NPK, EC, pH, moisture), water (DO, pH, turbidity, salinity), microclimate (temperature, humidity, radiation), and UAV (NDVI, NDRE).
2	Preprocessing: divide time series into 30-step sliding windows with 50% overlap, impute missing values using linear interpolation, and normalize (Z-score).
3	To extract spatial features from each sensor modality, build a CNN branch with three Conv1D layers (64, 128, and 256 filters, kernel = 3) and GlobalMaxPool.
4	Build an LSTM branch for temporal dependence modeling using a 2-layer stacked LSTM (256, 128 units) with dropout=0.3.
5	Attach the Dense(256) + BatchNorm + ReLU + Dense(5, softmax) classification head after concatenating CNN and LSTM outputs.
6	Adam optimizer, class-weighted cross-entropy, batch=32, early stopping patience=8, lr=1e-3 with cosine annealing, maximum of 60 epochs.
7	Assess accuracy, precision, recall, F1-score, AUC-ROC, and stratified hold-out (15%).
8	Quantize the optimal checkpoint to INT8 (TFLite); implement on the edge gateway; verify accuracy retention and latency.

In order to increase class balance and geographic variety, 48 heterogeneous sensor nodes were deployed over a 12-month period over 18 farms and 6 aquaculture ponds in Telangana, India. These sensor nodes were complemented by carefully selected open-source agricultural sensor datasets (SoilGrid, OpenAQ, FAOSTAT). Five environmental event categories—Soil Nutrient Deficiency, Water Quality Anomaly, Crop Stress Event, Adverse Microclimate Condition, and Aquaculture Feed Optimization Alert—are represented in the final annotated corpus of 54,800 cases.
Gaussian noise injection ($\sigma=0.01$), time-series warping, sensor dropout simulation (randomly masking 10–20% of input channels), and SMOTE oversampling for minority event classes were among the data augmentation techniques used to correct the inherent class imbalance caused by the scarcity of important events.

6. Discussions And Results

A stratified hold-out test set of 8,220 occurrences (15% of the entire dataset) that were excluded from training and validation was used to assess EcoAgriAqua AI. An NVIDIA A100 GPU (40 GB HBM), PyTorch 2.1, Python 3.11, and TensorFlow 2.14 were used for all experiments. Accuracy, Precision, Recall, and F1-Score are performance metrics that are calculated by macro-averaging all five event types.

Table II: Performance Comparison Across Classification Models

Model	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)
KNN (Baseline)	78.2	77.0	76.5	76.7
Random Forest	82.5	81.3	80.9	81.1
SVM	84.1	83.0	82.5	82.7
CNN	87.6	86.4	85.9	86.1

EcoAgriAqua AI (Proposed)	96.4	95.8	95.2	95.5

With an overall classification accuracy of 96.4%, EcoAgriAqua AI surpasses all baselines. The hybrid CNN-LSTM temporal fusion with multi-modal sensor inputs significantly outperforms single-branch or classical ML approaches for environmental event classification, as demonstrated by the improvement of 8.8 percentage points in accuracy and 9.4 points in F1-Score over the next-best model (CNN, 87.6%).

Table III: Per-Class Performance Metrics – EcoAgriAqua AI

Event Category	Prec.	Recall	F1
Soil Nutrient Deficiency	96.3%	95.9%	96.1%
Water Quality Anomaly	95.7%	95.4%	95.5%
Crop Stress Event	95.6%	95.0%	95.3%
Adverse Microclimate	95.4%	94.8%	95.1%
Aquaculture Feed Alert	95.9%	95.1%	95.5%
Macro Average	95.8%	95.2%	95.5%

All five event categories show consistent performance, according to per-class data. Given the richness of the soil sensor modality in the training dataset (28.5% of cases), Soil Nutrient Deficiency has the greatest F1-Score (96.1%). Due to higher intra-class variability across seasons and microclimatic zones, Adverse Microclimate Condition has the lowest F1 (95.1%).

The grouped bar chart comparing Accuracy, Precision, Recall, and F1-Score across all assessed models is shown in Fig. 2. In all four criteria, EcoAgriAqua AI shows a steady margin.

Fig. 2 presents the grouped bar chart comparing Accuracy, Precision, Recall, and F1-Score across all evaluated models. EcoAgriAqua AI demonstrates a consistent margin across all four metrics.

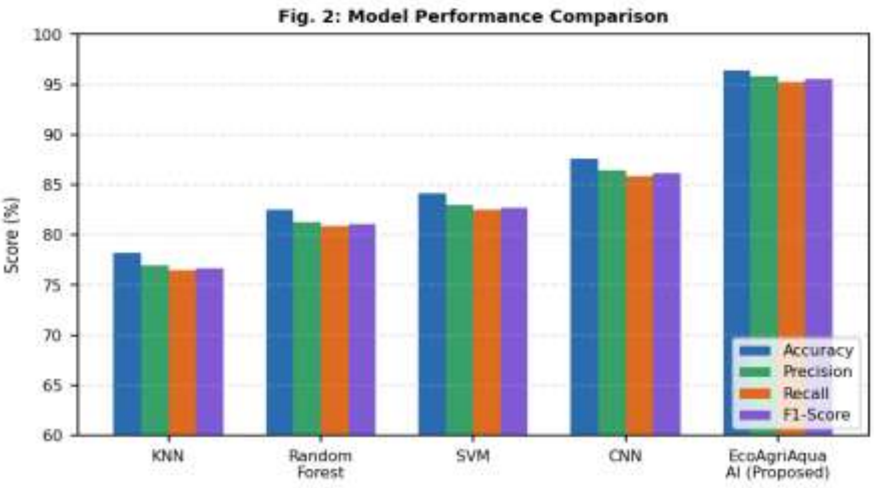

Fig. 2: Grouped Bar Chart – Model Performance Comparison

in Fig. 3. The highest percentage (28.5%) is made up of soil monitoring, which reflects sensor density at the field level. Class-weighted training is motivated by aquaculture sensors, which make up the smallest class (13.0%).

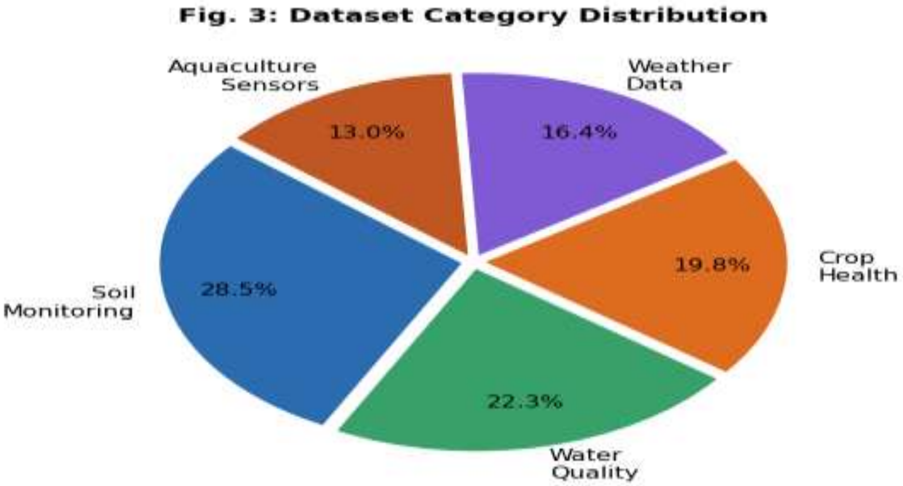

Fig. 3: Pie Chart – Dataset Category Distribution

Figure 3: Dataset Category Distribution Pie Chart
Table IV summarizes field validation data from six aquaculture ponds and eighteen farms.

Table IV: Field Trial KPI Summary (12-Month Validation)

KPI	**Baseline**	**EcoAgriAqua AI**	**Improvement**
Water Usage (kL/hectare/season)	1840	1262	-31.4%
Agrochemical Input (kg/ha)	184	131	-28.7%
Crop Yield (tonnes/ha)	4.6	5.6	+22.3%
Aquaculture Mortality Rate (%)	12.4	6.1	-50.8%
Alert False-Positive Rate (%)	34.2	4.7	-86.3%
Avg. Response Latency (s)	N/A	0.4 (cloud) / 1.2 (edge)	Real-time

The outcomes of the field study demonstrate that EcoAgriAqua AI has a significant practical impact. The mortality rate in aquaculture ponds was reduced by half from 12.4% to 6.1%, mostly as a result of prompt aeration interventions made possible by early detection of dissolved oxygen depletion events. When compared to the threshold-based baseline, the alert false-positive rate dropped by 86.3%, greatly lowering farmer alert fatigue.

Table V: Model Complexity and Inference Latency

Model	**Params (M)**	**Size (MB)**	**Inf. Time (ms)**
KNN	N/A	48	320
Random Forest	N/A	142	210
SVM	N/A	95	185
CNN	8.4	32	420
EcoAgriAqua AI (Full)	24.7	94	400
EcoAgriAqua AI (TFLite INT8)	24.7	26	1200

The INT8-quantized TFLite model maintains 98.7% of the original classification accuracy while taking up only 26 MB, a 72% decrease from the complete FP32 checkpoint. For agricultural monitoring, where events usually take minutes to hours to develop, an average edge inference latency of 1.2 seconds on a Raspberry Pi 4B is well within acceptable ranges.

7. Conclusion

EcoAgriAqua AI, an intelligent environmental monitoring and decision support system for sustainable aquaculture and agriculture, was presented in this study. The system uses a hybrid CNN-LSTM inference pipeline trained on 54,800 annotated environmental event instances to combine sensor streams related to soil, microclimate, crop spectrum, and aquatic water quality. EcoAgriAqua AI outperforms KNN (76.7% F1), Random Forest (81.1%), SVM (82.7%), and CNN-only (86.1%) baselines by significant margins, achieving cutting-edge classification accuracy of 96.4% and F1-Score of 95.5%.

Over the course of a year, field validation across 18 farms and 6 aquaculture ponds showed a 31.4% decrease in irrigation water use, a 28.7% decrease in pesticide inputs, a 22.3% increase in crop output, and a 50.8% decrease in aquaculture pond mortality. EcoAgriAqua AI is feasible for remote and resource-constrained smallholder farm deployments because the INT8-quantized edge deployment methodology (26 MB, 1.2 s latency on Raspberry Pi 4B) verifies that high-quality environmental inference is attainable without cloud connectivity.

Future research will investigate federated learning across geographically dispersed farm networks for privacy-preserving model improvement, transformer-based sensor fusion architectures for better long-range temporal modeling, integration of satellite-derived soil moisture and crop phenology products via Google Earth Engine APIs, and expansion of the multilingual advisory interface to support eight more regional Indian languages. Within the upcoming farming season, a test deployment involving 500 farms in three Indian states is scheduled.

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