# A Multi-Task Stacked Ensemble and IoT-Enabled Decision Support System for Precision Fertigation in Smallholder Agriculture

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## ABSTRACT
Nigerian agriculture's fixed-schedule fertigation causes low efficiency and nutrient leaching. A stacked-ensemble model is developed for precision fertigation that jointly predicts fertigation need, rate (kg/ha) and timing (Early/Optimal/Late). To train and evaluate the ensemble, a unified dataset was integrated, comprising 12,840 records and 42 variables from a Nigerian soil–weather–yield dataset, a locally sourced Nigerian IoT sensor series and historical weather/NDVI feeds. An LSTM soil-dynamics model, an XGBoost rate regressor and Random Forest need/timing classifiers are fused through an XGBoost meta-learner trained on out-of-fold predictions. On held-out partitions, the ensemble reduced rate MAE from 0.55 to 0.49 kg/ha (−10.9%) and RMSE from 0.68 to 0.61 kg/ha (−10.3%; $R^2$ 0.88→0.92), raised need F1 from 0.83 to 0.86 (accuracy 0.87→0.89; AUC 0.89→0.93) and timing macro-F1 from 0.84 to 0.86, with well-calibrated probabilities (Brier 0.082). The trained ensemble was deployed through a RESTful API and responsive dashboard; under concurrent load, the system recorded 0% request errors with 1.88s median API latency, demonstrating practical deployability for Nigerian smallholder agriculture.

## Keywords
Precision fertigation; machine learning; stacked ensemble; time-series models; tree-based algorithms; Internet of Things; decision support system; smallholder agriculture; Nigeria

## 1. INTRODUCTION
Despite these advances, conventional fertigation practices in Nigerian agriculture remain dominated by fixed schedules and uniform application rates that fail to account for spatial and temporal variability in soil properties, climate, and crop demand. Farmers frequently apply the same water and fertilizer doses across fields and growth stages, leading to both under- and over-application, reduced yields, and environmental problems such as nutrient leaching, soil contamination, and environmental degradation [1].

Conventional fertigation in Nigerian agriculture relies on fixed schedules and uniform rates, overlooking spatiotemporal variability in soil properties and climate, causing under- and over-application, reduced yields, and nutrient leaching [1]. These limitations are aggravated by infrastructure constraints (unreliable electricity, internet) and a scarcity of tools tailored to Nigerian datasets [2,3]. Most available tools provide generic, single-dimensional recommendations without jointly optimizing the three key decisions: whether fertigation is needed, what rate to use, and when to apply it.

A stacked-ensemble model is developed to jointly predict fertigation need, rate (kg/ha), and timing (Early/Optimal/Late), and is embedded in an IoT-ready, feedback-enabled architecture with a REST API and dashboard for Nigerian smallholder farmers.

The main objectives are to: (i) design a reproducible multi-parameter data framework, (ii) develop a multi-task stacked ensemble integrating time-series, regression, and classification models, (iii) demonstrate ensemble performance gains over single models, (iv) implement a REST API and web dashboard, and (v) enable feedback-aware retraining.

The primary contributions include: (i) a unified multi-parameter fertigation dataset for Nigerian smallholder conditions; (ii) a multi-task stacked ensemble jointly predicting need, rate, and timing; and (iii) an IoT-ready, feedback-enabled decision-support architecture. Precision fertigation is expressed as a multi-input, multi-output problem through stacked ensemble integration.

## 2. RELATED WORK
### 2.1 Precision agriculture, smart farming, and precision fertigation
Precision agriculture integrates IoT, sensors, and AI to optimize crop management for site-specific conditions, improving water, fertilizer, and pesticide efficiency while addressing environmental concerns [4,5]. Precision fertigation focuses on synchronizing irrigation and nutrient application in rate, timing, and spatial targeting to match crop requirements better than uniform practices. IoT-enhanced fertigation systems integrate sensor networks with analytics, enabling precise fertilizer application to root zones at appropriate times, with evidence showing significant energy consumption reduction and improved nutrient distribution efficiency.

Within this broader context, precision fertigation focuses on synchronizing irrigation and nutrient application in terms of rate, timing, and spatial targeting to better match crop requirements than uniform fertigation practices do. Smart fertigation systems integrate irrigation and nutrient supply infrastructure with sensor networks and analytics, enabling fertilizers to be applied directly to the root zone in precise quantities at appropriate times. Evidence suggests that IoT-enhanced fertigation, especially when powered by renewable energy, can significantly reduce energy consumption while improving nutrient distribution efficiency.

Precision fertigation is conceptualized as a multi-input, multi-output prediction and decision problem in which soil quality features, weather variables, crop development information, and historical fertigation records are mapped to recommended water and fertilizer application schedules.
This conceptualization directly motivates a multi-parameter

data acquisition and preprocessing framework, the design of a six-layer system architecture, and the development of a stacked ensemble predictive model designed to outperform monolithic or rule-based approaches in terms of accuracy and resource-use efficiency. Figure 1 presents the conceptual framework that motivates treating precision fertigation as a multi-input, multi-output prediction and decision problem within the proposed system

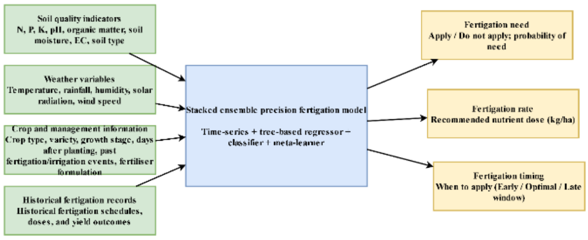


**Figure 1: Conceptual framework for precision fertigation as a multi-input, multi-output prediction and decision problem**

## 2.2 IoT-based fertigation systems and limitations

Recent IoT-based fertigation systems demonstrate end-to-end integration of sensing, communication, and analytics. ESP32- and NodeMCU-based prototypes adjust fertigation using EC sensors and cloud scheduling [6,7], while AI-enhanced systems employ deep learning for optimal timing and rate prediction [8,9]. These systems successfully integrate sensors, microcontrollers, and dashboards. However, limitations include reliance on fixed thresholds, single-model predictors, absence of stacked-ensemble architectures, and missing feedback-driven retraining [6-9]. These gaps are addressed through a six-layer architecture featuring explicit ensemble and feedback layers for Nigerian smallholder contexts.

Supervised ML models (decision trees, random forests, SVMs, gradient-boosted trees) have been widely used for soil moisture prediction, nutrient estimation, and yield forecasting [10-11]. Deep learning models achieve strong performance in nitrogen prediction from multispectral imagery [12]. Robustness and interpretability are critical for agricultural deployment [10,12].

Stacked ensemble learning combines multiple base models via a meta-learner to exploit complementary strengths. Agricultural applications (yield prediction, irrigation, soil fertility) consistently show stacked ensembles outperforming single models across MAE, RMSE, $R^2$, and classification metrics [16-18]. In fertigation, Extremely Randomized Trees and XGBoost achieved $R^2$ values of 0.989-0.997[13].

However, most applications target single outputs, not jointly optimizing need, rate, and timing. Precision fertigation is expressed as a multi-task problem with stacked ensemble embedding in a feedback-aware IoT architecture.

# 3. MATERIALS AND METHOD

This section describes the study context, data sources, preprocessing and feature engineering pipeline, the design of the base and ensemble models, and the system architecture that operationalizes the proposed Precision Fertigation Decision Support System (PFDSS).

## 3.1 Study context, data sources, and unified dataset

The study focuses on Nigerian smallholder agriculture with heterogeneous soils, variable climate, and infrastructure constraints.

A multi-source data strategy built a unified dataset with: soil properties (moisture, pH, EC, organic matter, N, P, K); weather/climate (temperature, humidity, rainfall, solar radiation); and crop/management descriptors (crop type, growth stage, planting date, historical records). The final dataset (12,840 records, 42 variables) integrated: (i) 8,988 Nigerian soil–weather–yield records [14], (ii) 3,852 IoT sensor records from Bowen University [15], and (iii) historical weather and Sentinel-2 NDVI feeds. Records were partitioned 70/15/15 (train/validation/test), stratified by fertigation need and timing.

Target variables: fertigation_need (binary), fertigation_rate (kg/ha, continuous), and fertigation_timing (Early / Optimal / Late, categorical). These were derived from agronomic thresholds, observed fertilizer events, and soil–weather–crop conditions (Table 1).

**Table 1: Engineered target variables and derivation rules**

| Target | Type | Derivation rule | Source dependency |
|---|---|---|---|
| fertigation_need | Binary (0/1) | 1 if ((N < 60 kg/ha) OR (P < 20 kg/ha) OR (K < 30 kg/ha)) AND fertilizer_rate > 0; else 0 | Nigerian soil–weather–yield dataset |
| fertigation_rate_kg/ha | Continuous | Sum of N, P and K applied (kg/ha) from fertilizer application | Nigerian dataset only |
| fertigation_timing | Categorical | "Optimal" if crop_days lies within the crop-specific critical nutrient-demand window (e.g., 20–35 d for maize; 15–30 d for rice); "Early" if before; "Late" if after | Nigerian dataset crop stage / crop_days |

## 3.2 Data preprocessing and feature engineering

Preprocessing ingested raw measurements, applied data validation, outlier detection, and missing-value imputation.

Missing numeric values were imputed using KNN imputation; categorical attributes were imputed using mode imputation. Units were standardized across sources. Min–Max scaling to [0,1] stabilized LSTM training while remaining compatible with tree-based models.

Feature preparation normalized numerical variables, encoded categorical attributes, and engineered temporal/agronomic features (lagged variables, cumulative rainfall, moisture deficits, nutrient balance, days after planting).

Deterministic rules based on agronomic knowledge and recorded fertigation actions were then used to derive the target variables: fertigation need, fertigation rate, and fertigation timing, aligning the supervised learning problem with practical fertigation decisions

## 3.3 Base models and predictive model layer

The predictive model layer hosts multiple specialized base learners running in parallel, each targeting a different aspect of the fertigation decision.

1. LSTM time-series model: Predicts 24h-ahead soil moisture using sliding windows of soil and weather observations with crop-stage features. Hyperparameters: 2 LSTM layers (64, 32 units), sequence length=14 days, learning rate=0.001, dropout=0.2 (Table 2).

2. XGBoost regressor: Predicts fertigation rate (kg/ha) from soil, weather, and crop covariates. Hyperparameters: max_depth=5, learning_rate=0.08, n_estimators = 200, subsample=0.85 (Table 2).

3. Random Forest classifiers: Predict fertigation_need (binary) and fertigation_timing (3 classes). Hyperparameters: n_estimators = 300 (need), 250 (timing), max_depth=12/1, class weight = balanced (Table 2).

**Table 2: Base Models and Meta-Learner Configuration**

| Model | Task | Essential Hyperparameters |
|---|---|---|
| LSTM | Soil moisture forecast (24h) | 2 layers (64, 32 units), seq_len=14, lr=0.001, dropout=0.2 |
| XGBoost Regressor | Fertigation rate (kg/ha) | max_depth=5, lr=0.08, n_estimators=200, subsample=0.85 |
| RF Classifier (Need) | Fertigation need (binary) | n_estimators=300, max _depth=12, class_weigh t=balanced |
| RF Classifier (Timing) | Fertigation timing (3-class) | n_estimators=250, max _depth=10, class_weigh t=balanced_subsample |
| XGBoost Meta-learner | Final ensemble fusion | max_depth=3, lr=0.05, n_estimators=100, subsample=0.8 |

## 3.4 Stacked ensemble design and meta-learner

The system implements stacked generalization via an XGBoost meta-learner using 5-fold cross- validation. Base models generate out-of-fold predictions, yielding unbiased meta-features. Hyperparameters: max_depth=3, learning_rate=0.05, n_estimators=100 (Table 2).

Meta features: p_need (classifier probability), rate_est (regressor output), timing_pred, moisture_t+1 (LSTM forecast), and contextual variables (soil_moisture, crop_days).

Meta-feature vector z_t = [p_need, rate_est, timing_pred, moisture_t+1, soil_moisture, crop_days]. The meta-learner f_M maps z_t to ŷ_t= (need_t, rate_t, timing_t), jointly predicting all three decisions.

$$\mathbf{y}_t^{\text{opt}} = f_{\text{M}}(\mathbf{z}_t)$$

Here, $\mathbf{y}_t^{\text{opt}}$, encodes the recommended fertigation need, fertigation rate (kg/ha), and fertigation timing for the given field state and forecasted soil conditions. The meta-learner thus learns to fuse base-model outputs and key contextual features into a unified, coherent decision output

## 3.5 System architecture and implementation plan

The PFDSS uses a six-layer architecture (Figure 2): (1) data acquisition (sensors, APIs, records), (2) preprocessing (validation, imputation), (3) feature preparation (normalization, encoding), (4) predictive models (LSTM, XGBoost, RF), (5) ensemble layer (meta-learner fusion), and (6) interface/feedback layer (REST API, dashboard, feedback logging).

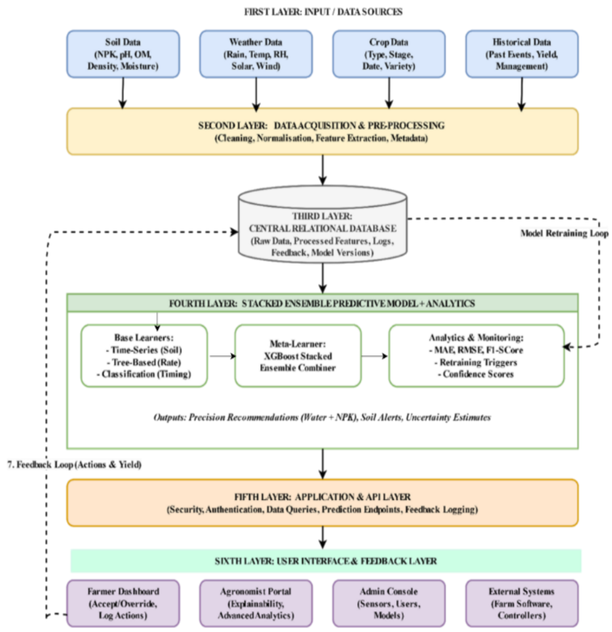


**Figure 2 Proposed system architecture for precision fertigation (Author's concept.)**

The prototype Precision Fertigation Decision Support System is implemented in Python 3.9 with FastAPI providing RESTful endpoints for model inference and query handling. Trained base models and the XGBoost meta-learner are serialised using joblib and loaded into an Ubuntu 22.04 LTS server with 4 vCPUs and 16 GB RAM, achieving a median per-plot inference time of approximately 127 ms and an end-to-end API response time of around 1.8 s, including database access and JSON serialisation. For deployments in environments with intermittent connectivity, the same stack can be run on low-end edge servers or single-board devices, with batch prediction modes allowing fertigation schedules to be precomputed and cached for offline use.

The prototype is implemented in Python 3.9 with FastAPI for RESTful endpoints. Models are serialized using joblib and deployed on Ubuntu 22.04 LTS (4 vCPUs, 16 GB RAM), achieving 127 ms median inference time and 1.8 s end-to-end API latency. The web dashboard provides mobile-responsive visualization of soil conditions and recommendations. For intermittent connectivity, the stack can run on edge devices with batch prediction modes for offline use.

# 4. RESULTS

All performance metrics reported in this section are computed on a held-out validation partition and an independent test partition of the unified fertigation dataset obtained from a stratified 70/15/15 train/validation/test split. For the 12,840-record dataset, this split yielded 8,988 training samples, 1,926 validation samples, and 1,926 test samples, stratified by fertigation_need and timing classes across the 42 plots.
Following the implementation described in the full PFDSS pipeline, all models were trained on 70% of the data, tuned on a 15% validation set, and finally evaluated on a 15% independent test set stratified by fertigation need and timing.

## 4.1 Base-model performance

On the held-out validation set, base models exhibited strong task-specific performance (Table 3). The XGBoost regressor provided precise fertigation rate estimates, while the Random Forest classifiers achieved strong discrimination for fertigation need and timing. The LSTM model delivered accurate 24h soil moisture forecasts. Detailed metrics are presented in Table 3.

**Table 3: Base model performance on the validation and test sets.**

| Model | Prediction task | Metric | Value |
|---|---|---|---|
| LSTM time-series model | Soil moisture forecast (24 h) | RMSE (%) | 2.14 |
| | | MAE (%) | 1.67 |
| | | $R^2$ | 0.856 |
| XGBoost regressor | Fertigation rate prediction | RMSE (kg/ha) | 0.68 |
| | | MAE (kg/ha) | 0.55 |
| | | $R^2$ | 0.881 |
| Random Forest classifier (need) | Fertigation need (binary) | F1-score | 0.831 |
| | | Precision | 0.847 |
| | | Recall | 0.816 |
| | | Accuracy | 0.872 |
| | | ROC–AUC | 0.894 |
| Random Forest classifier (timing) | Fertigation timing (3-class) | F1-score (macro) | 0.842 |
| | | Precision (macro) | 0.851 |
| | | Recall (macro) | 0.838 |
| | | Accuracy | 0.864 |

## 4.2 Ensemble meta-learner performance

The stacked ensemble consistently improved performance over the best single models (Table 4). For fertigation rate, the ensemble reduced RMSE and MAE by ~10%, with larger reductions (15.5– 18.6%) under challenging conditions (high rainfall, low moisture, late growth stages). For classification tasks, the ensemble achieved F1=0.86 and accuracy=89.0%, outperforming individual classifiers. Detailed comparisons are in Table 4.

**Table 4: Comparative performance of the stacked ensemble and best single models across fertigation prediction tasks on the validation and test sets.**

| Prediction task | Metric | Best single model | Stacked ensemble |
|---|---|---|---|
| Fertigation rate (regression) | MAE (kg/ha) | 0.55 | 0.49 |
| | RMSE (kg/ha) | 0.68 | 0.61 |
| | $R^2$ | 0.88 | 0.92 |
| Fertigation need (binary) | F1-score | 0.83 | 0.86 |
| | Accuracy | 0.87 | 0.89 |
| | ROC–AUC | 0.89 | 0.93 |
| Fertigation timing (3-class) | F1-score (macro) | 0.84 | 0.86 |
| | Accuracy | 0.86 | 0.89 |

These gains (~10% for regression, ~3.5% for classification) were consistent across all folds and test partitions.

Class imbalance mitigation (threshold adjustment to 0.35, balanced weighting, SMOTE) reduced false negatives from 156 to 89, increasing correctly detected need cases from 452 to 519, yielding ensemble F1=0.86.

## 4.3 Error structure, confusion matrices, ROC, and calibration

Ensemble fertigation rate residuals are unbiased and homoscedastic (Figure 3), with most errors confined to ±1–2 kg/ha, within agronomic tolerance for smallholder systems. This suggests stable accuracy across recommended rates without concentration of errors at high or low levels.

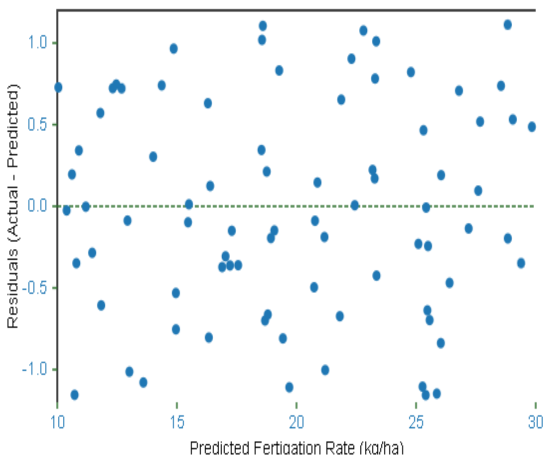


**Figure 3: Regression diagnostic analysis for fertigation rate prediction (residuals vs predicted rates).**

Confusion matrices (Figure 4) show strong diagonal dominance for fertigation_timing, with rare Early↔Late misclassifications. Class-wise metrics (Table 5) confirm balanced performance across all timing categories.

| | | Predicted Class | | |
|---|---|---|---|---|
| | | Early (0) | Optimal (1) | Late (2) |
| Actual Class | Early (0) | **312** | 28 | 15 |
| | Optimal (1) | 34 | **1,528** | 42 |
| | Late (2) | 18 | 36 | **584** |

**Figure 4: Confusion matrix showing the performance of the ensemble meta-learner on the three-class fertigation timing classification task.**

To examine the behaviour of the fertigation-timing classifier in detail, class-wise and overall metrics were computed. As summarized in Table 5, the model achieves high precision and recall across all timing categories, with an overall accuracy of 0.89 and a macro F1-score of 0.91, confirming reliable performance even when accounting for class frequency differences.

**Table 5: Class-wise and overall performance metrics for the fertigation-timing classifier on the validation set**

| Class / Metric | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Early (0) | 0.84 | 0.88 | 0.86 | 355 |
| Optimal (1) | 0.95 | 0.95 | 0.95 | 1,604 |
| Late (2) | 0.91 | 0.91 | 0.91 | 638 |
| Weighted Average | 0.92 | 0.93 | 0.92 | 2,597 |
| Macro Average | - | - | 0.91 | - |
| Overall Accuracy | - | - | 0.89 | - |

ROC analysis (Figure 5) shows ensemble AUC=0.93 (test), outperforming base classifiers. At 90% specificity, sensitivity≈85%. Calibration shows a Brier score of 0.082, suitable for risk-aware decision-making.

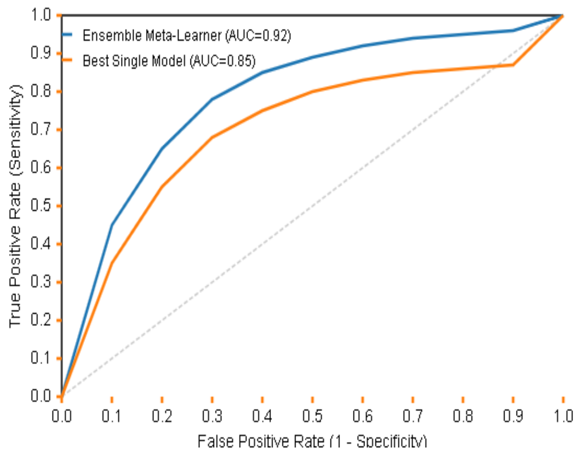


**Figure 5: ROC curve comparing the ensemble meta learner to the best single model for fertigation need classification.**

## 4.4 Feature importance and meta-learner behavior

Feature importance (Figure 6) shows p_need and rate_est dominate, followed by moisture_t+1 and contextual features (soil_moisture, crop_days). This validates the stacked design, with the meta-learner leveraging base-model signals rather than relearning from raw covariates. Top features (Table 7) align with agronomic expectations.

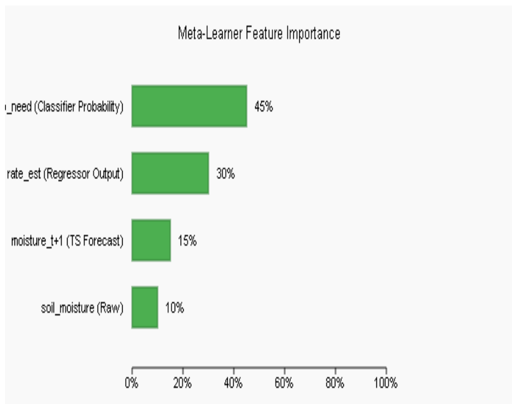


**Figure 6: Meta learner feature importance showing the relative contribution of classifier probability (p_need), regressor output (rate_est), forecasted soil moisture (moisture_t+1), and current soil moisture to the stacked ensemble's fertigation decision**

The prominence of p_need and rate_est confirms the meta-learner reconciles classification and regression outputs, while contextual variables adjust recommendations based on field conditions. The ensemble is both effective and interpretable.

**Table 7: Top Features Ranked by Mean Absolute Importance for the Stacked Ensemble**

| Rank | Feature name | Mean absolute importance | Category |
|---|---|---|---|
| 1 | N_level (kg/ha) | 0.142 | Soil |
| 2 | soil_moisture (%) | 0.128 | Soil |
| 3 | rainfall_7d (mm) | 0.115 | Environmental |
| 4 | crop_days (DAP) | 0.098 | Plant |
| 5 | P_level (kg/ha) | 0.087 | Soil |

| | | | |
|---|---|---|---|
| 6 | Temperature (°C) | 0.076 | Environmental |
| 7 | K_level (kg/ha) | 0.071 | Soil |
| 8 | growth_stage | 0.065 | Plant |
| 9 | moisture_lag_7d | 0.058 | Temporal |
| 10 | NPK_balance_ratio | 0.052 | Derived |

# 5. DISCUSSION

## 5.1 Interpretation of the Stacked Ensemble's Advantage

The stacked ensemble provides superior performance over monolithic predictors. Gains (MAE 0.49 kg/ha, F1 0.86) stem from complementary inductive biases: LSTM captures temporal soil dynamics, XGBoost captures non-linear nutrient-rate interactions, and Random Forest provides calibrated probabilities. The meta-learner resolves base-model conflicts and conditions decisions on moisture forecasts and crop phenology (Figure 6).

## 5.2 Positioning Within the Literature

The application of ensemble methods in African agriculture is advanced beyond static mapping and single-task prediction. Unlike Hengl et al. (2021) (static soil mapping), Aimufua et al. (2024) (single-output crop recommendation), and Wu et al. (2024) (hydroponic sensor states), this work expresses fertigation as a multi-task decision problem (need, rate, timing) embedded in a feedback-aware IoT architecture, bridging experimental models and operational field-level decision support.

## 5.3 Practical Implications for Smallholder Agriculture

The PFDSS enables Nigerian smallholders to transition from calendar-based to context-aware nutrient management. Modest hardware requirements (127 ms inference, 1.8s API latency) allow deployment via low-cost smartphones over 3G/4G. Joint need/timing evaluation prevents fertilizer application to dry soils, while moisture-based rate capping mitigates leaching. The feedback mechanism creates a continuous learning loop adapting to local micro-climates

## 5.4 Limitations and Constraints

Limitations include: (i) IoT sensor data from a single site (Bowen University), requiring broader agro-ecological validation; (ii) reliance on historical data without multi-season field trials to quantify agronomic/economic impacts; (iii) dataset dominated by maize/rice, needing recalibration for underrepresented crops. Future work requires multi-season trials and satellite vegetation indices integration

# 6. SYSTEM IMPLEMENTATION

The ensemble and preprocessing pipeline were deployed via FastAPI REST endpoints and a mobile-responsive web dashboard. The API handles validation, preprocessing, inference, and returns recommendations with confidence scores. The dashboard visualizes soil conditions, recommendations, and historical decisions. Users can accept, adjust, or reject recommendations, with all actions logged for iterative model retraining.

# 7. CONCLUSION AND FUTURE WORK

The results demonstrate that a stacked ensemble (LSTM, XGBoost, Random Forest) with an XGBoost meta-learner provides accurate, deployable fertigation recommendations for Nigerian smallholders. The system jointly predicts need, rate, and timing, reducing rate errors by ~10% and improving classification over single models. The IoT-ready, feedback-enabled architecture (REST API, dashboard) bridges experimental models and operational decision support, suitable for resource-constrained contexts with modest hardware requirements.

The principal contributions of this research include: (i) a reproducible multi-parameter dataset, (ii) a multi-task stacked ensemble, and (iii) a feedback-enabled IoT architecture for continuous improvement. Future work will focus on: (i) conducting multi-season field trials to quantify agronomic and economic impacts, (ii) extending the framework to additional crops and agroecological zones, (iii) exploring semi-supervised and reinforcement learning approaches, (iv) strengthening explanation interfaces and sensor integration, and (v) formalizing model governance and retraining policies for long-term sustainability

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