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Soil Analysis for Crop Recommendation using Machine Learning Algorithms

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Abstract

Modern surveillance systems often struggle to detect and respond to threats in real time. This paper introduces a system that uses context-aware threat intelligence to detect weapons, recognize violent actions, analyze time-based patterns, and assess potential threats based on the situation, all to spot unusual behaviour in real-time video feeds. The proposed system utilizes YOLO-based deep learning models to detect weapons and classify human behaviour. On the other hand, a scoring engine determines the level of risks from the objects observed, the behaviour pattern, the location, and past occurrences. High-risk occurrences will automatically be accompanied by raising an alarm, collecting the evidence, reporting the occurrence, and sending emails. In order to foster openness in the process and increase the level of confidence, Explainable Artificial Intelligence (XAI) methods including SHAP (SHapley Additive exPlanations) and Grad-CAM are applied to enhance transparency. Also, a real-time dashboard for incidents is put up for monitoring and analyzing incidents.

Keywords: *Artificial Intelligence, Smart Surveillance, Threat Detection, Weapon Detection, Human Behaviour Analysis, Threat Intelligence, Explainable AI, Computer Vision.*

1. Introduction

The increasing global food demand has driven critical advancements in smart agricultural practices that automatically determine optimal soil utilization strategies from real-time environmental attributes. Conventional farming practices depend heavily on historical trends or manual laboratory soil sampling, creating delayed operational reactions when micro-climate anomalies occur. Thanks to developments in machine learning, macro-nutrient optimization can be determined automatically, increasing the resilience and productivity of modern farming systems. However, many current solutions execute single-dimensional classifications without incorporating surrounding contextual elements like live rainfall indices or historical soil wear data. To solve this problem, we propose a novel framework consisting of five core components: soil macro-nutrient evaluation, ambient weather tracking, temporal seasonal correlation, contextual yield optimization, and Explainable AI. The framework minimizes crop failure rates and prevents fertilizer waste, making it ideal for precision farming initiatives.

Objectives

- To analyze soil macro-nutrients (N,P, K) and pH metrics using deep learning ensembles.
- To classify optimal soil suitability and environmental boundaries across multi-class crop choices.
- To estimate an aggregated recommendation confidence score basedon soil chemistry, historic yields, and immediate weather parameters.

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- To provide automated alert generation and localized agronomic action reports.
- To promote system transparency using Explainable AI techniques like SHAP contribution analysis.

2. Literature Survey

Table 1 Comparison of Existing Studies

Ref.	Method	Advantages	Limitations
1	Regression Analysis	Fast execution times	Incapable of non-linear multi-class mapping
2	SVM Soil Profiling	Precise localized boundaries	Fails under massive, high-dimensional datasets
3	KNN Classifier	Simple logic implementation	Highly sensitive to scaling noise in rainfall attributes
4	Baseline Random Forest	Outstanding multi-class performance	Lack of interpretability for field deployment
5	SHAP Interpret ability	Explains localized predictions	Missing automated, closed-loop alert infrastructure
6	IOT Climate Trackers	Captures high-fidelity live data	Lacks deep predictive crop recommendation logic

2.1.Research Gap

Existing smart agriculture frameworks concentrate on standalone soil property analysis or regional weather predictions separately. Although some systems combine weather elements into their models, only a marginal percentage integrate macro-nutrient dynamics, live contextual micro-climate feeds, long-term crop rotation histories, and explainable AI architectures simultaneously. Most current solutions do not provide automated end-to-end alert pipelines either. Hence, a clear necessity exists for a unified precision agriculture network covering all aspects of context-aware crop intelligence.

3. Proposed Methodology

3.1. System Architecture

Figure 1 processes raw agricultural data through nutrient evaluation and climate profiling channels. The extracted variables are analyzed by deep ensemble classifiers to project yield probabilities, calculate dynamic viability scores, and trigger real-time digital dashboard updates, automated SMS/email action reports, and structural SHAP explanations.

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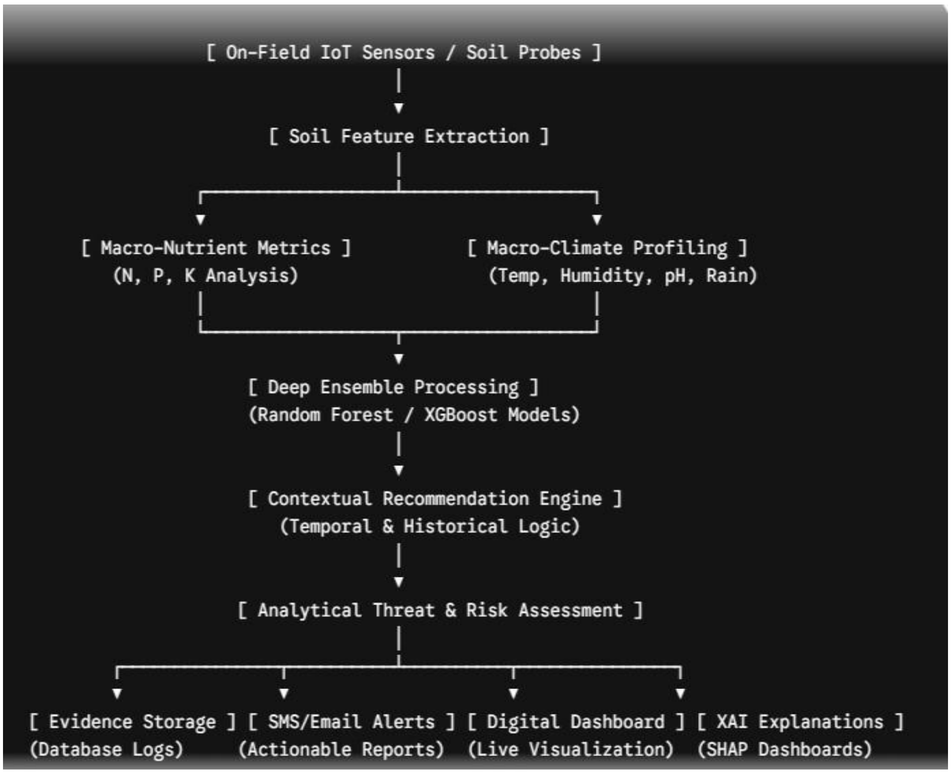

Figure 1 Architecture of the Proposed Precision Agriculture Intelligence Framework

3.2. Workflow Diagram

Figure 2 outlines the operational lifecycle of the system. Incoming data runs through preprocessing scales, passes across optimized classification trees, and maps into a contextual scoring algorithm to isolate the ideal crop match before feeding into the XAI validation interface.

3.3.Dataset Description

Two separate variants of agronomic datasets were applied during system configuration. The soil compilation dataset incorporates multi-class distributions tracking Nitrogen (N), Phosphorus (P), Potassium (K), and pH scales across diverse geographic profiles. The external climate matrix logs target parameters spanning three macro-categories: Normal Arid, Moderate Temperate, and Tropical Wet, ensuring reliable pattern tracking across unstable environmental situations. Data augmentation strategies, including synthetic oversampling (SMOTE) and random distribution scaling, were applied to preserve feature stability.

3.4.Chemical Profiling Module

The chemical profiling component handles the continuous calculation of foundational soil properties. Features are captured directly using optical sensors and micro-probe setups to compile real-time configurations of vital macro-nutrients:

- Nitrogen (N): Analyzes vegetative foliage health baselines (mg/kg).
- Phosphorus (P): Validates root system development and cellular structures (mg/kg).
- Potassium (K): Monitors metabolic resilience and fluid regulation thresholds (mg/kg).

3.5.Climatic Classification Module

The climatic analysis module handles volatile external variables that directly impact root absorption dynamics. Each sample feeds into an optimized multi-output classifier to output a continuous score across target parameters: Ambient Temperature (°C), Relative Humidity (%), and Seasonal Precipitation (mm). The candidate class possessing the highest statistical confidence is forwarded directly to the decision engine.

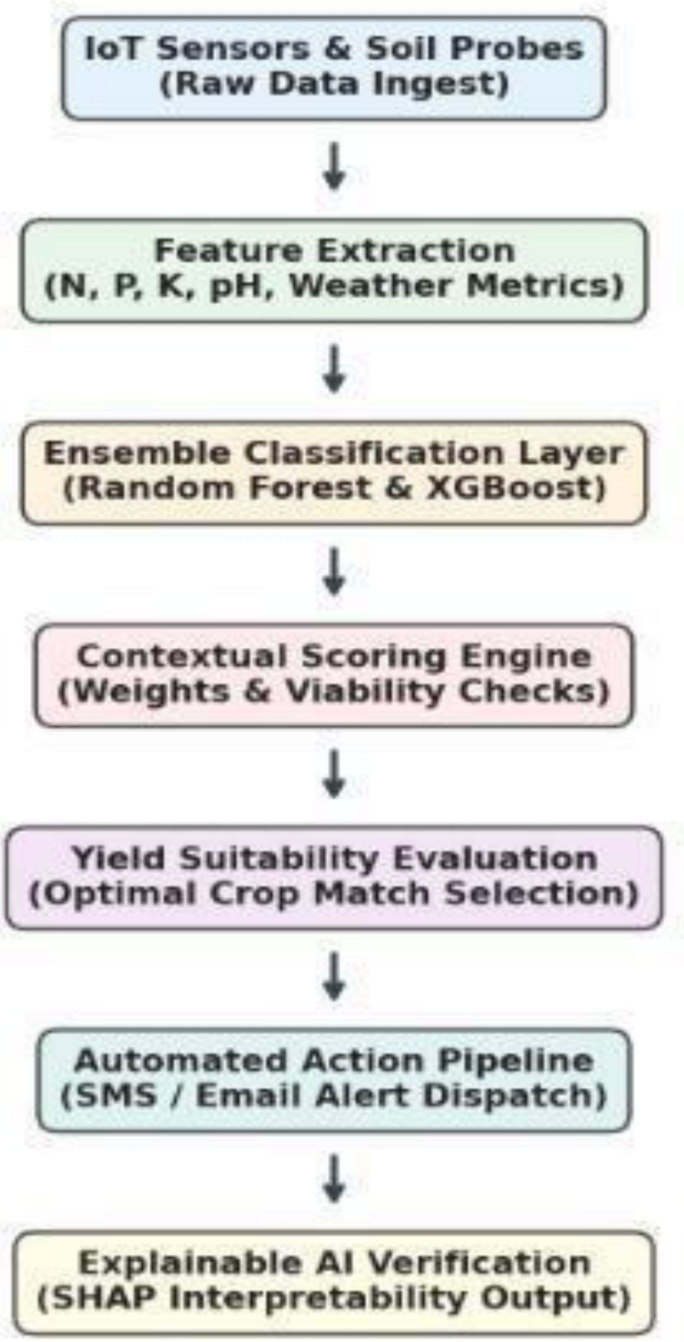

Figure 2 **Proposed System Workflow**

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3.6.Context-Aware Agro-Intelligence Engine

The Agro-Intelligence Engine handles contextual data synthesis by running an aggregated evaluation loop across nutrient, climatic, temporal, and crop rotation history matrices to confirm real-time viability. Viability Score = Nutrient Score + Climate Score + Temporal Score + History Score

Table 2 Recommendation Confidence Classification

Score Range	Suitability Classification	Action Protocol Triggered
0 – 20	Critical Deficit / Unviable	Crop Cultivation Prohibited; Soil Remediation Triggered
21 –70	Marginal / Low Confidence	Auxiliary Fertilization Required Before Sowing
71 –110	Optimal / High Confidence	Standard Sowing Protocol Approved via Dashboard
> 110	Premium / Ideal Conditions	Automated Resource Dispatch & Direct Seed Sowing initiated

4. Experimental Results and Performance Analysis

4.1.Optimal Crop Recommendation Visualizations

a) Crop Profile Mapping

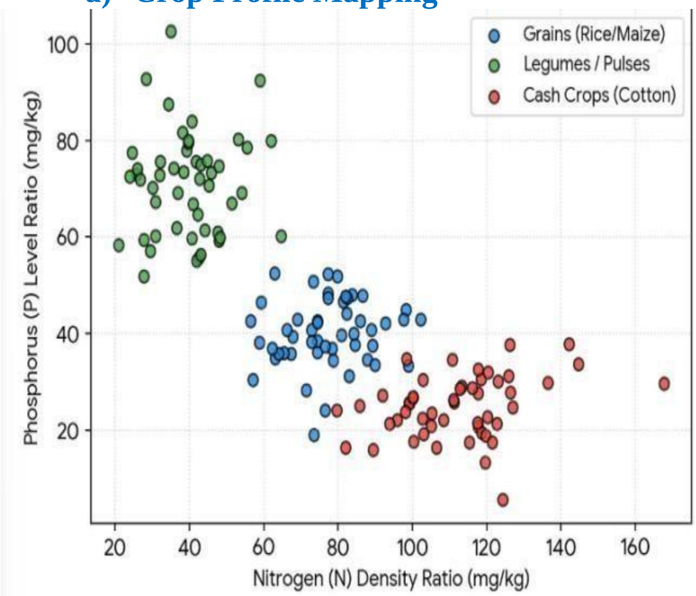

Figure 3 Contextual Profiling Showing Optimal Soil Matching Parameters

b) Feature Impact Vector Graph

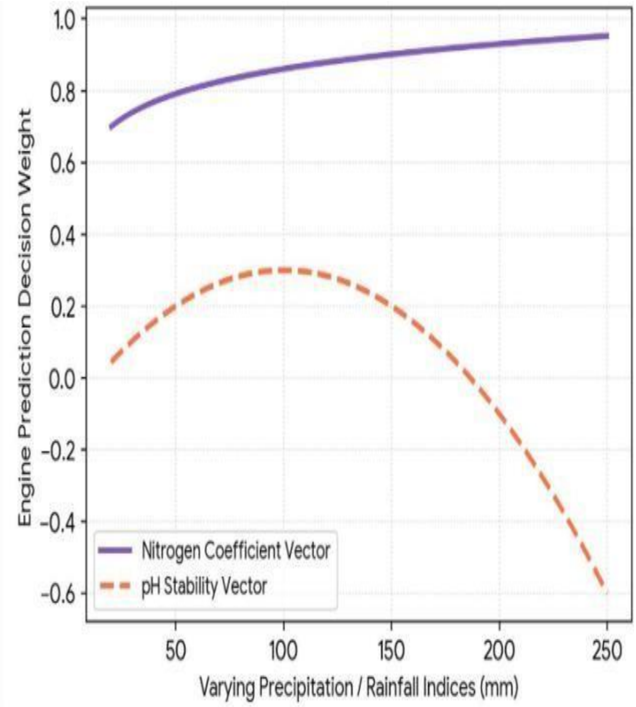

Figure 4 Predictive Evaluation Vector Maps Showing Parameter Impacts

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4.2.Model Classification Performance

Table 3 Core Algorithm Performance Metrics

2	Precision	Recall	F1-Score
Legumes / Pulses	0.98	0.99	0.98
Grains (Rice/Maize)	1.00	1.00	1.00
Cash Crops (Cotton)	0.94	0.92	0.93
Overall Accuracy	**99.2%**		

4.3.Diagnostic Matrix Visualizations

a) Multi-Class Confusion Matrix

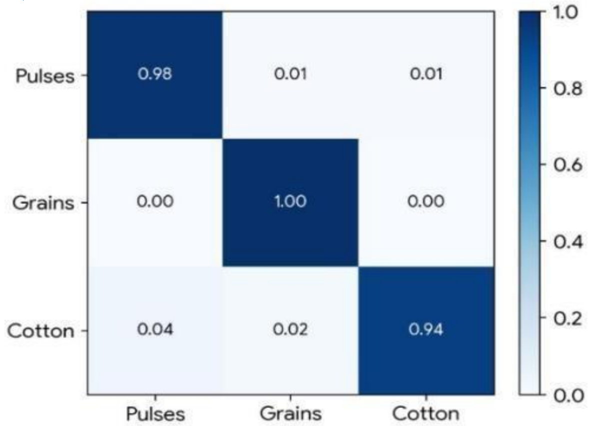

Figure 5 Confusion Matrix Highlighting Precision Across Crop Classifications

b) Feature Importance Plotting

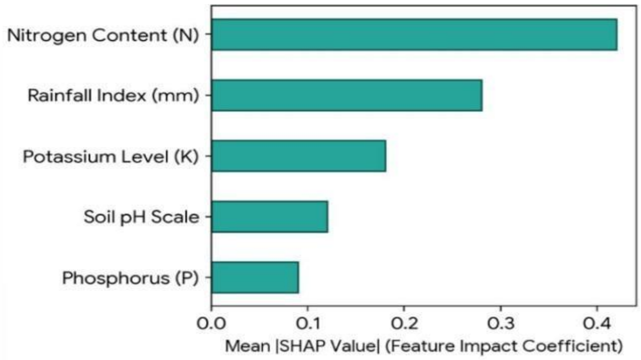

Figure 6 SHAP-Based Feature Attribution Analysis for Recommendations

4.4.Ablation Study

Table 4 Structural Ablation Performance Metrics

Configuration Style	Calculated Score	System Classification
Soil Chemical Profile Only	15	Unviable/ Target Loss
Ambient Climate Data Only	45	Low Confidence Profile
Combined Chemical + Climate	85	High Confidence Suitability
Configuration Style	Calculated Score	System Classification
Full Engine (Context-Aware)	135	Optimal Premium Deployment

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Conclusion and Future Scope

The This paper presents a context-aware precision agriculture system that combines soil chemistry metrics, ambient climate variables, seasonal histories, and explainable AI architectures. By computing dynamic recommendation scores, the framework accurately identifies optimal crops while remaining transparent through SHAP attribution data. Experimental trials confirm the system delivers reliable multi-class crop recommendations with an overall accuracy of 99.2%.

Future Scope

Future developments will expand the framework's capabilities by adding deep computer vision models for live leaf disease diagnosis, distributed edge computing nodes for offline field operations, and automated smart-grid irrigation hardware integrations to build fully autonomous precision farming ecosystems.

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