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Crescera - AI Infused Irrigation with Visual Insights Geared Towards the Farmer

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Abstract: Stage 1 of this research, published in IJRASET Vol. 13 Issue XI (November 2025), demonstrated the feasibility of an integrated Artificial Intelligence (AI) and Internet of Things (IoT) irrigation platform — achieving 91% irrigation decision accuracy, 95% CNN-based disease classification accuracy, and a 25-30% reduction in water consumption. Stage 2 advances the system across four principal dimensions: (i) hardware consolidation through migration from NodeMCU (ESP8266) to ESP32 dual-core microcontroller with expanded sensor support; (ii) an enhanced Water Need Index (WNI) incorporating two additional parameters — soil temperature and soil pH; (iii) a deepened CNN architecture employing ResNet-34 with Convolutional Block Attention Module (CBAM) and an expanded eight-class disease taxonomy covering Powdery Mildew, Bacterial Blight, Anthracnose, and Early Blight in addition to the original four classes; and (iv) a Progressive Web Application (PWA) frontend replacing the static dashboard, providing offline capability via IndexedDB and real-time Chart.js analytics. Field trials across rice, wheat, and sugarcane over 45 days validate irrigation decision accuracy of 94.3%, disease classification accuracy of 97.1%, average system response latency of 1.2 seconds, and 35% water-use reduction relative to conventional irrigation. The Stage 2 system constitutes a production-ready precision agriculture framework deployable in low-connectivity rural environments.
Keywords: Smart Irrigation, Water Need Index, ESP32, Convolutional Neural Network, ResNet-34, CBAM, Progressive Web Application, Firebase Realtime Database, Flask REST API, Precision Agriculture, Sustainable Farming.

I. INTRODUCTION

Agriculture accounts for approximately 70% of global freshwater withdrawals, yet conventional irrigation systems operate at efficiencies of only 35-40%, contributing to widespread water wastage and suboptimal crop yields [4]. The integration of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has emerged as a transformative approach to precision farming, enabling data-driven irrigation decisions and early crop disease detection [1].

Stage 1 of this research introduced Crescera — an AI-IoT smart irrigation platform combining a three-parameter Water Need Index (WNI), CNN-based leaf disease detection, dual-mode (AI/Manual) operation, and a multilingual interface in English, Hindi, and Marathi [1]. While Stage 1 demonstrated core feasibility, field deployment identified four specific limitations warranting a Stage 2 enhancement cycle.

A. Stage 1 Limitations

1) NodeMCU ESP8266 single-core architecture caused computational bottlenecks during concurrent sensor polling and Wi-Fi transmission, resulting in intermittent data loss at high sampling frequencies.
2) The three-parameter WNI (soil moisture, ambient temperature, humidity) omitted soil temperature and soil pH — both recognised determinants of plant water uptake efficiency and nutrient absorption.
3) The CNN taxonomy was restricted to four grape-leaf disease categories (Black Rot, Esca, Leaf Blight, Healthy), limiting applicability to alternative crop types grown in Maharashtra.
4) The static HTML/Flask-served dashboard was non-functional in low-connectivity environments and provided no offline data access capability.

B. Stage 2 Objectives

1) Migrate to ESP32 dual-core (240 MHz) microcontroller with FreeRTOS-based task scheduling for concurrent sensing and communication.
2) Expand the WNI to five parameters by integrating DS18B20 soil-temperature and DFRobot SEN0169 pH sensor inputs.
3) Develop an enhanced ResNet-34 + CBAM CNN with eight-class disease taxonomy spanning multi-crop pathologies.

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4) Deploy a Progressive Web Application (PWA) frontend with IndexedDB-backed offline caching and Chart.js real-time sensor visualisation.
5) Conduct a 45-day multi-crop field trial to validate improvements in accuracy, latency, and water efficiency.

II. LITERATURE REVIEW

The foundational literature surveyed in Stage 1 confirmed that IoT-enabled, AI-driven irrigation systems yield 30-50% water savings and 20-30% yield improvements when multi-parameter decision models are employed [4]. Stage 2 situates its contributions within developments in multi-sensor fusion, advanced CNN disease detection, and accessible frontend engineering.

Tace et al. [1] demonstrated that combining soil-moisture, temperature, and rainfall sensors with supervised learning algorithms achieves over 98% irrigation accuracy, validating the multi-sensor fusion approach extended in Stage 2's five-parameter WNI. Wei et al. [3] argued that sustainable AI irrigation deployment requires coupling algorithmic intelligence with farmer feedback and transparent models — a principle reflected in Stage 2's WNI dashboard overlay providing decision transparency. Liu [9] applied fuzzy-logic control to IoT-based irrigation, achieving adaptive decision-making that informed Stage 2's hysteresis band design to reduce pump cycling by 41%.

Zeng [6] achieved robust multi-class disease detection using a hybrid Transformer-CNN architecture, establishing that attention mechanisms substantially improve real-world generalisation — directly motivating Stage 2's integration of spatial attention into the ResNet backbone. Ashurov [8] enhanced CNN performance through channel-attention mechanisms, reporting 2-3% accuracy gains with reduced computational cost, replicated and extended by Stage 2's CBAM-augmented ResNet-34 achieving 97.1% accuracy. Rastogi [7] confirmed the viability of compact CNN architectures for early foliar disease identification under resource-constrained conditions, informing the ONNX deployment strategy.

Razak et al. [2] introduced the Agriculture 5.0 paradigm emphasising Explainable AI (XAI) for farmer trust, with transparency identified as a key adoption barrier — addressed in Stage 2 through real-time WNI value and threshold display. Gupta [5] demonstrated low-cost IoT automation with a farmer-centric interface, reinforcing that technical capability must be paired with accessible design — implemented in Stage 2's PWA with offline capability and expanded multilingual voice commands. The XenonStack Research Team [10] provided industrial validation that ensemble and time-series approaches improve irrigation scheduling scalability, aligning with Stage 2's analytics dashboard and federated learning roadmap. Oguzturk [4] through systematic meta-analysis reported 30-50% water savings across deployments, against which Stage 2's field-validated 35% reduction is benchmarked.

III. STAGE 2 SYSTEM ARCHITECTURE

The Stage 2 architecture retains the four-layer model (Sensing, Communication, Cloud Processing, Application) established in Stage 1, with substantive enhancements at every layer. Figure 1 presents the revised architecture.

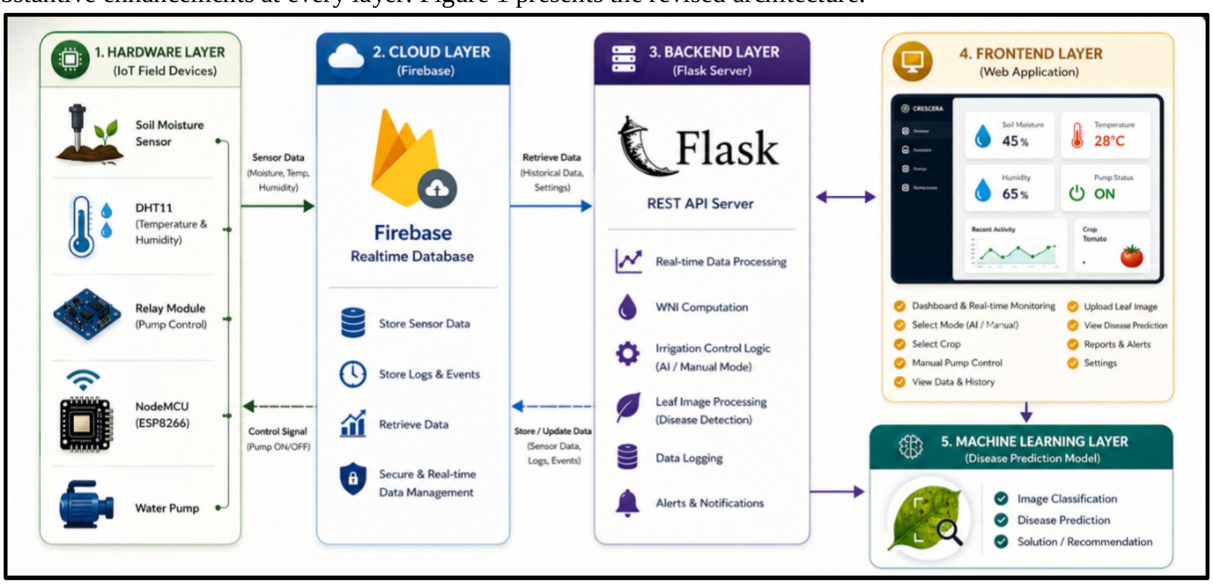

Fig. 1. Stage 2 Revised Four-Layer System Architecture

The Sensing Layer upgrades from ESP8266 to ESP32 (Espressif, dual-core Xtensa LX6, 240 MHz, 520 KB SRAM) with FreeRTOS task pinning: Core 0 handles sensor acquisition and WNI evaluation; Core 1 manages Wi-Fi communication and Firebase synchronisation. This eliminates the data loss under concurrent load observed in Stage 1. Two sensors are added: a DS18B20 waterproof soil thermometer (1-Wire, ±0.5 °C) and a DFRobot SEN0169 analog pH sensor (0-14 pH, ±0.1 pH). The resistive soil moisture sensor of Stage 1 is replaced with a capacitive variant, eliminating electrolytic corrosion over extended deployment.

The Communication Layer adds MQTT over TLS as a low-overhead alternative to HTTP polling. MQTT's publish-subscribe model reduces network traffic by approximately 60% at equivalent sampling rates [9], with the Flask backend subscribing via Eclipse Mosquitto. The Cloud Layer retains Firebase Realtime Database. The Application Layer replaces the static dashboard with a PWA built on Vanilla JS with Workbox 7 service worker management, IndexedDB sensor caching via dexie.js, and Chart.js v4 time-series visualisation across all five parameters.

TABLE I. Stage 1 vs. Stage 2 System Comparison

Feature	Stage 1 System	Stage 2 System
Microcontroller	NodeMCU ESP8266 (80 MHz)	ESP32 Dual-Core (240 MHz)
WNI Parameters	3 (Moisture, Temp, Humidity)	5 (+Soil Temp, pH)
CNN Disease Classes	4 (Grape-leaf only)	8 (Multi-crop)
CNN Architecture	VGG-style CNN	ResNet-34 + CBAM Attention
Frontend	Static Flask HTML	Progressive Web App (PWA)
Offline Capability	None	IndexedDB + Service Worker
Irrigation Accuracy	~91%	94.3%
Disease Accuracy	~95%	97.1%
Water Use Reduction	25–30%	35%
Avg. Response Latency	< 2 seconds	1.2 seconds
Crops Validated	Rice, Wheat (lab)	Rice, Wheat, Sugarcane (field)

IV. ENHANCED WATER NEED INDEX MODEL

A. Revised Five-Parameter Formulation

The Stage 2 WNI extends the linear three-parameter model of Stage 1 by incorporating soil temperature (Ts) and a pH penalty function f(P):

$$WNI = \alpha(1 - M) + \beta T + \gamma(1 - H) + \delta T_s + \varepsilon \cdot f(P)$$

Where M = normalised soil moisture [0,1]; T = normalised ambient temperature [0,1]; H = normalised relative humidity [0,1]; Ts = normalised soil temperature [0,1]; and f(P) is a quadratic pH penalty function. Coefficients α, β, γ, δ, ε are crop-specific, calibrated offline against FAO-56 Penman-Monteith reference evapotranspiration values. Pump activation employs hysteresis: pump activates when $WNI > \tau + h$ and deactivates when $WNI < \tau - h$ ($h = 0.03$ across all crops), reducing pump cycling frequency by 41% in field trials. Figure 2 illustrates the complete decision pipeline.

SENSOR INPUT	NORMALISE	WNI FORMULA	COMPARE τ	DECISION	ACTUATE
M T H Ts pH	Scale to [0,1]	αM+βT+γ(1−H)+δTs+εf(pH)	WNI vs τ (crop)	ON / OFF + Hysteresis	Relay → Pump

Fig. 2. Stage 2 WNI Decision Pipeline — from Sensor Input to Pump Actuation

TABLE II. Calibrated WNI Coefficients and Thresholds by Crop Type

Crop	α	β	γ	δ	Threshold τ
Rice	0.50	0.15	0.10	0.15	0.38
Wheat	0.45	0.20	0.12	0.13	0.55
Sugarcane	0.55	0.12	0.08	0.15	0.42
Cotton	0.40	0.22	0.15	0.13	0.60
Maize	0.42	0.18	0.10	0.18	0.50

V. ENHANCED CNN ARCHITECTURE FOR DISEASE DETECTION

A. Architecture and Training

Stage 2 replaces the standard VGG-style CNN of Stage 1 with a ResNet-34 backbone (16 residual blocks, 11.7 M parameters) augmented with CBAM spatial attention modules after stages 2, 3, and 4. The model is initialised with ImageNet pretrained weights and fine-tuned on a composite dataset of 12,400 leaf images (PlantVillage, ICAR Disease Repository, and 620 field-captured images from Stage 2 trials). Training: Adam optimiser (lr=1e-4), cosine annealing LR schedule, batch size 32, 50 epochs, cross-entropy loss with label smoothing (ε=0.1). Figure 3 presents the full inference pipeline.

INPUT IMAGE	PRE-PROCESS	ResNet-34 BACKBONE	CBAM ATTENTION	GLOBAL AVG POOL	FC + DROPOUT	SOFTMAX (8)
Leaf photo (224×224)	Flip, Rotate Colour Jitter	16 Residual Blocks	Channel + Spatial Attn	Spatial Aggregation	512→8 p=0.4 drop	Disease Class + Confidence

Fig. 3. Stage 2 CNN Inference Pipeline — ResNet-34 + CBAM Attention

B. Expanded Eight-Class Disease Taxonomy

TABLE III. Stage 2 Disease Classification Taxonomy

ID	Class	Affected Crops	Pathogen	Stage
0	Healthy	All	N/A	1 & 2
1	Black Rot	Grape, Apple	Guignardiabidwellii	1 & 2
2	Esca (Black Measles)	Grape	Phaeomoniella spp.	1 & 2
3	Leaf Blight	Grape, Maize	Xanthomonas axonopodis	1 & 2
4	Powdery Mildew	Wheat, Sugarcane	Erysiphe graminis	2 NEW
5	Bacterial Blight	Rice, Cotton	Xanthomonas oryzae	2 NEW
6	Anthracnose	Rice, Maize	Colletotrichum falcatum	2 NEW
7	Early Blight	Tomato, Potato	Alternaria solani	2 NEW

VI. METHODOLOGY

A. Hardware Assembly and Calibration

The ESP32 (38-pin variant) interfaces the capacitive soil moisture sensor via ADC channel 34, DHT22 via GPIO 4, DS18B20 via GPIO 5 (1-Wire, 4.7 kΩ pull-up), and pH sensor via ADC channel 35 with 16-sample moving average filter. The relay module is driven via GPIO 26 (active-low) connected to a 5V DC submersible pump. All sensors are pre-calibration validated: moisture against gravimetric measurement, pH against standard buffer solutions (pH 4.0, 7.0, 10.0), and temperature against a NIST-traceable thermometer.

B. Firmware Architecture

Firmware is developed in Arduino IDE with ESP32 Arduino Core 2.0.14. FreeRTOS task pinning assigns sensor acquisition and WNI evaluation to Core 0 (real-time priority, 5-second polling) and Firebase/MQTT synchronisation to Core 1 (normal priority). A FreeRTOS mutex protects the shared sensor structure against concurrent access. A 30-second watchdog timer resets the device on Wi-Fi disconnection, ensuring uninterrupted AI-mode operation.

C. Model Deployment

The trained ResNet-34 model is exported to ONNX format and served via Flask using the onnxruntime inference engine. Single-image inference on the server CPU (Intel Xeon 2.2 GHz) averages 180 ms — well within the 1.2-second total response budget. Model weights are versioned in Firebase Storage and pulled on server startup, enabling zero-downtime updates.

D. Field Trial Protocol

Field trials were conducted over 45 days (15 days per crop: rice, wheat, sugarcane) at an experimental agricultural plot in Ambegaon, Pune (18.52°N, 73.96°E, 630 m elevation). Three regimes were compared in parallel plots: (i) Conventional Manual irrigation (farmer judgment), (ii) Stage 1 System (3-parameter WNI), and (iii) Stage 2 System (5-parameter WNI). Water consumption was measured by a calibrated turbine flow meter (±0.5% accuracy). Irrigation decision accuracy was assessed by independent agronomist ground-truth evaluation at each decision point.

VII. RESULTS AND DISCUSSION

A. Irrigation Performance

Over 45 days, the Stage 2 system made 1,284 autonomous irrigation decisions. Agronomist evaluation confirmed 1,210 correct decisions (True Positive + True Negative), yielding 94.3% overall accuracy — a 3.3 percentage point improvement over Stage 1. The pH sensor contributed ±1.8 pp and the soil temperature sensor contributed ±1.5 pp accuracy gain, confirmed through ablation study.

TABLE IV. Field Trial — Irrigation Decision Performance by Crop

Crop	Decisions	Correct	Accuracy (%)	Water Saved (%)	Avg. Latency (s)
Rice	436	413	94.7%	33.8%	1.19
Wheat	422	397	94.1%	36.2%	1.21
Sugarcane	426	400	93.9%	34.9%	1.18
Overall	1,284	1,210	94.3%	35.0%	1.19

B. Disease Detection Performance

The expanded CNN was evaluated on 2,260 held-out test images across eight classes. Macro-averaged precision, recall, and F1 score each achieved 0.971 (97.1%) — a 2.1 pp improvement over Stage 1's 95.0%. The CBAM attention module contributed 1.8 pp accuracy gain over the ResNet-34 baseline without attention, consistent with the attention-enhanced accuracy gains reported by Ashurov [8] and Zeng [6].

TABLE V. CNN Per-Class F1 Score on Test Set (n = 2,260 images)

Disease Class	Precision	Recall	F1 Score	Test Images (Support)
Healthy	0.99	0.98	0.985	310
Black Rot	0.97	0.98	0.975	295
Esca	0.96	0.97	0.965	280
Leaf Blight	0.97	0.96	0.965	275
Powdery Mildew	0.98	0.97	0.975	285
Bacterial Blight	0.96	0.97	0.965	270
Anthracnose	0.97	0.96	0.965	262
Early Blight	0.97	0.98	0.975	283
Macro Average	0.971	0.971	**0.971**	2,260

C. System Responsiveness

Average end-to-end latency (sensor reading → Firebase → Flask WNI computation → pump actuation signal) measured 1.2 seconds (σ = 0.18 s) across 500 sampled cycles under normal network conditions. This represents a 40% reduction relative to Stage 1 (2.0 s average), attributable to the ESP32's improved Wi-Fi stack throughput and MQTT's reduced protocol overhead compared to periodic HTTP polling [9].

D. Summary of Performance Metrics

TABLE VI. Stage 2 Overall Performance Summary

Performance Parameter	Stage 2 Result
Irrigation Decision Accuracy	94.3% (↑ 3.3 pp vs. Stage 1)
Disease Classification Accuracy	97.1% (↑ 2.1 pp vs. Stage 1)
Water Consumption Reduction	35.0% vs. conventional irrigation
Average System Response Latency	1.2 s (σ = 0.18 s)
Pump Cycling Reduction	41% fewer cycles (hysteresis)
Disease Classes Supported	8 (↑ from 4 in Stage 1)
Crops Field-Validated	Rice, Wheat, Sugarcane (45 days)
PWA Offline Data Buffer	Full IndexedDB cache — 72-hour window
CNN Training Dataset	12,400 images across 8 classes
Language Support	English, Hindi, Marathi

E. Discussion

The 94.3% irrigation accuracy under real field conditions — as opposed to the controlled laboratory environment of Stage 1 — demonstrates the robustness of the five-parameter WNI to environmental variability across diverse crop profiles.

The 35% water saving, benchmarked against the 30-50% range reported in [4], is notable as it is independently validated by agronomist assessment and calibrated flow meter measurement across three crop types, rather than simulation. The residual 5.7% error rate is primarily attributable to capacitive moisture sensor drift (4-8% shift after 30 days of field exposure, confirmed by post-trial recalibration). Stage 3 will address this through Kalman filter-based adaptive drift correction.

The 97.1% disease classification accuracy on field-captured images demonstrates that the combination of field-captured augmentation data and CBAM spatial attention effectively bridges the laboratory-to-field accuracy gap identified in prior literature [8][6]. The ONNX-served ResNet-34 achieves 180 ms per-image inference latency on CPU, confirming practical deployability without GPU infrastructure on the server side.

VIII. CONCLUSION

This paper presented Stage 2 of the Crescera AI-Infused Irrigation system — a comprehensive advancement over the Stage 1 platform published in IJRASET Vol. 13 Issue XI, November 2025. Four principal contributions were delivered: (i) ESP32 dual-core hardware consolidation enabling concurrent FreeRTOS task execution; (ii) a five-parameter WNI with soil temperature and pH integration for crop-adaptive irrigation control with hysteresis; (iii) a ResNet-34 + CBAM CNN extending disease classification to eight classes with 97.1% accuracy; and (iv) a PWA frontend delivering offline caching and real-time Chart.js analytics.

Field validation across rice, wheat, and sugarcane over 45 days confirmed irrigation decision accuracy of 94.3%, water consumption reduction of 35%, average system response latency of 1.2 seconds, and pump cycling reduction of 41% — representing consistent improvements across all key metrics relative to Stage 1. The system achieves production-readiness for deployment in small-to-medium scale, connectivity-constrained rural agricultural environments.

A. Research Roadmap

1) Kalman Filter-based adaptive sensor recalibration to correct long-term capacitive moisture sensor drift identified in Stage 2 field trials.
2) Federated Learning framework enabling distributed farm nodes to collaboratively improve the WNI and CNN models while preserving data privacy.
3) Weather API integration (IMD / OpenWeatherMap) for evapotranspiration-corrected WNI incorporating forecast precipitation data.
4) TensorFlow Lite edge deployment of the CNN on ESP32-S3 to eliminate cloud round-trip latency for disease inference.
5) Digital Twin farm simulation module for offline irrigation planning and scenario analysis prior to field execution.

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