

Agri AI: An End-to-End Smart Farming System with Intelligent Automation Using Internet of Things and Machine Learning

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Abstract—Farming in many regions still depends on manual observation, fixed irrigation schedules and guesswork about fertilizer and pests, which wastes water, raises cost and lowers yield. In this paper we present Agri AI, an end-to-end smart farming system that brings IoT (Internet of Things), AI (Artificial Intelligence) and ML (Machine Learning) together on one low-cost platform. Field sensors for soil moisture, temperature, humidity, wind speed, soil nutrients and soil pH feed a NodeMCU ESP8266 (Node Microcontroller Unit) controller, while an ESP32-CAM (ESP32 camera module) captures crop images. The readings are stored in a Firebase cloud database and analysed by LSTM (Long Short-Term Memory) for soil moisture and irrigation prediction, XGBoost (Extreme Gradient Boosting) for nutrient analysis and fertilizer recommendation, and CNN (Convolutional Neural Network) with TinyML (Tiny Machine Learning) for pest detection. A water pump, solenoid valves and an ultrasonic pest repellent are operated automatically, and a multi-language chatbot with a market module in a mobile and web application gives farmers guidance and direct access to buyers. This paper reports the Phase-1 & continuation of the Phase 2 works, which cover requirement analysis, layered architecture, data flow, module design and the application prototype. The design aims to cut water wastage, limit fertilizer misuse and reduce manual effort.

Key words—smart farming, precision agriculture, Internet of Things, machine learning, LSTM, XGBoost, pest detection, ESP32-CAM, Firebase, chatbot

I. INTRODUCTION

Agriculture supports the food security and economy of most countries, yet a large part of farming still runs on experience and manual checking. Irrigation is often done on a fixed schedule rather than on actual soil need, fertilizer is applied out of habit, pests are noticed only after the damage is done, and small farmers have little direct access to buyers. The result is wasted water, higher input cost and lower yield. The spread of IoT (Internet of Things) devices, AI (Artificial Intelligence) and ML (Machine Learning) now makes it practical to watch a field continuously and to act on the data [1], [2].

Most solutions we came across tackle only one part of the problem, for example irrigation alone or pest detection alone. A farmer who wants all of these has to depend on several unconnected tools, and very few of them speak the farmer's own language. Through the final-year project work that we guided in the academic year 2026-27 at the Department of Computer Science and Engineering, SJM Institute of Technology, Chitradurga, our student team set out to build one connected platform, named Agri AI, that handles irrigation, nutrient management, pest control and farmer support together.

The main contributions of this paper are as follows. First, a layered architecture that joins field sensing, cloud storage, ML analysis and automatic actuation. Second,

irrigation that follows the crop growth stage and also uses wind speed to estimate evaporation. Third, three ML models, each matched to one task. Fourth, a solar-powered pest monitoring rover with an eco-friendly ultrasonic repellent. Fifth, a multi-language chatbot and market module delivered through a mobile and web application. The rest of the paper reviews related work, states the problem, describes the architecture, methodology and working flow, presents the Phase-1 & 2 prototype, and closes with the conclusion and future scope.

II. RELATED WORK

Surveys of ML and deep learning in agriculture show steady growth in applications for crop, soil and water management, and they point out that field data quality and the cost of deployment are the usual obstacles [3], [4]. We looked at the studies closest to our work, and they are summarised below.

On irrigation, Sinthuja and Canessane describe AI-based adaptive irrigation and crop monitoring for micro-farms [5]. Saravanan et al. report an AI-driven water management system, and water savings in the range of roughly 25 to 40 % have been reported for irrigation and nutrient monitoring studies of this kind, although implementation cost, sensor faults and regular calibration remain a burden [6].

Chanda et al. built an AI and IoT rover that combines image processing with sensor data for crop monitoring, irrigation and pest detection, and reported 86.4 % accuracy, 43 % lower water use and 72 hours of operation [7]. They also note that lighting conditions and motion blur reduce pest detection accuracy and that scaling the rover is difficult. On the market side, Ishak and Rahaman present a platform for crop prediction and crop marketing that reached an accuracy of about 85 to 90 %, but its results depend heavily on dataset quality and it does not adapt in real time [8]. Ramdinthara et al. address yield prediction and smart irrigation using AI [9]. My own earlier work combined ML and IoT for precision agriculture [10], and the present system extends that line toward a complete platform.

Table I places these works side by side. The pattern is clear: each work serves one or two needs of the farmer, so the farmer still has to combine several tools. Agri AI is designed to close this gap.

TABLE I
FOCUS AND REPORTED LIMITS OF RELATED WORK

Ref.	Main focus	Reported limitation
[6]	AI-based irrigation and water management	Cost, sensor issues, calibration
[7]	Rover for irrigation and pest repelling	Lighting, motion blur, limited scalability
[8]	Crop prediction and marketing	Depends on dataset quality, no real-time adaptation
Agri AI	Irrigation, nutrients, pests, chatbot and market in one platform	Field testing pending (Phase 2 end)

III. PROBLEM STATEMENT AND OBJECTIVES

Traditional farming faces excessive water use, inefficient irrigation, improper fertilizer application, pest attacks, lack of real-time field monitoring and dependence on manual labour. Farmers also find it hard to predict soil conditions, manage crop health and reach good markets. Existing systems usually cover only one aspect of farming, and many farmers do not get guidance in their regional language. What is needed is a low-cost, automated system that monitors the field in real time, optimises water and fertilizer, detects pests and supports the farmer through a multi-language application.

The objectives of the work are: to develop a smart farming system using IoT and ML; to monitor soil and environmental conditions in real time; to automate irrigation and nutrient management; to detect pests and provide eco-friendly pest control; to support farmers through a mobile application and a multi-language chatbot; and to connect farmers with buyers while promoting sustainable farming.

IV. PROPOSED SYSTEM

A. Overview

Agri AI is divided into four modules that work together. The irrigation and wind monitoring module controls water supply. The nutrition management module analyses soil nutrients and suggests fertilizer. The pest detection and control module finds pests and diseases and drives the repellent. The marketing module, together with the multi-language chatbot, supports the farmer's decisions and sales.

B. Hardware Components

The field unit is built around the NodeMCU ESP8266 (Node Microcontroller Unit), which reads the sensors and sends data over Wi-Fi (Wireless Fidelity). The ESP32-CAM (ESP32 camera module) is used for crop images. Table II lists the components and their roles. For model training and application development, a computer with a 1.5 GHz processor, 4 GB of RAM (Random Access Memory) and 10 GB of storage is the minimum recommended.

TABLE II
HARDWARE COMPONENTS AND THEIR ROLES

Component	Role in the system
NodeMCU ESP8266	Main controller and Wi-Fi link to the cloud
ESP32-CAM	Captures crop images for pest detection
Soil moisture sensor	Trigger for irrigation decisions
NPK sensor	Nitrogen, phosphorus and potassium levels
Soil pH sensor	Soil acidity or alkalinity

Component	Role in the system
Temperature and humidity sensor	Weather condition at the field
Wind speed sensor	Evaporation estimate for water use
Water pump, solenoid valves	Automatic irrigation
Ultrasonic pest repellent	Chemical-free crop protection

C. Software Platform

Python is used for ML work because of its strong library support. Embedded C through the Arduino IDE (Integrated Development Environment) programs the NodeMCU and ESP32-CAM. The mobile and web application is built with Flutter or Android Studio. TensorFlow, Keras, Scikit-learn, XGBoost and OpenCV (Open Source Computer Vision Library) provide the ML and image processing functions. Firebase Realtime Database and Firestore store sensor data, reports, user records and chatbot responses, and MySQL can be added for structured market data if required.

V. SYSTEM ARCHITECTURE

Fig. 1 shows the architecture, which I kept modular so that new sensors and farming modules can be added later without disturbing the rest. It has six layers and one concern that runs across all of them, security.

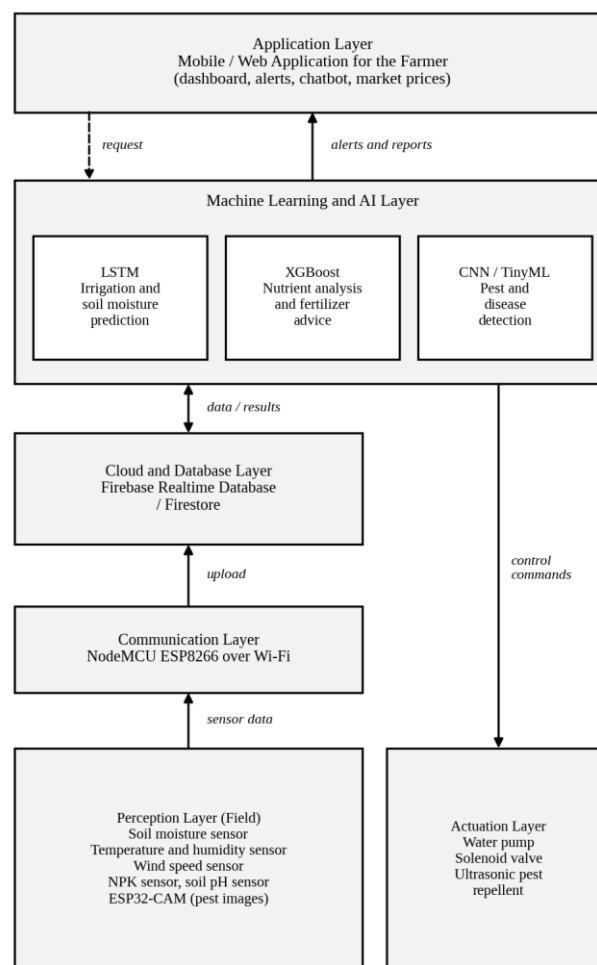


Fig. 1. Layered architecture of the Agri AI system.

The *perception layer* holds the soil moisture, temperature and humidity, wind speed, NPK and soil pH sensors and the ESP32-CAM. The *communication layer* is the NodeMCU ESP8266, which pre-processes the readings and pushes them to the cloud through Wi-Fi. The *cloud and database layer* keeps real-time and historical data in

Firestore and keeps the application in sync. The *ML and AI layer* reads this data and runs the three models, and it also holds the training module and the testing module. The *application layer* is the mobile and web interface through which the farmer views reports, receives alerts, talks to the chatbot and contacts buyers. The *actuation layer* receives control commands and runs the pump, the solenoid valves and the ultrasonic repellent.

Security runs across all layers. Login and registration protect the application, sensitive data is encrypted in the cloud, and Firestore security rules limit database access to authorised users, so that a farmer can monitor the farm remotely with confidence.

VI. METHODOLOGY

A. Data Acquisition and Pre-processing

The sensors measure soil moisture, temperature, humidity, wind speed, nutrient levels and soil pH at regular intervals. The NodeMCU ESP8266 acquires the raw values, formats them and does a local validation before upload, so that faulty readings do not reach the models. Crop images from the ESP32-CAM are sent for image processing with OpenCV before classification.

B. Smart Irrigation Using LSTM

Irrigation is planned by crop type, soil condition and growth stage, namely seedling, vegetative, flowering and fruiting. An LSTM (Long Short-Term Memory) network [11] is trained on the history of soil moisture and weather values, because it learns time patterns well, and it predicts the moisture level ahead of time. Wind speed is used to estimate the evaporation rate, following the idea of reference evapotranspiration [12], so that the water given is adjusted to the real loss from the soil. When the predicted moisture falls below the level needed for the crop stage, the system switches on the water pump and solenoid valve and informs the farmer.

C. Nutrient Analysis Using XGBoost

Nitrogen, phosphorus, potassium and pH values form the input to an XGBoost (Extreme Gradient Boosting) model [13], which I chose because it handles tabular data well and trains quickly. The model identifies the nutrient deficiency and recommends the type and amount of fertilizer. The application also lets the farmer type in soil test values by hand, and it shows a few practical tips such as testing the soil every six months and applying fertilizer in cool hours.

D. Pest Detection and Control

A solar-powered pest monitoring rover carries the ESP32-CAM through the field. A CNN (Convolutional Neural Network), which has proved effective for image-based plant disease detection [14], classifies the pests and diseases from the captured images. To run the model near the edge on a small device, TinyML (Tiny Machine Learning) techniques are used [15]. When a pest is found, the system raises an alert with treatment suggestions and starts the ultrasonic repellent, which protects the crop without harmful chemicals.

E. Chatbot, Alerts and Marketing

A chatbot answers agriculture queries in regional languages. The notification system sends irrigation alerts, pest warnings, nutrient deficiency messages and weather updates. In the market module, the farmer can upload crop

details, check current prices and connect directly with buyers, which removes the dependence on middlemen.

VII. WORKING FLOW

The working of Agri AI passes through three phases, and Fig. 2 shows the decision flow of the running system.

Data collection and training phase. The sensors and camera collect data, the NodeMCU sends it to Firestore, and the stored historical data, crop conditions and pest images are used to train LSTM, XGBoost and CNN with TinyML. LSTM learns moisture and irrigation patterns, XGBoost learns nutrient and fertilizer relations, and CNN with TinyML learns to recognise pests.

Monitoring and prediction phase. Live readings arrive continuously and the trained models predict irrigation need, nutrient deficiency, weather impact and pest presence. Results and reports appear in the application.

Alert and automation phase. If an abnormal condition is found, the system alerts the farmer and acts. For example, when soil moisture is low it starts the pump and sends a notification, and when a pest is detected it sends an alert with treatment advice.

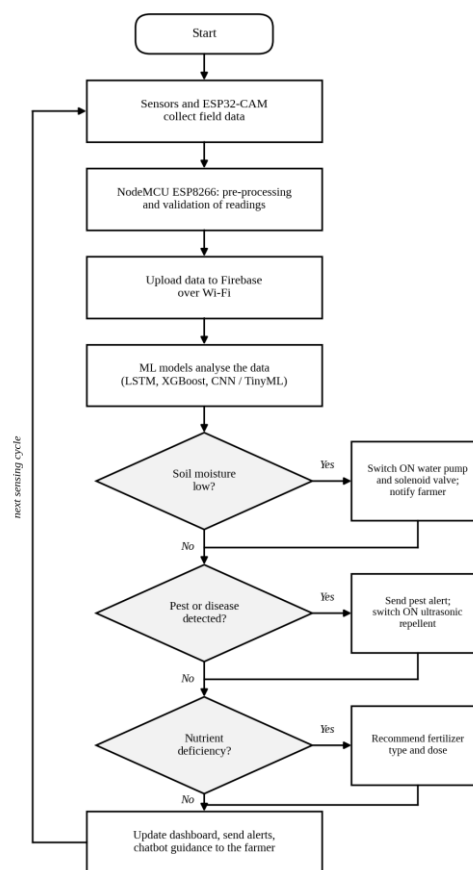


Fig. 2. Working flow of the Agri AI system.

VIII. APPLICATION PROTOTYPE AND PHASE-1 OUTCOMES

A working prototype of the farmer application was prepared in Phase 1. The home screen shows today's weather, a crop health overview and four farming modules, namely smart irrigation, soil nutrition, pest detection and market price. The smart irrigation screen shows the irrigation status with a switch, live soil moisture, temperature, humidity and wind speed, and a moisture trend for the day. The soil nutrition screen takes nitrogen, phosphorus and potassium values and returns a

recommendation. The pest detection screen accepts an uploaded plant image, and the market screen lists current crop prices with an option to contact buyers. Separate screens give the weather forecast, the list of recent alerts and the farmer's profile with a language setting.

In Phase 1, the requirement analysis, system architecture, workflow, sensor selection, NodeMCU ESP8266 communication, ESP32-CAM integration, Firebase connectivity and AI model planning were completed. The prototype design and workflow of irrigation, nutrient analysis, pest detection and chatbot support are ready. We want to be clear that numerical performance results are not reported here, because the full hardware testing and model training belong to the next phase.

In Phase 2, we plan to measure the water used against a fixed-schedule baseline, the prediction error of the LSTM model, the accuracy of the XGBoost and CNN models, and the delay between an event in the field and the alert on the farmer's phone. These measurements will show whether the expected benefits, namely less water wastage, controlled fertilizer use and lower manual effort, are actually achieved.

IX. CONCLUSION AND FUTURE SCOPE

This paper presented Agri AI, an integrated smart farming system that combines IoT sensing, ML analysis, cloud storage, automatic actuation and a multi-language mobile application. Phase 1 established the foundation: the requirements, architecture, data flow and module design are complete, and the application prototype is ready. Because irrigation, nutrient management, pest control and farmer support work as one connected system, the platform is suited to low-cost precision agriculture.

Future work includes advanced weather forecasting for better irrigation planning, drones for large-area monitoring and spraying, deeper learning models for pest and disease detection, automatic fertilizer dispensing, real-time price prediction with e-commerce support, solar-powered energy management, and scalable IoT networks for larger fields and many crops.

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