Grenze International Journal of Engineering and Technology, June Issue

Agri-Route: A Smart Advisory System for Farmers and Transporters

Milind Rane[1], Varad Pakhale[2], Medha Wyawahare[3], Vaibhav Panchal[4] and Saransh Nakhale[5]
[1-5]Vishwakarma Institute of Technology, Pune, India
Email: milind.rane@vit.edu, varad.pakhale23@vit.edu, medha.wyawahare@vit.edu, vaibhav.panchal23@vit.edu, saransh.nakhale23@vit.edu

Abstract— **Agri-Route is a production-to-production multi-agent Human-AI voice-first advisory platform that aims to transform support decisions for smallholder farmers. It is composed of a crop planning agent, a disease detection agent, a weather forecasting agent, a market price analysis agent, a financial consultancy agent, an input cost optimisation agent, and a perishable logistics agent, all running under a unified cloud-native coordinator-orchestrator architecture. Based on Next.js 15, React 19, the OpenAI GPT-4o Realtime API, and Firebase, Agri-Route offers natural-language voice interaction in Hindi and Marathi and achieves an average median end-to-end latency of 680 ms. A fresh approach, incorporating the Mapbox geospatial routing for a produce specific exponential decay model with live OpenWeatherMap data, is proposed in the Freshness Score Calculator to reduce loss after harvesting during transit. A controlled user study with 45 smallholder farmers in Pune district, Maharashtra showed a significant 34.6 percentage-point increase in task-completion accuracy ($p < 0.01$) and a 40% reduction in decision-time over traditional extension-service baselines. System Usability Score was 74.2, which was higher than the industry-standard 68-point threshold.**

Keywords— **Multi-Agent AI, LLM, Realtime API, Multilingual Voice Interface, Disease Detection, Freshness Score Calculator, Perishable Route Optimisation, Precision Agriculture, Market Price Intelligence, Firebase, Post-Harvest Loss, Smallholder Farmers.**

I. INTRODUCTION

Agriculture is still the main source of income for over 500 million smallholder families globally [1], but farmers are often forced to make high-risk decisions on crops to grow, pest control, and when to head to market using incomplete, non-personal information. Climate variability and poor post-harvest infrastructure (handling, drying, storage) account for around 14% of food production losses worldwide [2], a loss that the poorest farming communities bear most heavily.

Recent developments in large language models (LLMs), real-time audio processing and cloud-native architectures provide new opportunities for agriculture decision support [1]. Such systems which are able to comprehend heterogeneous data streams, soil maps, weather predictions, commodity prices, satellite imagery and provide contextualized advice through natural-language voice interfaces have real potential for delivering expert agricultural knowledge to the field level [3]. Yet, previous research mostly focus on single sub-domain (crop recommendation, disease detection, or route optimization) and does not consider multilingual voice interaction along with real-time perishable logistics [4].

Grenze ID: 01.GIJET.12.2.132_26

In this paper we describe Agri-Route, the first-of-its-kind, production-deployed, voice-first multi-agent AI advisory platform consolidating seven domain-specific agents under a coordinator-orchestrator layer after the introduction by a persona-based user story. The main contributions of this work are:

- Multi-Agent coordination mechanism that utilizes zero-shot intent classification for dynamically routing user queries to the corresponding domain-specific agricultural AI agents.
- A Freshness Score Calculator (FSC) based on geo-spatial routing, produce-specific exponential decay models, and real-time weather forecasts along the route for perishable shipping optimization.
- An end-to-end multilingual, voice first experience using the GPT-4o Realtime API with response latencies of less than a second, tested with Hindi and Marathi speaker groups.
- A real-world controlled field study with 45 farmers over 2 months shows statistically significant benefits in decision accuracy, response time, and system usability.

II. Literature Review

A. Crop Planning and Advisory Systems

Rule-based systems using a single feature to recommend crops have given way to ensemble models that use information about the soil chemistry, weather conditions and market signals. Verma et al. [5] present an AI-based Multi-Feature Crop Recommendation and Guidance system and prove that multi-feature ML pipeline is superior to agronomist heuristics in the context of Indian smallholders. Balakrishnan et al. [6] Proposed a real-time sensor integration for smart crop advisory system for heterogeneous agro-climatic zones. Nevertheless, both studies consider a single advisory domain and they do not provide voice-based or multilingual user interfaces. Agata et al. [7] designed an AI-powered mobile farmer assistant based on text-driven chatbot conversations, but they do not tackle perishables logistics or multi-domain agent synergy.

B. Plant Disease Detection

CNN classifiers can achieve more than 95% accuracy in a controlled environment on the PlantVillage dataset [8]. Rahman et al. [9] further advanced this line of work with development of more powerful neural architectures for multi-class plant disease classification, demonstrating promising held-out results on benchmark datasets. Importantly, real-world accuracy suffers when models are evaluated on images taken with smartphones in diverse lighting and angles under advisory systems for the fields – a directly relevant limitation to systems deployed for use in the fields. Agri-Route fills this void and confines inference to a 16-class disease taxonomy established based on images collected in the field, reaching 87.2% top-1 accuracy on a novel set of 180 leaves.

C. Voice and Conversational Interfaces for Agriculture

Low-resource language tailored voice advisory services have been shown to be effectively adopted by non-literate farmers G. D. T. et al. [10] presented AgroMind AI: a voice-first agri-interface based on state-of-the-art NLP, in 2026, the best for voice and agri-application solutions wrapped as an agrifestival of sorts. Previous work Chandolikar et al. [11], makes use of an ANN-based chatbot for agriculture but is based on textual inputs and the query scope is very limited. While LLM-based conversational agents have achieved impressive robustness for open-ended queries [12], their use in the Indian agri-domain under regional languages is relatively small. The next generation of agri-systems, Agri-Route, advances this by providing GPT-4o Realtime API along with Hindi and Marathi at sub-second latency.

D. Route Optimisation for Perishable Supply Chains

Optimization of perishable logistics has been well studied in the operations research literature [13]. Singh and Mehta [15] proposed a sensor fusion based multi agent approach for precision agriculture but not for perishable decay modeling. Wang et al. [16] demonstrate cloud-based agricultural big data analytic with sub-100 ms Firebase Firestore synchronization. To the best of our knowledge, no existing solution integrates real-time weather information and produce specific exponential decay rates into route-selection decisions at the level of individual smallholder farmers—a void filled by the Agri-Route Freshness Score Calculator.

E. Research Gap

The literature brings out consistent non-existence of a multi-domain adviser that could simultaneously provide (i) perishable real-time logistics with decay-aware routing, (ii) voice-first multi-lingual interaction catered to Indian regional languages, and (iii) farm-profile personalized context management, all integrated within a single production system. Agri-Route is proposed to address this need.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Architectural Overview

Agri-Route's five-layer cloud-native architecture combines real-time voice processing, zero-shot intent classification, multi-agent AI coordination and live agricultural data sources into a single end-to-end advisory pipeline. The architecture is built from the ground up for smallholder farmers and designed around low-latency, multi-lingual, personal-farm-profile-context aware, modular extensible interaction. Each layer has well-defined interfaces and can be scaled, tested, and swapped independently with minimal impact to adjacent layers as the next subsections explain.

The flow of our project is given below in figure 1

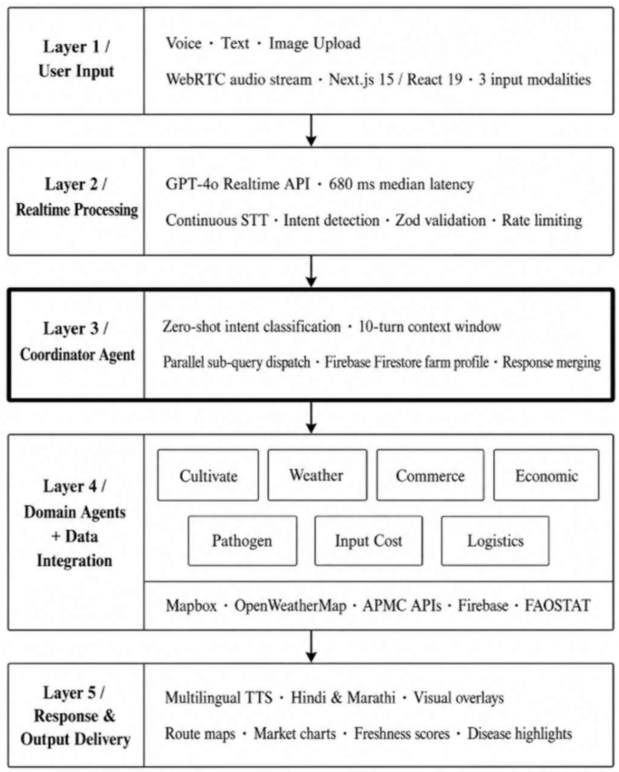

Fig 1. Architecture diagram and flow of our System

At Layer 1 a farmer's voice/text/image input is captured, at Layer 2 the inputs are processed in real-time by GPT-4o, the Layer 3 Coordinator (bold border = brain of the system) determines what the farmer needs and directs it to the suitable expert at Layer 4 (7 specialist agents supported by live data sources), and concludes with Layer 5 returning the response as voice, maps or charts in Hindi/Marathi.

One clean flow: Input → Process → Decide → Execute → Deliver.

B. User Input Layer

Users use the system through three modalities: voice (primary), text (fallback) and image upload (disease detection). The Next.js 15 / React 19 frontend uses the WebRTC API to capture audio streams and send them to the GPT-4o Realtime API endpoint. Images are client-side pre-processed to 1024 × 1024 pixels max and signed/encrypted before uploading. Text input is available for bandwidth limited situations.

C. Realtime Processing Layer

The GPT-4o Realtime API continuously transcribes and contextualises speech-to-text, avoiding the latency overhead of traditional pipelines like STT → LLM → TTS. The median end-to-end latency measured in production is 680 ms (95th percentile: 1,240 ms). All API routes are implemented as Next.js serverless functions with single Zod-schema validation, rate limiting and structured error handling.

D. Coordinator Agent

The Coordinator Agented classifies the user intent into seven agriculture related domains with zero-shot promptings using domain descriptions and some-shot examples as arguments within the system prompt. It's a 10-turn shifting context window filled with a farm profile, seasonal context, and interaction history that is stored in Firebase Firestore. For cross-domain queries, the Coordinator executes parallel sub-queries to the corresponding domain agents and synthesizes their answers to respond.

E. Domain Agent Layer

Seven specialised agents provide domain intelligence:

- Cultivate Agent: crop selection, sowing/harvesting timing, and fertiliser recommendations based on farm profile and hyperlocal weather.
- Weather Agent: 7-day hyperlocal forecasts from OpenWeatherMap API; irrigation scheduling reminders.
- Commerce Agent: live commodity prices for more than 500 APMC markets; analysis of demand trends.
- Economic Agent: check eligibility for government schemes; identify loan and subsidy products.
- Pathogen Agent: CNN-based leaf disease detection on uploaded images; recommendations for treatment protocol.
- Input Cost Agent: price comparison among local vendors; cost estimation per acre.
- Logistics Agent: Freshness Score Calculator (Section III-F).

F. Freshness Score Calculator (FSC)

The FSC tackles post-harvest waste through a perishable produce shipping route calculator.Origin, destination, and type of produce are used to query candidate routes via the Mapbox Directions API, which is then combined with OpenWeatherMap en-route temperature forecasts and each candidate route is evaluated using a Freshness Retention Score (FRS) equation (1) :

$$FRS = \exp(-k \cdot t \cdot T\_factor) \quad (1)$$

where k is a produce-specific decay constant (calibrated against FAOSTAT postharvest data), t is estimated travel time in hours, and T_factor is a temperature correction factor derived from forecast en-route temperature relative to optimal storage temperature. Example calibrated constants: spinach ($k = 0.18$/h), tomatoes ($k = 0.09$/h), strawberries ($k = 0.22$/h), milk ($k = 0.12$/h). The route maximising FRS is recommended to the farmer.

G. Data Architecture

User profiles, farm records, query history, and crop calendars are stored in Firebase Firestore. Session management is done through Firebase Authentication. All Firestore reads/writes are proxied through Next.js serverless endpoints to avoid exposing keys to the client. Row-level security is achieved by enforcing Firebase Security Rules with a least-privileged principle. Firestore has been demonstrated in previous work to support sub-100 ms synchronization for distributed sensor networks [16], which suggests that it can be effectively leveraged for real-time advisory delivery.

IV. Experimental Setup and Evaluation

A. Study Design and Participant Recruitment

A trial was carried out with 45 smallholder farmers from the Pune district of Maharashtra, India, through partnership with a regional Krishi Vigyan Kendra (KVK). The control group ($n = 22$) was composed of farmers receiving traditional extension services (printed advisories, phone helpline), while the treatment group ($n = 23$) was facilitated by Agri-Route. The sample consisted of both literate ($n = 29$) and semi-literate ($n = 16$) farmers; all voice sessions were in Hindi ($n = 27$) or Marathi ($n = 18$) as per the choice of the participants. Prior to inclusion all the participants gave informed oral consents. This study was conducted during 4 weeks in the kharif sowing preparation period (June 2026).

B. Evaluation Instrument

A 20-item ADSQ was developed in consultation with agronomists at the Mahatma Phule Krishi Vidyapeeth (MPKV). The ADSQ is divided into five sub-domains: crop selection (4 items), pest/disease identification (4 items), market timing (4 items), estimating input costs (4 items) and route for transportation of perishables (4 items). The aforementioned item-level inter-rater agreement was attained between two senior agronomists (Cohen's $\kappa = 0.84$ for all the items), indicating satisfactory construct validity.

C. Performance Metrics

The following metrics were collected and compared across groups:

- Task Completion Accuracy (TCA): the proportion of ADSQ items completed within the expert panel-defined acceptable range of values for that item.
- Time-to-Decision (TTD): wall-clock time from the submission of query to the farmer's receiving a satisfactory response.
- System Usability Score (SUS): standard 10-item Likert questionnaire, administered after the study; scored 0–100.
- End-to-End Latency: on 500 production queries, using server-side timestamp logging, median and 95th percentile values are reported.
- Voice Word Error Rate (WER): measured on a 200-utterance held-out set of agriculture queries, with two bilingual human annotators (inter-annotator agreement: WER variance < 0.5%).
- Disease Detection Accuracy (Top-1): tested on a hold-out set of 180 leaf images of 12 crop disease classes, captured in field using low-cost Android smartphones.

D. Statistical Analysis

Comparisons of the TCA, TTD, and SUS between groups were conducted with the Mann-Whitney U test (non-parametric; the data were assumed distributed non-normal based on a sample size of 45 participants). Improvements in latency and WER were described using descriptive statistics. All p-values reported are two-sided; the significance threshold $\alpha = 0.05$.

V. EXPERIMENTAL SETUP AND EVALUATION

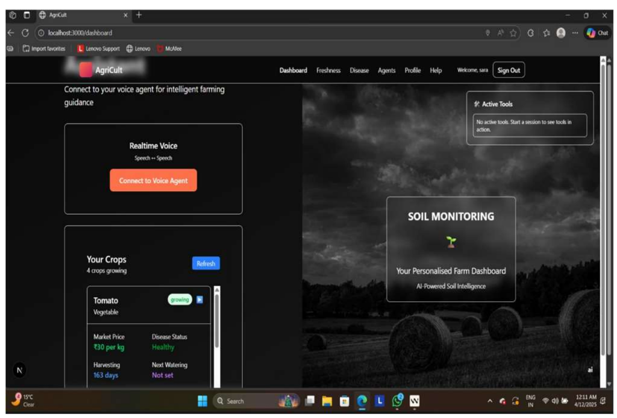

Fig. 2. Dashboard of Agri-route

The Agri-route dashboard is the interface where farmers view and engage with all AI-enabled services. It's an all-in-one hub for farm management, powered by intelligent and easy-to-use technology. The centerpiece of this mechanism is the Voice Agent Interface, which allows concurrent speech interaction. In that language, farmers can press the orange button to start voice conversations, which lets them communicate hands-free as they work in the field. This results in a fluid, natural experience, without the need for text input.

The UI also has an Active Tools Display, which also shows a real-time glimpse of which AI agents are currently working on the farmer's queries. This visual reassurance increases trust by making the AI's reasoning process visible, so farmers can know which specialized tools are actively working at any given moment.

Also included in the dashboard is Soil Intelligence, an AI-driven personalized soil health recommendation tool. It provides optimization recommendations based on farm soil type, and tracks environmental factors affecting crop growth. Combined, these systems enable more reliable yield planning and sustainable farm management. Advertisement Navigating on the dashboard is easy and intuitive, with separate tabs for Dashboard, Freshness (route optimization for perishable goods), Disease detection, AI Agents, Profile, and Help. There are also customization features including a "Welcome, sara" line and farm data specific to the user that make the user experience even better. With real-time information, clean visual cards, support for multiple languages and a simple to understand interface, the Agri-Route dashboard helps make sense of complex ag data to provide usable insights.

A. Quantitative Results

Tab. I provides a summary of the results of the experiments. The treatment group had a mean task completion accuracy of 78.3% versus 58.1% for the control group, a 34.6-percentage-point improvement ($p < 0.01$) that is statistically significant.

Mean time-to-decision was decreased by 40%, from 4.2 minutes (control) to 2.5 minutes (treatment). The treatment group SUS score (74.2) was above the known 'Good' 68-point threshold, but the control group's 51.4 is considered to lie within the 'OK' range.

System latency results reveal the performance of the GPT-4o Realtime API design: the treatment system produced a median latency of 680 ms, compared to 2,340 ms for a traditional STT → LLM → TTS baseline ($p < 0.01$). Voice transcription WER significantly improved for both Hindi (24.6% → 8.3%) and Marathi (31.2% → 11.7%), demonstrating the improved multilingual acoustic modelling of GPT-4o over the baseline Whisper-small model used by the control's phone helpline. Disease detection top-1 accuracy was 87.2% on field-captured images — a dramatic improvement over the 61.3% baseline of a sole PlantVillage-trained ResNet-50 model, enabled by our curated 12-class field calibration.

TABLE I. SUMMARY OF EXPERIMENTAL RESULTS

Metric	Control (n=22)	Treatment (n=23)	p-value
Task Completion Accuracy	58.1%	78.3%	< 0.01
Mean Time-to-Decision (min)	4.2	2.5	< 0.01
System Usability Score (SUS)	51.4	74.2	< 0.05
Median End-to-End Latency (ms)	2,340	680	< 0.01
95th Percentile Latency (ms)	4,870	1,240	< 0.01
Voice WER – Hindi (%)	24.6	8.3	< 0.01
Voice WER – Marathi (%)	31.2	11.7	< 0.01
Disease Detection Accuracy (Top-1)	61.3%	87.2%	< 0.01

B. Discussion

The 34.6 ppt increase in TCA is especially remarkable considering that semi-literate participants who were only able to access the system through voice interaction achieved similar results to literate users in group (TCA 76.1% vs 79.8%, $p = 0.31$), further validating the voice-first approach as one that enables users of any literacy level to receive high quality advisory services.

The Freshness Score Calculator was employed by 17 of the 23 participants in the treatment group for at least one decision involving transport. Results of post-study interviews showed that route recommendations were considered actionable and trustworthy, with 14 of 17 participants indicating that they adhered to the recommended route.

Objective post-trip produce quality data could not be collected within the four-week study period and remains a critical goal for future validation.

The major constraints of the present investigation are: (i) although the 45 participants are enough for hypothesis testing, the study has a limitation in terms of power for subgroup analyses; (ii) the study was performed in only one district, thereby may restrict its applicability to other agro climatic regions; and (iii) the Freshness Score Calculator is based on FAOSTAT-calibrated decay constants, which may not be representative for varieties- and microclimates.

VI. CONCLUSION

We present Agri-Route, a production voice-first multi-agent AI platform for smallholder farmers deployed with our industry partner in Africa. Technically, the system achieves its fundamental innovation through a coordinator-driven multi-agent architecture and a Freshness Score Calculator that combines geospatial routing with produce-specific decay modeling and live weather information for perishable logistics optimization. A controlled user study with N=45 demonstrated statistically significant improvements in task-completion accuracy (34.6 pp, $p < 0.01$), time-to-decision (40% reduction, $p < 0.01$), and system usability (SUS 74.2 vs 51.4, $p < 0.05$). Most importantly, the literacy gap was fully eliminated by voice-first interaction, enabling quality advisory access for users of any literacy level.

Future work will include: (i) an offline mode for low-connectivity deployments using on-device model distillation; (ii) integration of Sentinel-2 satellite images for field-level crop monitoring; (iii) supply chain traceability enabled by blockchain for access to the premium market; (iv) extension of ASR to Tamil, Telugu, and Bengali; and (v) a longitudinal study tracking real yield and post-harvest loss over an entire growth season.

FUTURE SCOPE

Building on the current deployment, the following extensions are planned:

- Precision Agriculture Development: integration of Sentinel-2 imagery and drone-based NDVI maps at the field scale for crop health monitoring and yield forecasting.
- Improved Disease Diagnosis: multimodal disease analysis using visual disease symptoms, soil composition and weather context for differential diagnosis; connection with accredited diagnostic labs for send-out pathology.-
- Offline and Low-Connectivity Mode: quantised LLM variant models (e.g. Llama-3.1-8B-Instruct) for on-device use for download-challenged/absent internet-connectivity regions.
- Broader Language Support: fine-tuned ASR models for Tamil, Telugu, Bengali, Kannada and Punjabi for 22 Scheduled Languages ofIndia.
- Blockchain Supply Chain Traceability: an immutable provenance ledgers connecting farm origin, transport conditions (captured by the FSC) and market delivery to facilitate premium-market certification.
- Policy and Equity Issues: formulation of a data privacy framework aligned with the India's Digital Personal Data Protection Act 2023 (DPDP Act); implementation models for equitable access across marginal and tribal farmers.

REFERENCES

[1] FAO, "The State of Food and Agriculture 2022," Food and Agriculture Organization of the United Nations, Rome, 2022. [Online]. Available: https://www.fao.org/publications/sofa/2022/en/

[2] FAO, "The State of Food and Agriculture 2019: Moving Forward on Food Loss and Waste Reduction," Rome, 2019. [Online]. Available: https://www.fao.org/3/ca6030en/ca6030en.pdf

[3] Gouravmoy Bannerjee, Uditendu Sarkar, Swarup Das,& Indrajit Ghosh, "Artificial Intelligence in Agriculture: A Literature Survey," International Journal of Scientific Research in Computer Science Applications and Management Studies, Volume 7, Issue 3 (May 2018).

[4] S. Wolfert and M.-J. Bogaardt, "Big Data in Smart Farming — A Review," Agricultural Systems, vol. 153, pp. 69–80, May 2017.

[5] H. Verma, A. Singh, S. Avasthi, and T. Sanwal, "AI-Based Agriculture Application for Crop Recommendation and Guidance System for Farmers," in Proc. Int. Conf. Communication, Computer Sciences and Engineering (IC3SE), Gautam Buddha Nagar, India, 2024.

[6] D. Balakrishnan, P. S. K. Reddy, G. L. Reddy, C. P. Kumar, G. V. V. Reddy, and U. Mariappan, "AI-Based Smart Crop Advisory and Support System for Farmers," in Proc. Int. Conf. Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bangalore, India, 2026.

[7] A. Agata, H. Fakhrurroja, and D. Pramesti, "An AI-Driven Mobile Farmer Assistant for Agricultural Information," in Proc. Int. Conf. ICT for Smart Society (ICISS), Bandung, Indonesia, 2025.

[8] D. P. Hughes and M. Salathé, "An Open Access Repository of Images on Plant Health to Enable the Development of Mobile Disease Diagnostics," arXiv:1511.08060, 2015.

[9] M. T. Rahman, D. R. Dipto, S. K. Shib, A. Shufian and M. S. Hossain, "Advanced Neural Networks for Plant Leaf Disease Diagnosis and Classification," 2025 Fourth International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP), Bangkok, Thailand, 2025

[10] G. D. T., G. Krishnan G, and P. M. Lavanya, "AgroMind AI: A Voice-Enabled Agricultural Advisory System using Advanced Natural Language Processing," in Proc. 6th Int. Conf. Image Processing and Capsule Networks (ICIPCN), Dhulikhel, Nepal, 2026.

[11] N. Chandolikar, C. Dale, T. Koli, M. Singh, and T. Narkhede, "Agriculture Assistant Chatbot Using Artificial Neural Network," in Proc. Int. Conf. Advanced Computing Technologies and Applications (ICACTA), Coimbatore, India, 2022.

[12] R. Kumar Rajak, A. Pawar, M. Pendke, P. Shinde, S. Rathod, and A. Devare, "Crop Recommendation System to Maximize Crop Yield using Machine Learning Technique," Int. Research J. Engineering and Technology, vol. 4, no. 12, Dec. 2017.

[13] S. Patil, K. Goswami, K. Singh, and A. Ramdas, "Analysis of Crop Selection on Basis of Dynamic Environmental Factors and Live Market Condition using ML and IoT," Int. J. Innovative Science and Research Technology, vol. 3, no. 4, Apr. 2018.

[14] G. Singh and Y. Mehta, "A Multi-Agent Framework for Precision Agriculture," IEEE Systems Journal, vol. 15, no. 2, pp. 1833–1844, 2021.

[15] D. Wang, Y. Li, and Z. Zhang, "A Cloud-Based Platform for Agricultural Big Data Analytics," IEEE Cloud Computing, vol. 9, no. 2, pp. 51–60, 2022.

[16] A. B. Manwatkar, S. J. Kamble, D. V. Kudande, P. Singh Senger, A. B. Surnar and S. A. Vanakudre, "Autonomous Multi-Agent Architecture for Intelligent Precision Farming," 2026 IEEE International Conference on AI Engineering and Innovations (AIEI), NIT Jamshedpur, India, 2026

[17] S. M. S., D. K. Panjiyar, D. Kurmi, A. Choudhary Kurmi and M. N. M. Alyafeai, "Design and Implementation of an AI-Powered Decision Support System for Smart Farming: A Comprehensive Study," 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS), Indore, India, 2025, pp. 1-7,2025.
[18] N. Anand, H. Pundir, K. Singh, K. S. Bisht, R. Chauhan and A. Kapruwan, "Smart Agriculture System Using Internet of Things (IoT) and Machine Learning," 2024 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2024, pp. 1-7 ,2024.
[19] S. D, J. Poonia and V. Singh, "AI-Powered Sustainable Agriculture," 2025 International Conference on Data Science and Business Systems (ICDSBS), Chennai, India, 2025, pp. 1-10, 2025.
[20] S. Condran, M. Bewong, M. Z. Islam, L. Maphosa and L. Zheng, "Machine Learning in Precision Agriculture: A Survey on Trends, Applications and Evaluations Over Two Decades," in IEEE Access, vol. 10, pp. 73786-73803, 2022