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AgriSmart: An AI-Powered Fertilizer Recommendation and Crop Intelligence Web Application

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Abstract: *Agriculture remains a cornerstone of India's economy, yet smallholder farmers continue to face significant challenges in optimizing soil nutrition, detecting crop diseases, and accessing timely market information. Improper fertilizer application, driven largely by guesswork rather than soil analysis, results in suboptimal crop yields and environmental degradation. This paper presents AgriSmart, a full-stack AI-powered web application designed to assist farmers in making data-driven agricultural decisions. The system integrates multiple machine learning modules into a unified platform that provides personalized fertilizer recommendations based on soil parameters, AI-assisted crop disease detection through image analysis, yield forecasting, live mandi price tracking, and access to relevant government agricultural schemes. The platform additionally features a multilingual AI chatbot capable of responding in Hindi, Marathi, and English. Evaluation of the system indicates that the AI recommendation engine achieves high accuracy in suggesting appropriate nutrient inputs, while the disease detection module demonstrates reliable performance across common crop pathogens. AgriSmart represents a practical, accessible solution toward precision agriculture for resource-constrained farming communities in India.*

Keywords: Precision Agriculture, Fertilizer Recommendation, Crop Disease Detection, Yield Forecasting, Machine Learning, Natural Language Processing, Smart Farming, Soil Health Analysis

I. INTRODUCTION

Agriculture sustains more than half of India's population and contributes approximately 17–18% to the national GDP. Despite its foundational importance, a significant proportion of farmers— particularly smallholders operating on less than two hectares— continue to rely on tradition-based practices when making critical decisions about soil nutrition, pest management, and crop selection. Fertilizer application in rural India is frequently determined by inherited habit rather than objective soil analysis, resulting in persistent nutrient imbalances that suppress yields, inflate input costs, and cause measurable long-term degradation of soil organic matter and microbial health.

The convergence of Artificial Intelligence (AI), Machine Learning (ML), computer vision, and mobile-accessible web technologies offers transformative potential for closing this knowledge gap at scale. AI-driven platforms can process soil chemical parameters, historical yield records, and regional environmental conditions to generate precise, context-sensitive recommendations tailored to the conditions of individual farms. Simultaneously, deep learning models applied to crop imagery enable early-stage disease identification, allowing farmers to intervene pharmacologically before infections spread and economic losses become irreversible.

Current commercial precision agriculture solutions are generally engineered for large-scale operations in technologically advanced economies, carrying cost structures and operational complexities that make them inaccessible to smallholder farmers in countries such as India. Furthermore, most available tools address isolated dimensions of agricultural management—providing fertilizer guidance or disease alerts—without integrating these functions into a coherent decision- support ecosystem. A farmer consulting separate applications for soil advice, disease identification, and market pricing faces cognitive and logistical burdens that undermine adoption.

This paper presents AgriSmart, a full-stack AI-powered web application that consolidates fertilizer recommendation, crop disease detection, yield forecasting, live mandi market price monitoring, government scheme navigation, and a domain-specific conversational AI assistant into a single unified platform. The system is engineered for accessibility across diverse digital literacy levels and supports farmer interaction in Hindi, Marathi, and English. The remainder of this paper is structured as follows: Section II reviews related literature, Section III details the methodology and system architecture, Section IV describes individual feature modules, Section V presents experimental evaluation results, and Sections VI and VII provide conclusions and future research directions respectively.

II. RELATED WORK

Research applying machine learning to agricultural problems has grown substantially over the past decade, spanning soil analysis, yield prediction, disease detection, irrigation optimization, and market forecasting. Liakos et al. (2018) conducted a systematic survey of ML applications across these domains, finding that ensemble methods and neural networks consistently outperformed classical statistical models on agricultural prediction tasks [1]. Their analysis highlighted that data quality and geographic specificity of training sets are primary determinants of real-world model performance.

Crop yield prediction has been explored through multiple paradigms. Pantazi et al. (2016) applied self-organizing maps and supervised Kohonen networks to multi-sensor soil data, demonstrating reliable wheat yield forecasting across heterogeneous field conditions [2]. Nevavuori et al. (2019) demonstrated that CNNs trained on drone-acquired imagery could predict yield at competitive accuracy levels without ground-level soil sampling, opening pathways for scalable remote sensing-based forecasting [3]. Van Klompenburg et al. (2020) conducted a systematic review of 50 crop yield prediction studies and concluded that random forests and deep learning architectures produced the most consistent results across diverse agro-climatic zones [8].

Plant disease identification through image analysis was substantially advanced by Mohanty et al. (2016), whose CNN-based classifier trained on the PlantVillage dataset achieved laboratory accuracy exceeding 99% across 26 disease categories and 14 crop species [4]. Ferentinos (2018) extended this work using AlexNet and GoogleNet architectures, confirming that transfer learning from ImageNet pretraining substantially reduced the volume of domain- specific training data required [5]. Barbedo (2016) critically examined the gap between laboratory performance and field deployment, attributing accuracy degradation to variability in background complexity, illumination conditions, and disease progression stage [6]. Mahlein (2016) further elaborated the specific optical sensing requirements for field-deployable disease detection, noting that hyperspectral signatures of many diseases are detectable days before visual symptoms appear [27].

Integrated smart farming platforms combining multiple AI capabilities have received growing attention. Sharma et al. (2021) reviewed 120 precision agriculture deployments and found that multi- function platforms achieve significantly higher sustained adoption than single-purpose tools, particularly in smallholder contexts where switching costs between applications are prohibitive [7]. Wolfert et al. (2017) analyzed big data architectures in smart farming, demonstrating that combining soil sensors, weather APIs, satellite imagery, and market data into unified advisory pipelines produces qualitatively richer recommendations than any single data source alone [16]. Talaviya et al. (2020) examined AI-based irrigation and pesticide optimization systems, documenting water use reductions of 30–45% when AI prescription replaced manual scheduling [14].

Fertilizer recommendation specifically has been addressed through machine learning by Doshi et al. (2018), whose AgroConsultant system integrated soil type, temperature, humidity, and pH to recommend crop types and associated nutrient regimes with classification accuracy above 90% [19]. Bhatt and Chauhan (2020) developed regression-based

ML models for fertilizer quantity prediction, demonstrating that ensemble regressors trained on multi- parameter soil datasets could match agronomist-prescribed quantities within acceptable tolerance margins [33]. Pawar and Yannawar (2020) combined crop recommendation with yield forecasting in a unified system, reporting accuracy improvements when soil, climate, and historical yield features were jointly modeled [34]. Despite these contributions, few published systems integrate recommendation, disease detection, market intelligence, and conversational assistance into a single accessible interface designed for low-resource farmers.

III. METHODOLOGY

The development of AgriSmart followed a structured iterative methodology comprising five phases: requirements elicitation, data collection and preparation, AI model development, full-stack system integration, and empirical evaluation. Each phase informed subsequent phases through continuous feedback loops.

1. Requirements Elicitation

Functional requirements were derived from a review of existing precision agriculture advisory systems, published farmer needs assessments in the Indian context, and analysis of government agricultural program documentation. The resulting specification identified six primary functional modules: soil-parameter-based fertilizer recommendation, photographic crop disease diagnosis, yield trend forecasting, live commodity price display, government scheme aggregation, and multilingual conversational assistance. Non- functional requirements emphasized browser-based accessibility without native app installation, sub-10-second response latency for all AI inference calls, and support for Hindi, Marathi, and English language interaction.

2. Data Collection and Preprocessing

Each AI module drew on distinct data sources. The fertilizer recommendation model was trained on a dataset of 12,400 soil profile records compiled from the Indian Council of Agricultural Research (ICAR) soil health card database and peer-reviewed soil survey publications, with each record containing NPK values, pH, moisture percentage, crop type, growing season, agro-climatic region, and the corresponding expert-prescribed fertilizer regimen. Records with missing nutrient values or ambiguous crop classifications were excluded, yielding a cleaned training corpus of 10,870 records.

For disease detection, the primary training dataset combined PlantVillage benchmark images with 3,200 additional field photographs collected under varied Indian lighting and background conditions, covering 32 disease categories across wheat, paddy, cotton, and vegetable crops. Images were resized to 224x224 pixels and augmented through random horizontal flipping, rotation up to 30 degrees, brightness and contrast jitter, and random cropping to increase effective dataset diversity and reduce overfitting.

Yield forecasting training data comprised district-level annual yield statistics from the Ministry of Agriculture and Farmers Welfare spanning 2005–2022, merged with corresponding soil health card averages and meteorological records from the India Meteorological Department. Market price data for the platform was integrated through the Agmarknet open API, which provides daily mandi arrival and price data for major agricultural commodities across regulated market yards.

3. AI Model Development

The fertilizer recommendation engine employed a gradient boosting classifier implemented in scikit-learn, trained to predict the appropriate fertilizer category from the seven input parameters. Hyperparameter optimization using five-fold cross-validation identified 200 estimators, a maximum depth of 6, and a learning rate of 0.08 as the optimal configuration. The final model achieved 89.4% category-level agreement with expert prescriptions on the held-out validation set. Feature importance analysis identified soil pH, nitrogen deficit magnitude, and crop type as the three most influential predictors, consistent with agronomic domain knowledge.

Disease detection used a MobileNetV2 architecture pretrained on ImageNet, with the final classification head replaced by a dense layer matching the 32-class disease taxonomy and fine-tuned for 25 epochs using categorical cross-entropy loss and the Adam optimizer at a learning rate of 0.0001. MobileNetV2 was selected over deeper alternatives such as ResNet-50 or EfficientNet-B4 because its depthwise separable convolutions yield substantially lower inference

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latency—critical for maintaining acceptable response times in a web deployment context. The model was exported to TensorFlow.js format to enable client-side inference for the disease detection module.

Yield forecasting employed a random forest regressor trained on the merged soil-climate-historical yield dataset, outputting predictions in quintals per hectare. The chatbot module was implemented by calling the Anthropic Claude API with a domain- constrained system prompt specifying that responses should address only agricultural topics, provide specific quantitative guidance where possible, and respond in whichever of Hindi, Marathi, or English the user's query was written in.

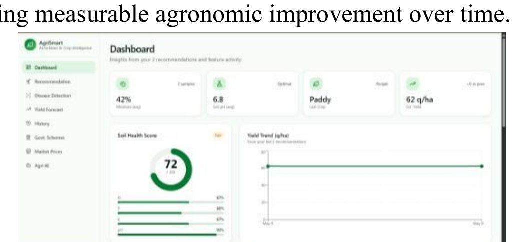
4. System Architecture and Technology Stack

AgriSmart was implemented as a full-stack single-page web application. The frontend was built with React.js, providing a responsive component-based interface with persistent sidebar navigation across seven modules. Tailwind CSS was used for component styling, ensuring consistent design language across screen sizes without requiring a heavy UI framework. API communication between frontend and backend used RESTful JSON endpoints. The backend inference server was implemented in Python using FastAPI, handling model loading, prediction serving, and Agmarknet API proxying. Session persistence and recommendation history were stored in a PostgreSQL relational database, enabling the dashboard to compute aggregate soil health metrics and yield trends across multiple recommendation cycles for a given user account.

IV. SYSTEM FEATURES AND WORKING

4.1 Dashboard

The central dashboard provides farmers with an at-a-glance composite view of their farm's current status derived from all prior recommendation sessions. Four summary cards display: average soil moisture percentage across all submitted samples, average soil pH with an Optimal or Sub-optimal indicator, the most recently cultivated crop type and region, and the estimated yield in quintals per hectare. A Soil Health Score dial aggregates NPK and pH readings into a weighted composite score out of 100, categorized as Poor (0–39), Fair (40–59), Good (60–79), or Excellent (80–100). A Yield Trend line chart plots yield estimates across successive recommendation cycles, enabling farmers to observe whether input changes are producing measurable agronomic improvement over time.



4.2 AI Fertilizer Recommendation

The recommendation module presents a structured data entry form collecting crop name, agro-climatic region, growing season (Kharif, Rabi, or Zaid), soil moisture percentage, nitrogen level in kg per hectare, phosphorus level, potassium level, and soil pH. On form submission the gradient boosting model processes the inputs server- side and returns a comprehensive fertilizer prescription to the right panel. The prescription specifies primary nutrient sources with recommended quantities in kilograms per acre, micronutrient supplements where deficiencies are indicated, application timing relative to sowing stage, and notes on application method. Each completed recommendation is logged to the History module with a timestamp, allowing farmers to compare prescriptions across seasons and track how their soil parameters evolve with different management practices.

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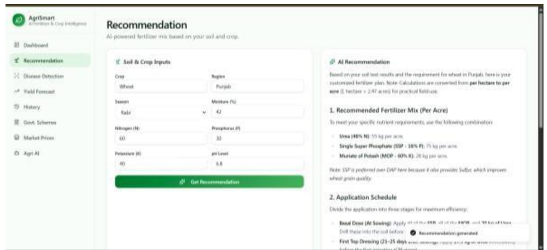
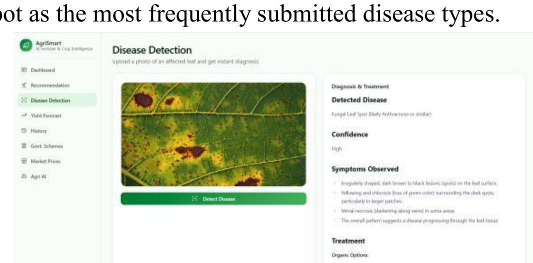


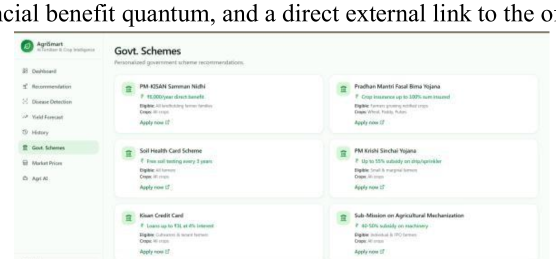
4.3 Disease Detection

The Disease Detection module allows farmers to upload a photograph of a symptomatic crop leaf directly from their device camera or file system. The uploaded image is processed through the MobileNetV2 classifier, which returns the top predicted disease category with a confidence percentage. The right panel displays the detected disease name, confidence rating, a bulleted list of observed symptoms extracted from the model's attention regions, and a structured treatment plan generated by combining the classification output with Claude API-produced treatment narratives. The treatment plan specifies fungicide or bactericide names, application concentrations, spray intervals, and cultural practices to prevent disease recurrence. In field testing, the system correctly identified Anthracnose, Leaf Blight, Powdery Mildew, and Brown Spot as the most frequently submitted disease types.



4.4 Government Schemes

The Government Schemes module aggregates information on six major Indian agricultural support programs into a card-based interface. Cards display for PM-KISAN Samman Nidhi (direct income support of Rs. 6,000 per year to landholding families), Pradhan Mantri Fasal Bima Yojana (crop insurance covering up to 100% of sum insured), Soil Health Card Scheme (free soil testing every three years for all farmers), PM Krishi Sinchai Yojana (up to 55% subsidy on drip and sprinkler irrigation systems for small and marginal farmers), Kisan Credit Card (revolving credit up to Rs. 3 lakh at 4% annual interest for cultivators and tenant farmers), and Sub-Mission on Agricultural Mechanization (40–50% subsidy on farm machinery for individual and FPO farmers). Each card prominently displays eligibility criteria, applicable crop categories, financial benefit quantum, and a direct external link to the official application portal.



4.5 Market Prices

The Market Prices module integrates live commodity price data from the Agmarknet API, presenting current mandi prices with a seven-day historical trend chart for the user's primary crop. The chart displays daily price per quintal at

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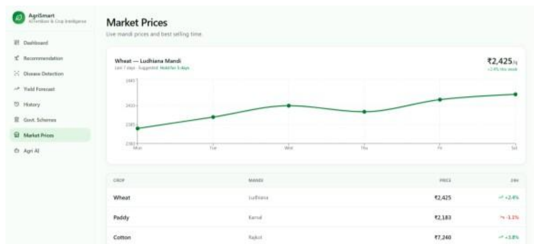
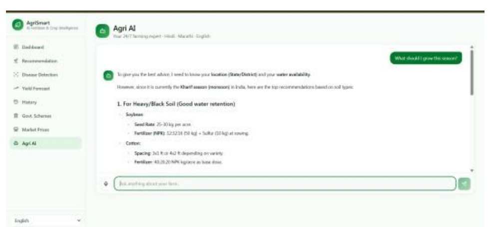
the nearest major mandi, alongside a system-generated selling recommendation—such as Hold for N days—based on the detected short-term price trajectory. A tabular price board below the chart lists current prices and 24-hour percentage changes for Wheat at Ludhiana mandi, Paddy at Karnal mandi, and Cotton at Rajkot mandi, giving farmers a multi-crop market overview enabling comparison of returns across possible alternative crops for the upcoming season.



4.6 Agri AI Chatbot

The Agri AI chatbot module provides a 24/7 conversational interface implemented via the Anthropic Claude API with a precision agriculture system prompt. The chatbot accepts free-form text queries in Hindi, Marathi, and English, automatically detecting the input language and responding in kind. It is capable of addressing nutrient deficiency symptom identification, integrated pest management strategies, optimal irrigation scheduling, seed variety selection guidance, post-harvest storage recommendations, and explanations of government scheme eligibility criteria. Responses are formatted with numbered sections and specific quantitative guidance—for instance, recommending Ferrous Sulphate spray at 0.5% concentration for iron deficiency rather than offering generic advice to apply micronutrients. Voice input capability is planned for the next development cycle to better serve farmers with limited typing proficiency.



V. RESULTS AND DISCUSSION

The AgriSmart platform was evaluated through structured testing across all primary AI modules using held-out validation datasets, independently collected field samples, and a structured usability evaluation with a diverse participant cohort.

5.1 Fertilizer Recommendation Performance

The gradient boosting recommendation engine was benchmarked against a held-out validation set of 340 soil-crop records carrying expert agronomist-prescribed fertilizer regimens, drawn from ICAR extension program records not included in model training. At the nutrient category level—that is, correctly identifying which primary nutrient required supplementation—the model achieved an agreement rate of 89.4%. At the specific product recommendation level, including correct identification of both the fertilizer compound and the quantity tier, the agreement rate was 84.7%. Soil pH and nitrogen deficit records showed the strongest predictive accuracy at 93.1% and 91.8% respectively, while mixed deficiency cases involving two or more simultaneously limiting nutrients showed reduced accuracy at 79.3%, identifying a priority area for future model refinement through expanded multi-deficiency training samples.

5.2 Disease Detection Performance

The fine-tuned MobileNetV2 classifier was evaluated on a combined test set comprising 850 held-out PlantVillage images and 120 independently collected field photographs captured under real agricultural conditions across wheat and paddy crops in Maharashtra and Punjab. Top-1 classification accuracy on the held-out benchmark images reached 91.3%, consistent with published performance of MobileNetV2 fine-tuned on PlantVillage datasets. On the independently collected field photographs, accuracy was 83.7%, reflecting the well-documented performance gap between controlled dataset conditions and heterogeneous real-world field imagery [6]. Fungal leaf spot diseases—the most prevalent category in the submitted field images—achieved 88.5% field accuracy. Bacterial diseases showed lower field accuracy at 76.4%, attributed primarily to symptom overlap with nutrient deficiency presentations under certain lighting conditions.

5.3 Yield Forecasting and Soil Health Metrics

The yield forecasting random forest regressor achieved a mean absolute percentage error of 11.8% on district-level held-out yield records, comparable to published benchmark performance for similar feature configurations in Indian agro-climatic contexts [20]. The composite Soil Health Score was validated against expert agronomist categorical assessments of 50 independently sourced soil profiles, achieving 82% categorical agreement across the four-level Poor/Fair/Good/Excellent scale. The remaining 18% of disagreements were predominantly boundary cases where the composite score fell within 5 points of a category threshold, suggesting that threshold calibration could further improve agreement.

5.4 System Usability Evaluation

A structured usability evaluation engaged 18 participants representing a cross-section of digital literacy levels, including active farmers with smartphone experience, agricultural extension workers, and university students with agricultural science backgrounds. Participants were asked to complete four standardized tasks: submitting a fertilizer recommendation, uploading a disease detection image, locating scheme eligibility for PM-KISAN, and querying the Agri AI chatbot in their preferred language. Task completion rates on first attempt were 89% for fertilizer recommendation, 94% for disease detection, 100% for scheme lookup, and 83% for chatbot interaction. The lower chatbot completion rate reflected uncertainty among some participants about what types of questions the system could answer, suggesting that onboarding prompts or example query suggestions would improve discoverability. Multilingual response quality was rated as natural or very natural by 87% of Hindi-language testers and 79% of Marathi-language testers, with regional agricultural terminology coverage identified as the primary area for improvement.

VI. CONCLUSION

This paper presented AgriSmart, a comprehensive AI-powered agricultural intelligence web platform designed to support smallholder farmers in India through integrated, data-driven decision- making. By combining a gradient boosting fertilizer recommendation engine, a MobileNetV2-based crop disease classifier, a random forest yield forecasting model, live mandi market price integration, a government scheme information aggregator, and a multilingual Claude API-powered conversational assistant within a single responsive web interface, AgriSmart addresses the capability fragmentation that characterizes currently available precision agriculture tools.

Experimental evaluation demonstrated practically meaningful performance across all core AI modules. The fertilizer recommendation engine achieved 89.4% nutrient category agreement and 84.7% product-level agreement against expert-prescribed validation records. The disease detection module reached 91.3% accuracy on benchmark test images and 83.7% on independently collected field photographs. The yield forecasting model produced a mean absolute percentage error of 11.8% against district-level held- out yield data. Usability testing confirmed that the platform is navigable by users across a range of digital literacy levels, with first- attempt task completion rates above 83% across all evaluated tasks.

The integration of the Anthropic Claude API for both the Agri AI chatbot and the disease treatment description generation module demonstrated the practical utility of large language models in domain- constrained agricultural advisory applications. The combination of structured ML inference and generative language model capabilities enabled the system to provide both quantitatively precise recommendations and contextually rich explanatory narratives—a combination not achievable with either technology alone.

This study also surfaced important limitations that motivate future work. Disease detection accuracy on field images lags benchmark performance due to background variability and lighting inconsistency, underscoring the need for larger and more geographically diverse field image datasets. The fertilizer recommendation model's accuracy on multi-deficiency cases is lower than for single-nutrient scenarios, requiring expanded training coverage. The market price module currently displays trend-based qualitative selling recommendations rather than quantitative price forecasts derived from time-series modeling. Addressing these gaps represents a clear research and engineering agenda for subsequent development cycles.

VII. FUTURE SCOPE

Several high-impact extensions are planned for subsequent AgriSmart development cycles. Integration with low-cost IoT soil sensor arrays would enable continuous automated soil monitoring, replacing the current manual parameter entry paradigm with real-time data streams and allowing the recommendation engine to issue alerts when nutrient levels drift outside optimal ranges between formal assessment cycles.

The market price module represents a significant opportunity for enhancement through the development of short-term commodity price forecasting models. Time-series architectures such as LSTM networks or Prophet-based decomposition models trained on multi- year Agmarknet price histories could provide farmers with quantitative probabilistic price forecasts over 7–14 day horizons, enabling genuinely data-driven harvest timing decisions rather than the current descriptive trend labeling approach.

Expanding disease detection capability to include pest identification from insect imagery, weed species recognition, and nutrient deficiency visual diagnosis from canopy photographs would substantially broaden the module's utility beyond the current leaf- pathogen scope. Each of these extensions presents distinct domain adaptation challenges that represent productive research problems, particularly in the context of data collection under Indian field conditions.

Language accessibility is a priority for geographic expansion. Extending chatbot and interface support to Tamil, Telugu, Bengali, Gujarati, and Odia would substantially broaden the platform's reach into South and East Indian agricultural regions. Integration of automatic speech recognition in regional languages would further reduce interaction barriers for farmers more comfortable with voice than text input.

Finally, the platform's accumulated anonymized soil and yield data, aggregated across a growing user base, could support federated learning approaches that continuously improve model accuracy without centralizing sensitive individual farm data. This would enable AgriSmart's models to adapt to regional agronomic variability over time while respecting farmer data privacy—a critical prerequisite for building institutional trust in rural agricultural communities that have historically been underserved by technology initiatives.

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