A Review on AI-Driven Smart Crop Advisory Systems for Small and Marginal Farmers

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Abstract. The Indian economy relies heavily on agriculture, yet crop diseases, poor disease diagnosis, and inaccurate crop selection continue to cause significant reductions in crop yield and farmers' income. Early and accurate disease detection, data-driven crop recommendation, and weather-based advisory can help prevent these losses and promote sustainable farming practices. Recent advances in artificial intelligence and machine learning have enabled the development of automated advisory systems using techniques such as ensemble models and convolutional neural networks (CNNs). This review focuses on the key components of an integrated smart crop advisory system, highlighting the performance and effectiveness of machine learning and deep learning models in this domain. It presents a literature review of (1) crop recommendation approaches using models like Random Forest and XGBoost, (2) plant disease detection using various CNN architectures, and (3) weather-based advisory integration. The paper also evaluates the strengths, limitations, and real-time applicability of these solutions. This review compares and contrasts the available machine learning methods applied in smart agricultural advisory systems to detect plant diseases and make crop recommendations.

Keywords: Crop Recommendation, Disease Detection, CNN, RandomForestClassifier, XGBoost, Weather-based Advisory, Smart Agriculture, Small and Marginal Farmers.

1 Introduction

The high rate of the world population has posed a great challenge to the agricultural systems in the achievement of productivity, efficiency, and sustainability in the long run. In India, this challenge is of special importance because agriculture is one of the main economic sectors, supporting more than half of the country's workforce and providing a significant share of national GDP [5], [16]. However, orthodox farming methods are not keeping up with modern-day farming challenges. Farmers still face the

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challenge of unpredictable climatic events, reduced soil fertility, poor water availability, and large yield losses due to pests and diseases [6], [15]. These conditions open up significant vulnerabilities in food production systems and affect the economic resilience of farmers directly. Small and marginal farmers suffer disproportionately because of their insistence on relying on traditional knowledge systems, which often fail to match the requirements of the present dynamic agricultural scenario. The lack of reliable and local information, including an index of soil health, up-to-date data on real-time weather intelligence, and early disease alerts, widens the gap between knowledge and technology [4], [16]. High input costs, limited access to expert agronomic advice, and digital awareness further prevent them from attaining a level of regularity in productivity and financial resilience [6]. To solve these problems, the agriculture industry is increasingly moving to digital/data-driven approaches. Advances and findings in artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) have made it possible to switch from reactive decision-making to proactive decision-making in farming operations [3], [7]. ML-based crop prediction models have demonstrated a great capability in analysing complex interactions between soil nutrients like nitrogen, phosphorus, and potassium, and pH in combination with environmental variables. Multiple studies indicate good results of ensemble-based learning, including Random Forest and XGBoost, to perform crop recommendation tasks, but the results vary based on the features of their datasets and agro-climatic conditions and hence are hugely appropriate for the crop recommendation task [1], [4], [14].

Similarly, the deep learning frameworks, especially convolutional neural networks (CNNs), have demonstrated great accuracy at identifying plant diseases from leaf images. Light-weight and efficient architectures like EfficientNet and MobileNetV2 offer light-weight and efficient feature extraction for rapid and timely disease detection capabilities despite resource-constrained environments [8], [11], [12]. In parallel, the integration of real-time meteorological information via API, e.g., OpenWeatherMap, provides actionable weather information for sowing, fertiliser irrigation and pesticide treatment, and harvesting. These localised advisories are another fundamental level of risk modification in climate-sensitive farming systems [2], [5], [10]. Despite all these technological advances, old agricultural solutions remain fragmented. Most of the systems are one-dimensional and address only either crop recommendation, disease detection or weather advisory, requiring that farmers have to traverse different disconnected tools [5], [9]. Furthermore, many platforms do not include critical features that are required in a rural environment, such as multilingual, voice-based, and offline functionality, which limits the usability of these platforms among low-literacy and low-connectivity communities [6], [10]. This serves to present the need for an integrated, user-centric, and accessible advisory framework that should bring all the necessary services under one single service.

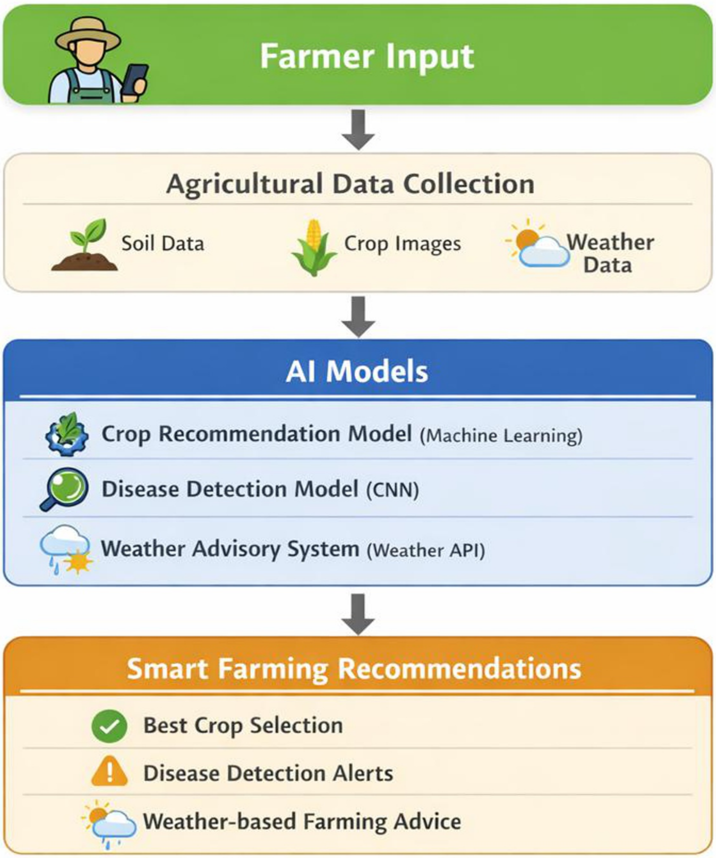

Fig. 1. Conceptual architecture of an AI-driven Smart Crop Advisory System

In Fig. 1, we clearly see that the objective of this paper is to review and analyse the existing literature to identify the most accurate, scalable, and context-appropriate ML and DL models that can be taken up for the development of a unified smart crop advisory system. By assessing the top-performing algorithms from ensemble-based crop recommendation methods to CNN-based disease detection algorithms, the present work is intended to present the state-of-the-art technologies that could support a complete decision support system to help small and marginal farmers in India.

2. Literature Review

Authors in [1] conduct a comparative analysis of various classifiers that are used in machine learning in crop recommendations using Indian agriculture data. The evaluation of this model is performed under questions of model performance (accuracy, precision, and recall) for some characteristics like soil nutrients (N, P, and K), pH, rainfall, and temperature, and data imbalance and noise are integrated, using ensemble methods (mainly Random Forest) against single models for deviated and noisy data in agronomy. Also, you see in Table 1, the authors discuss feature importance analysis, which demonstrates the importance of site-specific parameters such as pH and seasonal rainfall in recommendations, providing for explainability to the farmer-facing outputs. Strengths of the paper include rigorous cross-validation and clear comparison metrics; the limitations include relatively small geographic coverage and a lack of discussion of deployment constraints (multilingual UI and offline use). For a smart crop advisory system, such work gives a validation of ensemble learners, such as Random Forest, and best practices for evaluating the crop recommendation module.

Authors in [2] studied farmers' perception, adoption, and utility of weather-based agro-advisory services in Himachal Pradesh, since the socio-technical use of such services can only be assessed through survey data and the data on their use of such methods. Their mixed methodology approach includes that localised, timely, and actionable forecasts play a significant role in influencing farmer decisions on sowing and irrigation, but also that utility is limited by literacy, language barriers, and intermittent connectivity. The human-centred evidence provided on the necessity for localised advisories and socio-economic determinant factors for adoption is the key contribution of the paper. It has the limitation of being regional and limited technological treatment of how API- or ML-based downscaling was implemented. This study highlights the need to incorporate user experience design (multilingual voice/text and offline caching) and socio-economic profiling in a weather advisory component of a Smart Crop Advisory System.

Authors in [3] describe an end-to-end "Smart Crop Advisor" prototype for farmers in India that combines crop recommendations using machine learning with a light-weight web interface. The authors say they applied gradient-boosting models to past records of soil and yields and implemented a Read-only Exec Service (REST) API for front-end queries by showing a slight increase in precision of recommendations over baseline approaches that use simple heuristics. Notable strengths include the full-stack implementation and practical evaluation in a pilot, and the limitations are that it did not include deep-learning disease detection, and it was not evaluated on diverse agro-climatic zones. For an integrated system, this work is useful as a practical reference when designing APIs, serving models, and validating at an early stage in the field.

Authors in [4] created an AI-based crop advisor system that takes into account agro-climatic parameters and soil parameters to suggest appropriate crops in Karnataka with the help of region-based feature engineering and farmer-focused outputs. They compare the tree-based ensembles and XGBoost and talk about hyperparameter tuning and the benefit of locality-specific training data. The strength of this study is careful regional adaptation and demonstration to improve relevance for the cropping patterns of the region; the weakness is limited discussion of the study's scalability and very little discussion of the model's interpretability for those other than the technical study team. This research provides input on the need for regionally fine-tuned models and localised datasets in the scale-up of a national smart crop advisory system.

Authors in [5] put forth "Smart Farm Advisor", an artificial intelligence (AI)-powered, end-to-end farming advisor with a combination of recommendations for crops to be planted and alerts about diseases to be on the lookout for, as well as a link to markets where those crops could be sold. Their architecture includes a combination of ML-based recommendation engines with CNN-based image classifiers for disease identification and an analytics dashboard hosted on the cloud, and they provide encouraging accuracy metrics and case study benefits in pilot farms. The strength is the holistic approach, where the agronomy is linked with the market intelligence, and the limitations include how little it talks about offline operation and explains how models generalise without having seen any region. This paper is of special relevance as a blueprint for integrating several advisory modules into a single one accessible to farmers.
Authors in [6] propose a scalable web application named Smart AI Farmer aimed at solving agricultural problems where IoT devices are not required and instead rely on user inputs and remote sensing/weather APIs. The low hardware dependency and accessibility feature of employing ML algorithms for the recommendations and easy image upload disease check features are emphasized in the study. Its strength is an accessible design for low-resource settings. The limitation is a reduced level of automation and a heavy reliance on user-provided inputs, which reduces accuracy and places a greater burden on users. For an integrated advisory system, their way up contains tradeoffs with IoT enhancement for automation and concrete to the accessibility for smallholders.

Researchers in [7] describe a crop advisory system in real-time based on the usage of IoT sensors for soil moisture and microclimate monitoring coupled with ML for irrigation scheduling and disease-risk prediction. They show how live telemetry enhances the temporal information of the advisories (e.g., irrigation timing) and discuss the velocities of the latencies and energy limitations. Strengths include the engineering detail of the IoT integration and performance processing in real-time, while limits include a higher cost of deployment and the higher maintenance cost, which will be key focal points for small-scale farmers. This work is directly applicable to the design of a hybrid smart crop advisory system to support the deployment of both sensor-equipped and sensorless deployments of the system.

Authors in [8] introduce "Farmer's Assistant", which is one of the first applications of machine learning (ML) in the agricultural field (arXiv preprint) that provides recommendations on cropping, and simple detection for diseases using classical classification and simple CNNs is provided. The paper is unique because it provides an example of a pipeline for low-compute CNNs as well as several common pitfalls for CNNs (overfitting on small datasets; augmentation is required). While preliminary and limited in scale, their focus on light-weight models is something that is useful for environments that are bandwidth and compute-constrained. This study proposes techniques (data augmentation and transfer learning) to enable the practical application of CNN-based disease detection within a smart crop advisory system.

Table 1. Summary of the existing literature review

Source	Findings
[1]	Compares six ML models for crop recommendation. Finds that XGBoost surpassed others, achieving 93.2% accuracy in determining the most suitable crop for given soil parameters.
[2]	Studies farmers' perception of weather-based agro-advisory services (AAS). Finds 76% of farmers were satisfied with biweekly bulletins, and 72.20% found rainfall forecasts most critical.
[3]	Compares Random Forest and Naive Bayes for crop forecasting. Concludes Random Forest is superior due to its robustness and ability to handle mixed data, achieving over 99% accuracy.
[4]	Proposes an AI-based crop recommendation system for Karnataka. Finds Random Forest is the best-performing algorithm, achieving a ~90% agreement rate with expert suitability recommendations.
[5]	Introduces "KrishiMitra", an all-in-one AI farmer assistant. Uses a CNN (TFLite) for offline disease detection (96.3% accuracy) and integrates real-time weather/market APIs.
[6]	Presents "Smart AI Farmer", a scalable web app that provides crop recommendations, disease detection (CNN), and weather forecasts without requiring expensive IoT devices.
[7]	Proposes an AI and IoT-based crop advisory system. Uses IoT sensors (NPK, moisture, temp, and pH) and a Random Forest model to achieve 92% crop prediction accuracy.
[8]	Creates "Farmer's Assistant", a web app using Random Forest for crop recommendation (99.5% accuracy) and an EfficientNet (CNN) for disease detection (99.8% accuracy).
[9]	A systematic review of ML for crop recommendation. Confirms that Random Forest and Gaussian Naive Bayes are widely shown to be the best-performing models in the literature.
[10]	Proposes "AgriVoice", a multilingual voice/text assistant using Google TTS/STT and the OpenWeatherMap API. Focuses on accessibility for low-literacy farmers.
[11]	Develops an AI-based drone using MobileNetV2 (CNN) for early detection of anthracnose in cashew. Achieved 95% accuracy for disease and 99.2% for healthy leaves.
[12]	It presents a comprehensive exploration of using a custom Convolutional Neural Network (CNN) for plant disease classification, achieving 92.23% accuracy.
[13]	A systematic review on the adoption of climate information services (CIS) in Africa. Finds that education and ICT literacy are key factors in farmer adoption.
[14]	Proposes "Med-Crop", an AI-powered advisory for medicinal crops in South Karnataka. The Random Forest model yielded the highest accuracy at 92.3%.
[15]	Implements an IoT-based system using Arduino and multi-sensors (NPK, pH, temp, moisture). Validated with a < 2% error margin against laboratory tests.

[16]	Proposes a "Smart Agriculture Crop Advisor" web platform to provide personalised, region-specific guidance on crop suitability, climate, and soil type.

2.1 Datasets

The most widely used benchmark for plant disease detection is the PlantVillage dataset, an open-source collection containing over 60,000 labelled images across 38 classes, making it highly effective for initial model training but less generalisable to real-world conditions due to its controlled laboratory environment. To address this limitation, researchers commonly apply data-augmentation techniques such as rotation and zooming to simulate field variability. There are numerous studies on plant disease detection based on publicly available datasets like the PlantVillage dataset and extended versions at Kaggle. For crop recommendation, a structured dataset containing features such as crop name, pH range, temperature range, and rainfall is employed to identify the most suitable crop for a given field based on environmental and soil characteristics. This dataset includes 7,000 samples with five key features, providing a strong foundation for accurate prediction and decision support. Standard practice in the literature involves splitting datasets into training and testing subsets, typically using an 80/20 split to ensure robust model evaluation and reliable performance assessment.

3. Research Findings & Discussion

After reviewing and evaluating the latest sources, a number of important facts, issues, and developments in the field of smart crop advisory systems have been identified:

In the literature under analysis, ensemble machine learning models have been mostly applied to predict the suitability of crops owing to their capacity to process a complicated set of agricultural data. The comparative analysis in [1] identified XGBoost (93.2% accuracy) as having the best of the five other models. Nevertheless, in crop recommendation studies, random forest is the most common method, and an absolute accuracy of over 90 per cent has been noted in numerous studies, but the outcome would depend on the datasets and the methods of evaluation. [3, 4, 7, 8]. Other studies also confirm that Random Forest and Naive Bayes are found to be the most effective models to do this task (a review in [9]). Convolutional Neural Networks (CNNs) are the dominant and state-of-the-art method of image-based disease detection [12]. A lightweight pre-trained architecture approach is the choice due to the focus on the high accuracy and efficiency ratios. In one study, EfficientNet was found to obtain the accuracy of 99.8% [8], whereas MobileNetV2 was applied to obtain the accuracy of 95-98% in a drone-based detection system [11].

Over-reliance on the PlantVillage data [5, 8] is one of the major setbacks, specifically for disease detection. They are taken in controlled laboratory environments, which are not simulators of the field scenario of diverse lighting, shadows, and background flutter. This may cause rough model generalisation when applied to a farm [11]. Offline and Lightweight Model Optimisation: One difficult condition of real-world deployment to rural areas is offline functionality. This is met by the KrishiMitra system [5] that transforms its CNN model into a TensorFlow Lite (TFLite) version to make on-device inferences in low-connectivity areas possible. On the same note, the MobileNetV2 model [11] was quantised (edge device optimised), indicating that high accuracy is achievable in a small model.

The literature demonstrates that almost all real-time weather data is integrated through Application Programming Interfaces (APIs) in the third place, instead of physical equipment. In other studies [5, 10], the tool of choice that is used to offer hyper-local and multi-day forecasts is the OpenWeatherMap API. Among the key challenges that have been pointed out in the literature, the lack of technological infrastructure and digital tools among farmers working in rural territories should be mentioned [13]. The implementation of an advisory system depends on the adoption by the farmers. Other researchers [5, 6, 10] point out that systems should be convenient to users with low digital literacy. Some of the essential solutions are multilingual interfaces, voice-based commands (text-to-speech/speech-to-text) [10], and offline features [5]. The functions of most applications used are often fragmented and only provide one functional aspect [5, 16]. A farmer may require an app that detects diseases, another with prices in the market, and a third with weather [5]. This is a deterrent to adoption, but an all-in-one platform that is integrated [5, 6, 8] is described as the optimal solution. In general, the literature substantiates the fact that the fundamental AI models of a smart advisory system are developed and very precise. The main research problem has changed, as it is no longer focusing on building the models but rather on actual application, i.e., combining all these components in an uncomplicated, easily reachable, and straightforward application that can be utilised by farmers in real situations with limited resources.

4. Conclusion

Agriculture today requires how fast and accurately farmers can detect the problems in the crops, select the right crop, and take appropriate action against the diseases before they can spread. This review discussed how the modern technologies of AI and ML can be used to support these needs with a unified smart crop advisory system. Based on the 16 papers reviewed, it is evident that ensemble models such as Random Forest and XGBoost are a good fit for crop recommendation, while CNN-based models such as EfficientNet and MobileNetV2 provide highly accurate and efficient plant disease detection. Use of real-time weather information APIs has also been useful, with many farmers expressing real satisfaction through weather-based advice. However, there are still a number of challenges in the way. Many disease detection models are based on controlled datasets, such as PlantVillage, that do not necessarily reflect what is occurring in the field. Farmers also encounter some real-life barriers like low digital literacy, low internet connectivity, and the need to switch between multiple single-purpose applications. To move forward, systems of the future must implement all key functionalities – crop recommendation, disease diagnosis, and weather guidance – into one easy-to-use system. Equally important is enhancing model performance with new images from a variety of fields, adding multilingual and voice-based functionality, and adding offline functionality for use in rural areas. By filling these gaps, advisory tools powered by AI can extend help in making farming greener, more sustainable, and more accessible. Agricultural advisory systems using AI have high potential in taking farmers through the process of crop and disease selection, but additional research and practical studies should be carried out.

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