

AgriSmart: An AI-Powered Farming Assistant and Crop Management Platform for Precision Agriculture

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Agriculture is an area plagued with problems around crop selection, post-harvest management of plant diseases, and expert advisory knowledge at the correct time, adversely affecting the output and economics in the agriculture sector, especially in developing nations such as Pakistan. In this research, we propose Agri Smart: a modular unified knowledge-based system consisting of an integrated hybrid AI application which comprises a crop recommender system, plant disease identification system, and an intelligent multilingual farm advisory chatbot, all integrated seamlessly within a single real-time platform. We used supervised machine learning algorithms such as Extreme Gradient Boosting (Boost) for the crop recommender system, deep learning models based on YOLO for a plant disease identification system, and advanced NLP techniques for the multilingual conversational agent. The results exhibited 99% classification accuracy for the crop recommender system with 22 classes, while the plant disease identification system achieved an F1 score of 0.70 and mAP@50 of 74%, with all modules working in real time. The Agri Boot module delivered accurate contextual comprehension responses with bilingual support, ensuring farmer accessibility. Overall, Agri Smart successfully demonstrates the application of integrated AI technology.

Keywords: Agricultural Chatbot; Crop Recommendation; Machine Learning; Plant Disease Detection; Smart Agriculture.



Introduction:

Agriculture is an essential component of developing economies, supporting economic growth, food availability, and employment. It represents over 22.7% of the Gross Domestic Product of Pakistan and employs roughly 37% of the population. Although a considerable share of the national economy, massive land and water resources, and agricultural inputs are dedicated to the sector in Pakistan, productivity has not been high due to traditional farming practices, inadequate adoption of agricultural advances, poor water use efficiency, and rising climatic uncertainties. As a result, crop planning is not accomplished effectively, plant diseases are encountered frequently, and losses after harvesting are prohibitively high, leading to farmers' livelihood as well as national food security issues.

The losses due to a number of plant diseases are as high as 40% of the crop produced in the affected areas; the non-availability of proper advisory services results in a large number of farmers having to depend on experience-based decisions rather than data-based decisions. In the case of fruits and vegetables, losses are as high as 40% of the crop value; thus, it can create a big impact on an agricultural value chain. With such high losses, there is a clear requirement for intelligent, accessible, and holistic solutions.

AI-based methods have already been implemented in the agricultural domain for disease detection, crop recommendation, and advice. For plant disease identification, the classification accuracy of more than 96% [1] and over 99% [2] was obtained using deep CNNs. [3] proposed lightweight CNN models, practical for mobile applications.

In crop recommendation, [4] for Soil and Climate used Random Forest and Support Vector Machine models, achieving good prediction accuracy. [5] showed an enhancement in prediction when nitrogen, potassium, and pH of the soil are combined with weather variables (rain and temperature). On the other hand, [6] highlight the importance of temperature and rainfall in yield prediction.

Some conversational AI systems have been created to assist farmers. For example, [7] designed an agricultural chatbot that combined weather and market data. Nevertheless, other systems tend to be constrained in terms of contextual understanding and language availability.

Although most current systems have been developed according to one task, either disease identification, crop prediction, or chatbot-based advisory.., they do not provide a single platform with those features integrated. In addition, most of these solutions have not been adapted to different dialects, real-time data with localisation, and integration. As a consequence, farmers have to use several disconnected solutions that can be confusing.

In order to address the above-mentioned problems, this work has designed AgriSmart, which is an integrated *AI farmer's assistant* comprising a crop recommender, plant disease detection, and a multilingual chatbot providing on-the-fly agricultural advice, functionalities integrated into a website. Through the use of predictive modeling, computer vision, as well as conversational Artificial Intelligence, AgriSmart offers efficient, reliable, and easy-to-understand farming inputs. This solution seeks to facilitate farming decisions, reduce crop losses, optimize productivity, and encourage sustainable farming practices.

In Table 1, you can see a comparative overview of existing studies by outlining their key limitations and research gaps, while illustrating how the proposed AgriSmart system effectively addresses these challenges. Unlike prior works that focus on isolated tasks, AgriSmart integrates crop recommendation, plant disease detection, and multilingual advisory services into a unified platform. This integration enables real-time analysis, improved accessibility, and practical decision support, thereby enhancing system usability, efficiency, and reliability for sustainable agricultural management.

Table 1. The table explain the limitations and contributions of the systems in the field

Study	Domain	Techniques Used	Advantages	Limitations
[3]	Plant Disease Detection	Lightweight CNN	Optimized for mobile devices; low computational cost	Slight trade-off in accuracy; restricted to disease detection only
[4]	Crop Recommendation	Random Forest, SVM	Strong predictive performance using soil & climate data	Does not consider disease risk or real-time advisory
[5]	Crop Recommendation	ML models with soil + weather data	Improved prediction using combined features	Static predictions; no integration with disease detection or farmer guidance
[6]	Yield Forecasting	ML-based predictive models	Highlights the climatic impact on yield	Focus is limited to yield; lacks actionable recommendations
[7]	Agricultural Chatbot	Conversational AI	Integrates weather and market info	Limited contextual awareness; restricted language support; no disease diagnosis
AgriSmart (Proposed)	Integrated Smart Farming Platform	CNN + ML + Conversational AI	Unified platform; real-time disease detection, crop recommendation & advisory; multilingual support; web-based accessibility; localized decision-making	Requires internet connectivity; system performance depends on data quality.

Material and Methods:**Data Sources and Acquisition:****Plant Disease Detection Dataset:**

The plant disease detection module was trained on a combination of public and customized datasets. For training, annotated datasets of leaf images were first collected from the Roboflow public repository, which hosts licensed high-quality labeled images of leaves for a variety of crops and diseases. *A customized dataset was then generated using images collected from fields, captured from various camera angles, different backgrounds, and illumination conditions.*

The final dataset consisted of 2876 samples of healthy and diseased leaves for 28 crop types, annotated with bounding boxes for the object detection task. This hybrid dataset was used to achieve diversity and robustness for disease detection in real-time.

Table 2. The table elaborates the class details of the disease detection system

Plant	Classes
Apple	Apple_scab, Apple_rust, Apple_healthy
Corn	Corn_gray_leaf_spot, Corn_common_rust, Corn_leaf_blight, Corn_healthy
Cotton	Cotton_bacterial_leaf_blight, Cotton_powdery_mildew, Cotton_healthy
Grape	Grape_black_rot, Grape_healthy
Pepper	Bell_pepper_leaf_spot, Bell_pepper_healthy
Potato	Potato_early_blight, Potato_healthy, Potato_late_blight
Sugarcane	Sugarcane_redrot_leaf, Sugarcane_rust_leaf, Sugarcane_healthy
Tomato	Tomato_bacterial_spot, Tomato_early_blight, Tomato_healthy, Tomato_late_blight, Tomato_leaf_mold, Tomato_septoria_leaf_spot, Tomato_mosaic_virus, Tomato_yellow_leaf_curl_virus

Crop Recommendation Dataset:

The crop recommendation system used a structured tabular dataset obtained from Kaggle, *consisting of agricultural attributes such as nitrogen (N), phosphorus (P), potassium (K), soil pH, temperature, humidity, and rainfall.* The data set consisted of labeled entries for 22 classes of crops.

Missing values were subsequently eliminated so as to improve the reliability of the model. Feature normalization was then applied to scale all features, and consistency checks were performed across the features in the dataset. Data was then split into training and testing sets in an 80:20 ratio.

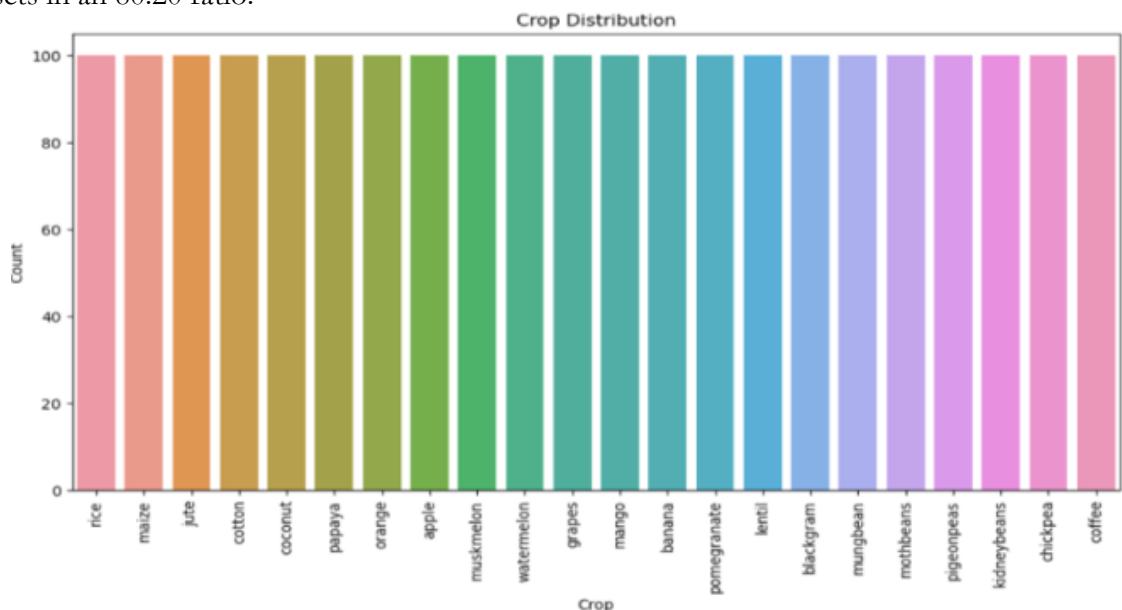


Figure 1. Figure demonstrates the classes of the crop recommendation system

Data Preprocessing:

All images for plant disease detection were resized to 224 x 224 pixels and pre-processed and normalized, augmented using rotation, flipping, and zooming in and out to prevent overfitting.

Preprocessing for the crop recommendation task was similar to the classification preprocessing. Null values were discarded, *the continuous variables were normalized*, and categorical variables encoded (if possible). Clearly defined ranges for the scale of the features contributed to a steady convergence.

Users' questions to AgriBot were classified using keywords to limit answers to the field of agriculture. Model Development and Training

Plant Disease Detection:

The framework used was YOLO (You Only Look Once), since the object detection needs to be real-time. First, the basic version of YOLOv8 was trained on the base dataset to learn generic features. Then, in order to improve the localizations, adapt the model to real-world situations and reduce the training time, the model was fine-tuned with YOLOv11 on the customized dataset. This training improved generalization and reduced complexity.

Crop Recommendation Model:

The performance of multiple machine learning classifiers, such as Decision Tree, Random Forest, and XGBoost, was tested, among which XGBoost was the best performer. With an overall accuracy of about 99% based on the regularization of the model, gradient boosting, and overfitting avoidance, XGBoost was selected as the final prediction model.

AgriBot Advisory System:

AgriBot was built using the Google Gemini 2.5 Flash model for natural language understanding and response generation. For speech-to-text conversion, Speech Recognition was used; for text-to-speech conversion, pyttsx3 and Pyaudio were used. An interactive voice-based approach was used, and for translation between Urdu and English, Google Translate API was used, allowing farmers to interact through speech. Google Translate API was used.

System Deployment and Integration:

All trained models were incorporated into a Flask application-based back-end system. Module APIs allowed each service to be independently integrated. The front-end system was built using HTML, CSS, Bootstrap, and JavaScript for platform-independent deployment. User authentication and sessions were established through JSON Web Token (JWT). The system allows image uploading, input of soil parameters, and text or voice-controlled interaction.

System Architecture of AgriSmart Platform:

The AgriSmart platform is designed using a modular architecture consisting of plant disease detection, crop recommendation, a multilingual farming assistant, and a Flask-based deployment layer. Its workflow ensures real-time processing and user-friendly interaction for farmers.

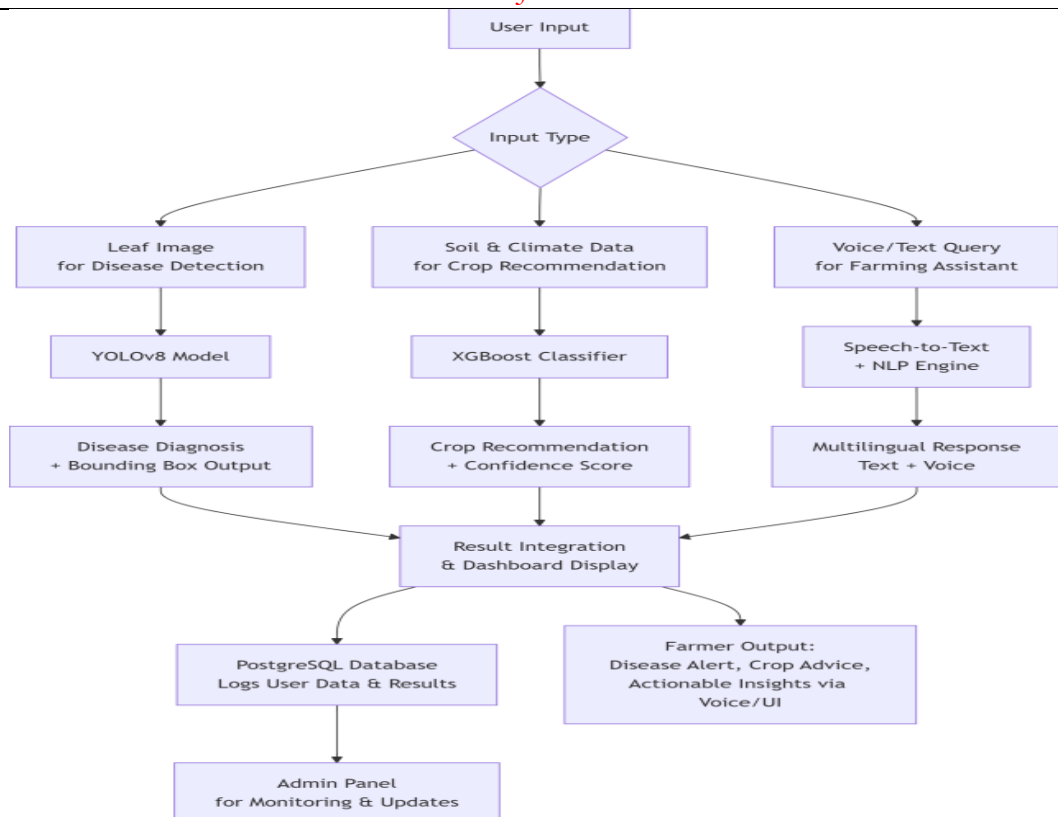


Figure 2. The figure explains the workflow of the system architecture

Results and Discussion:

Crop Recommendation Performance:

The XGBoost classifier obtained an overall accuracy of 99% across 22 crop classes. All classes exhibited high precision and recall, making the model robust and reliable.

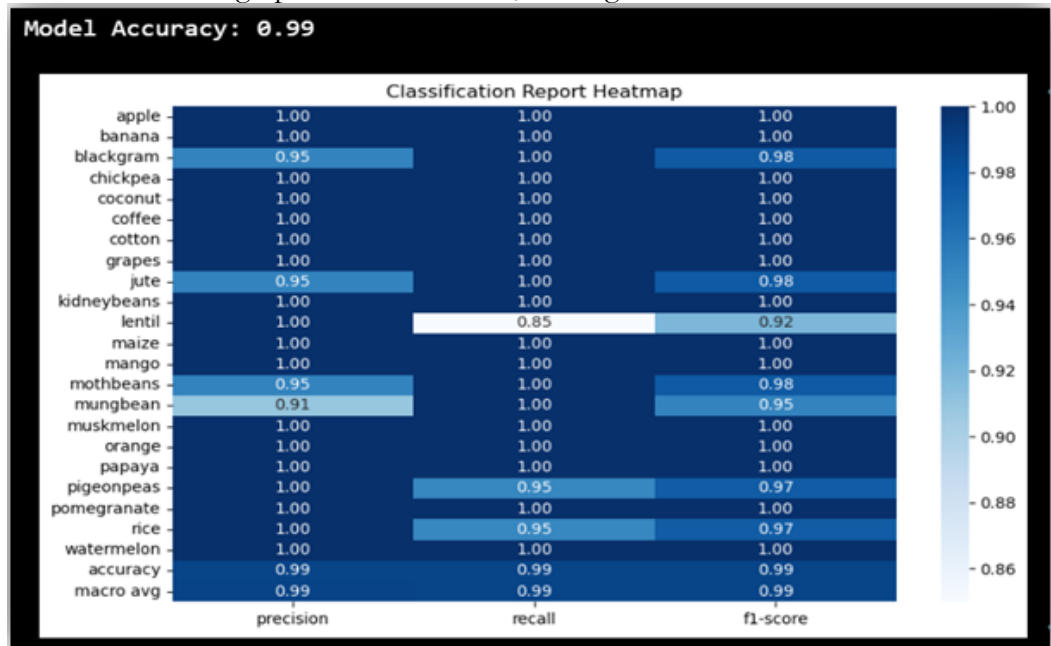


Figure 3. Figure illustrates the accuracy score of the crop recommendation system

The confusion matrix analysis showed low misclassification, indicating good generalization. These results show the efficiency of ML-based crop planning compared to a traditional rule-based system.

Plant Disease Detection Performance:

The YOLO-based detection model achieved:

fP=high single precision (~70%)

Recall: ~72%

The F1 score is 0.70

mAP@50: 74%

mAP@50, 95: 55%

The confusion matrix showed *very high classification accuracy*. Slight misclassifications occurred between visually similar disease classes. The training and validation losses converged smoothly, which confirmed that the model has strong generalization ability and stability. The model was robust to variations in lighting, background noise, and leaf orientation., and was therefore suitable for real-world environments.

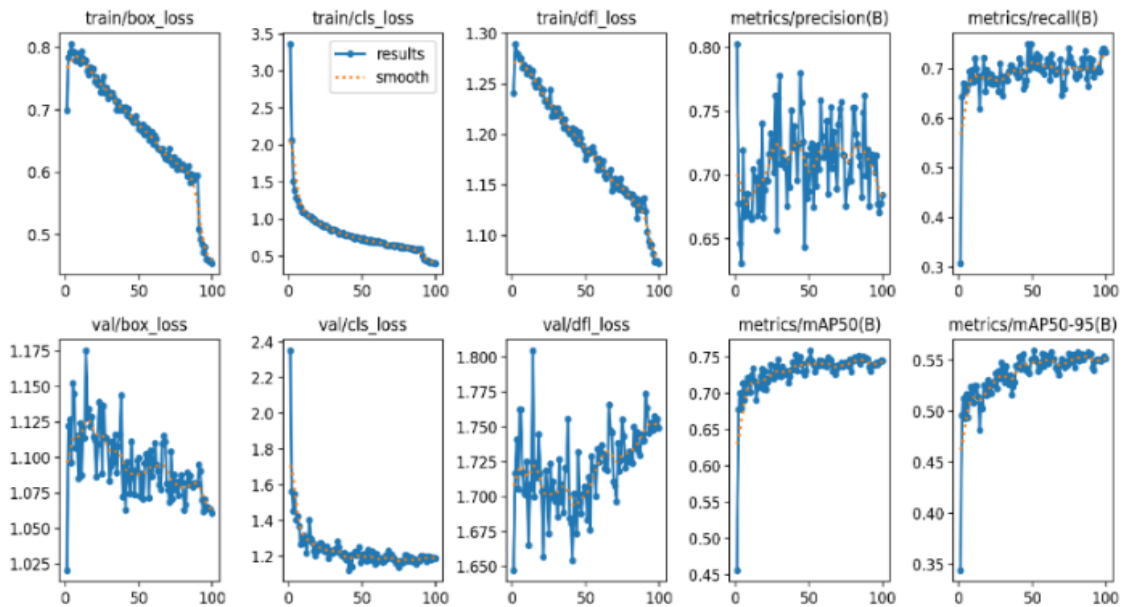


Figure 4. The figure illustrates the mAP values of the disease detection model, which determines the overall accuracy.

AgriBot Evaluation:

AgriBot responded to farmers' inquiries in real time and in a bilingual mode through text and voice interaction. Based on user tests, the response accuracy, domain relevance, contextual understanding, and usability of the service were impressive. The chatbot successfully tackled the farmers' problems related to fertigation, irrigation, and disease management, and so on.

Comparative Analysis:

AgriSmart stands out from other existing stand-alone apps because of its comprehensive, AI-enabled ecosystem merging prediction, detection, and advisory services. This boost in accessibility will allow farmers to make faster and more efficient decisions while simultaneously reducing the need for manual consultations.

Conclusion:

The paper presented AgriSmart—an AI-enabled agricultural platform that is designed and implemented to deliver maximum crop yield, equipped with advanced tools for disease detection, and simultaneously empowered with ready access to advisory services. This model makes use of machine learning, deep learning, and NLP to deliver useful, reliable & up-to-date information to farmers.

The crop recommendation module attained 99% accuracy, which was fruitfully utilized for crop planning. Our real-time disease detection system yielded promising results by

employing YOLO-based architecture. Our multilingual AgriBot effectively delivered expert support round the clock, regardless of literacy levels.

AgriSmart is a a progressive step toward the digital transformation of agriculture, especially in the developing world. It proves the feasibility of AI in sustainable agriculture practices that would eventually help increase productivity and agriculture's contribution to rural economies.

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Author's Contribution:

Author 1: Web development, System design, and system deployment

Author 2: Data processing, model evaluation

Author 3: Model development, manuscript preparation, and proofreading

Conflict of Interest:

The authors declare no conflict of interest.

Project Details:

This research was conducted as part of the Final Year Project titled AgriSmart: AI-Powered Farming Assistant and Crop Management Platform, completed in 2025.

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