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XAI-Based SmartAgriGo: An Intelligent Agriculture Framework for Transparent Crop Recommendation and Plant Disease Detection

Dr. Dipalee Rane[1], Ms. Arusha Gade[2], Ms. Tanushka Chaudhary[3], Ms. Bhakti Darawade[4], Ms. Ashlesha Pal[5], Mrs. Ashwini Athawale[6]
Dept. of Computer Engineering, D.Y. Patil College of Engineering, Akurdi Pune-44, MH, India

Abstract: Agriculture in India is challenged due to inappropriate crop selection, climate change, soil nutrient imbalance, and late identification of plant diseases. To overcome these problems, this paper proposes SmartAgriGo, an Explainable Artificial Intelligence (XAI)-based smart agriculture framework for transparent crop recommendation and automated plant dis-ease identification. The proposed framework combines machine learning, and explainable AI for accurate and interpretable agri-cultural decision support. Crop recommendation is done based on soil nutrients, pH, temperature, humidity and rainfall, where XLNet-based feature extraction and Support Vector Machine (SVM) classification identify the best-suited crop. Plant disease identification is done based on Convolutional Neural Network (CNN) and Softmax classification of leaf images. To improve interpretability, SHAP values are used for crop recommendation, and LIME values are used for disease identification.The interface designed for farmers shows the prediction results with confidence and explanation. SmartAgriGo fills the gap between state-of-the-art AI approaches and real-world agriculture by providing accurate, interpretable, and data-driven agricultural support.
Index Terms: Smart Agriculture, Explainable Artificial Intelligence, Crop Recommendation, Plant Disease Detection, XLNet, Convolutional Neural Networks, SHAP, LIME, Machine Learning.

I. INTRODUCTION

Agriculture is a highly significant factor in the socio-economic growth of India, as it provides employment to a large number of people and contributes largely to the GDP of the country. However, despite the advancements in technology, the methods of agriculture in most rural areas of the country remain traditional and are based on experience-driven decision-making. The farmers are often faced with problems like unpredictable rainfall, imbalanced nutrients in the soil, inappropriate crop selection, and late diagnosis of plant diseases.

The recent development in area of Artificial Intelligence (AI) and data-driven agriculture has opened up some av-enues for improving agricultural practices. Machine learning algorithms have been widely used for crop yield prediction, irrigation systems, and disease diagnosis [2], [5], [10]. Deep learning, Convolutional Neural Networks (CNNs), has shown huge success in image-based plant disease diagnosis [11]. In a similar manner, recommendation systems have been proposed for crop recommendation based on environmental factors [1], [4]. However, most of these systems are black boxes, providing predictions but no explanations [8]. It is difficult for farmers and agricultural officials to blindly follow the suggestions of AI systems when their livelihoods depend on these. Another significant drawback of the current smart agriculture systems is that they rely on non-authoritative or crowd-sourced datasets, which can be regionally irrelevant or scientifically unproven. This is a concern for reliability, validity, and responsible use. In critical applications like agriculture, the need for transparency and authentic data is paramount. Explainable Artificial Intelligence (XAI) is a remedy for this problem, as it offers explanations for predictions made by models in human-understandable terms [6], [8]. Methods like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) allow users graphically interpret importance of features and local decision boundaries. XAI enhances trust, debugging, and regulatory compliance. SmartAgriGo, an integrated XAI-enabled intelligent agriculture system specifically tailored for Indian agricultural settings, is proposed in this paper. The proposed system integrates two important agricultural tasks:

(1) crop recommendation based on soil and weather attributes, and (2) plant disease identification from leaf images. Un-like most existing systems, SmartAgriGo relies on authentic datasets from government-authorized sources.

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(1) crop recommendation based on soil and weather charac-teristics, and (2) plant disease identification from leaf images. Unlike most existing systems, SmartAgriGo uses authentic datasets from government-authorized sources. The model takes multi-dimensional environmental inputs—Nitrogen, Phospho-rus, Potassium, soil pH, temperature, humidity, and rain-fall—and maps them to contextual embeddings using XLNet. These embeddings are then classified using Support Vector Machines (SVM) to suggest the appropriate crop. For disease diagnosis, CNN-based feature extraction with Softmax clas-sification is used to identify diseases and stages. SHAP and LIME are combined for explaining predictions using feature importance charts and heat maps. Moreover, SmartAgriGo has a dynamic user interface that let farmers to enter their inputs, upload leaf images, and obtain real-time predictions along with confidence intervals and explanations. The application is built to be compatible with both mobile and web interfaces.

II. RELATED WORK

A. Crop Recommendation System

Recent developments in Artificial Intelligence (AI) and machine learning has greatly impacted smart agriculture, es-pecially in crop recommendation and precision agriculture. Various data-driven models have been proposed by researchers to enhance agricultural productivity by utilizing soil properties, weather data, and climatic factors. However, most existing models are primarily concerned with predictive accuracy and may not consider interpretability, authenticity of the dataset, and practical implementation issues. Various studies have an-alyzed crop recommendation using traditional machine learn-ing algorithms [1], [4], [12]. Traditional models employed algorithms like Random Forest and Support Vector Machines (SVM) to make predictions about crop recommendation using soil nutrients and pH levels. These models showed moderate accuracy but lacked robust feature modeling, absence of large-scale datasets, and insufficient integration of climatic factors. Later studies incorporated ensemble learning algorithms like Random Forest, Gradient Boosting for improving predictive accuracy, alleviate overfitting. These models showed better classification accuracy and improved generalization perfor-mance on various datasets [3], [9]. Although accuracy im-proved, these models remained non-transparent and lacked the ability to offer interpretable explanations for crop recommen-dations, thus limiting acceptance among farmers in rural areas. Crop prediction systems that are aware of the weather have also been explored, incorporating rainfall, temperature, and humidity information into learning systems. Some researchers included meteorological data that was extracted from national databases to enhance robustness against changing environmen-tal conditions. Although these studies highlighted the signifi-cance of climate information in crop prediction, they mainly concentrated on enhancing the accuracy of [7] and neglected the aspects of interpretability and usability for non-experts. On the other hand, soil analysis-based recommendation systems have also been designed using laboratory soil test values and simple climatic factors. Although these models provided valuable information, they often used static data and did not incorporate real-time weather information. Additionally, most of these systems used traditional machine learning models without considering the latest feature extraction and inter-pretability techniques. Another major drawback of previous studies is the limited use of government-approved agricultural data. Scientifically validated agricultural data is provided by institutions; however, it remains largely unexplored in intelli-gent crop recommendation studies.

B. Plant Disease Detection and Explainable AI in Agriculture

Convolutional Neural Networks (CNNs), has been widely explored for plant disease recognition [11]. Several studies have utilized transfer learning methods using pre-trained mod-els to sort leaf images into healthy and diseased leaves. These studies have shown classification accuracy above 80 percent , indicating the success of CNNs in plant disease recognition. However, in most deep learning-based implementations, the model is used as a black-box classifier. The model pro-vides disease classification without specifying the areas in the image that contributed to the classification. The lack of interpretability tools makes the model less trustworthy and less useful as a teaching tool for farmers trying to learn about plant diseases. Moreover, the datasets used in most of these studies are either generated artificially or obtained from publicly available sources, which may not be authentic in the region.

The agricultural use of CNN models coupled with smartphone cameras has also been proposed for real-time disease diagnosis. Although these systems improved accessibility and ease of use, they were generally restricted to disease diagnosis and did not incorporate crop suggestions or environmental analysis. Moreover, confidence estimation and explanation tools were also less frequently used, making it challenging for users to evaluate the reliability of predictions.

C. Explainable AI in Agriculture

Recently, Explainable Artificial Intelligence (XAI) have gained prominence promising technique to improve trans-parency of AI-based systems [6], [8]. Methods like SHAP and LIME has proved to be successful in applications such as healthcare and finance by explaining feature contributions and boundaries. However, their use in agricultural applications is still very limited. Only a few studies have used XAI to explain crop yield predictions or irrigation system decisions, and even fewer have used XAI in plant disease diagnosis models. In addition, the existing agricultural AI systems are primarily focused on either crop recommendation or plant dis-ease identification, without offering a comprehensive decision-support system. This is a major limitation in terms of practical applicability, as farmers need a holistic solution that covers soil preparation, crop selection, disease treatment, and weather adaptation. The SmartAgriGo framework is distinct from the existing literature in that it offers a comprehensive solution for both crop recommendation and plant disease identification using a single explainable platform. Unlike the existing black-box models, the SmartAgriGo framework uses SHAP-based feature attribution for crop recommendation and LIME-based visual explanations for plant disease identification. Moreover, it highlights the importance of data authenticity by using government-approved Indian datasets and focuses on farmer-centric system design. By leveraging supervised learning, deep learning, and XAI methods, the SmartAgriGo framework overcomes the limitations of the existing literature and offers a comprehensive smart agriculture solution.

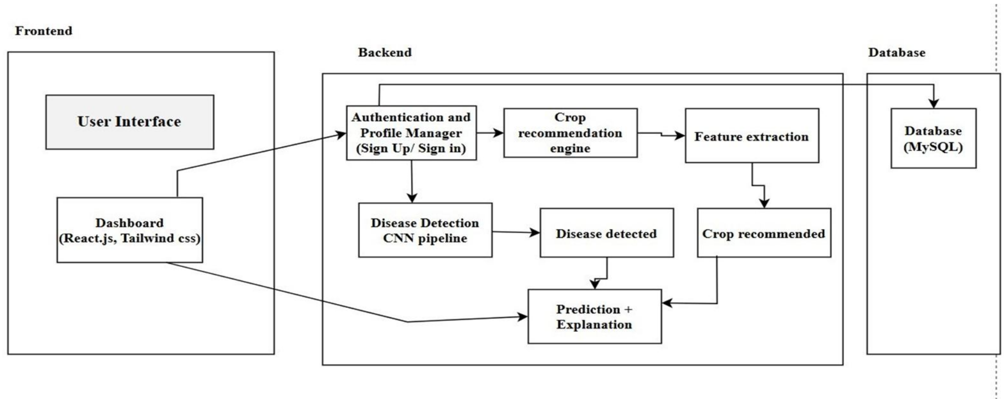

Fig. 1. System Architecture of SmartAgriGo

III. ANALYSIS OF ALGORITHM

A. AI Algorithms Employed in SmartAgriGo

1) Support Vector Machine (SVM): Crop Recommendation It is supervised learning algorithm employed in SmartAgriGo for recommending crops based on soil nutrients, pH, rainfall, humidity, and temperature [1], [5]. The SVM algorithm involves finds best hyperplane which maximizes gap between various types of crops in high-dimensional feature space. In cases where the agricultural data is non-linear, kernel functions are used to transform the input features into separable space. The SVM algorithm performs well on agricultural data with a moderate number of features. It is also ideal for crop classifica-tion since soil and climatic factors have measurable numerical relationships. The SVM algorithm has limitations since it does not provide interpretability. Additionally, it requires careful selection of kernel functions and hyperparameters. Large agri-cultural datasets also pose computational complexity.

2) Random forest: Enhanced Crop Prediction It is ensemble learning method that contains several decision trees trained on bootstrapped samples of data [3], [9]. In the SmartAgriGo system, Random Forest is used to enhance the robustness of predictions and prevent overfitting during crop recommendation. The method involves splitting the data ran-domly into subsets of features at each node, ensuring diversity among the trees. The last decision is done with who has majority of votes. Random Forest is suitable for agricultural settings where the relationship between soil nutrients and crop yield is complex and nonlinear. The key advantages of Random Forest are its large accuracy in classification, robustness to overfitting, and ability to rank features by importance.

3) Convolutional Neural Network(CNN) with softmax: Plant disease detection Convolutional Neural Networks (CNNs) are specially devel-oped for image processing tasks [11]. In the SmartAgriGo sys-tem, it is employed based on leaf images taken by smartphone cameras. The CNN structure involves convolution layers for feature extraction, activation functions (ReLU) for non-linear mapping. The network learns hierarchical features like leaf texture, color differences, and disease patches automatically. CNN has shown a high level of classification accuracy in identifying diseases like blight, rust, and leaf spot. However, CNN models are computationally complex and require large amounts of data for training. Moreover, CNN models are black-box models that are difficult to interpret without the use of explainable AI.
4) SHAP and LIME: Explainable AI integration To overcome the black-box problem in SVM, Random Forest, and CNN, SmartAgriGo incorporates Explainable Artificial Intelligence (XAI) methods, namely SHAP and LIME [6], [8]. SHAP (SHapley Additive Explanations): It assigns weights to every input based on its contribution to the predicted output using cooperative game theory. SHAP is applied to the crop recommendation system to provide an explanation of the role of soil nutrients and climatic factors in recom-mending the crop. LIME (Local Interpretable Model-Agnostic Explanations): It tells the model locally using interpretable models. In plant disease diagnosis system, LIME identifies areas on the leaves that contributed most to the classification result. Although SHAP is capable of providing both global and local explanations, it is computationally intensive. LIME is computationally less expensive but only provides local explanations.

Alg.	Use Case	Strength	Acc.
SVM	Crop Recomm.	Effective in high-dimensional struc-tured data	88–92%
Random Forest	Crop Recomm.	High robustness and feature importance	90–94%
CNN	Disease De-tection	Excellent image classification	92–96%
SHAP	Model Explanation	Global and local interpretability	–
LIME	Image Explanation	Visual region-based explanation	–

TABLE I Comparison of Algorithms in Smart Agriculture

IV. PRACTICAL CONSTRAINTS AND DEPLOYMENT CHALLENGES

Real-world implementation of AI-based smart agriculture frameworks like SmartAgriGo in agricultural settings is asso-ciated with several practical issues. These issues arise because of resource constraints in rural settings, data availability issues, environmental factors, and agricultural data-related regula-tory issues. Although machine learning algorithms provide high predictive precision, their practical implementation in agricultural settings demands consideration of computational efficiency, scalability, and interpretability. This section dis-cusses the key issues in practical implementation and provides strategies for mitigation.

A. Resource Constraints

Agricultural settings, especially in rural areas, tend to have limited computational resources. The farmer would be using smartphones or other low-cost devices that may not be capable of handling computationally intensive tasks. The plant disease detection module using CNNs requires intense computational resources for image processing, and SHAP value explana-tions for crop suggestions require additional computations for feature contribution analysis. Because of these problems, model optimization methods like pruning and quantization can be employed to make the models more compact and efficient. Light models of CNN architectures can also be used for faster prediction on devices. A hybrid edge-cloud computing approach is suggested, where simple inference is done on the edge device, and computationally intensive tasks such as model retraining and SHAP value analysis are done on cloud servers. However, the intermittent nature of internet connectivity in agricultural settings may impact cloud synchronization.

B. Regulatory and Data Governance Issues

SmartAgriGo relies on government-approved data sets from organizations like the Indian Council of Agricultural Research Although such data sets improve authenticity and credibility [7], it is necessary to adhere to proper licensing and citation requirements. Personalized data about soil and land for farmers can also be retained. Secure data storage, encrypted communication, and anonymization are necessary to safeguard confi-dential agricultural data. Justification for AI recommendations through Explainable AI is critical in ensuring transparency in regulations.

C.

D. C. Scalability and environmental variability

The agricultural system is naturally heterogeneous and geo-graphically distributed. SmartAgriGo has to work in different soil types, climate conditions and crop varieties. This leads to scalability issues in model generalization and data processing. With an increasing number of users, the number of soil data records, weather data, and leaf images will substantially rise.

To deal with large agricultural datasets, distributed machine learning platforms can be used. Cloud computing platforms allow parallel model training and easy processing of high-dimensional data. Hybrid edge-cloud systems improve scala-bility by splitting the workload. Edge devices handle initial image processing and model inference with optimized CNN models, while periodic model retraining and evaluation with collective datasets occur in centralized cloud servers. This system ensures that the model can be scaled horizontally with the rise in the number of users and agricultural areas. How-ever, environmental variability is still a major challenge. The growth of crops is affected by seasonal variations, unexpected changes in rainfall, pests, and microclimates. There may be a degradation of model performance due to extreme changes in the climate. There is a need for continuous retraining of models and adaptive learning methods to ensure that the model performs accurately. In addition, latency in cloud communica-tion may impact real-time disease diagnosis in areas with low connectivity.

V. IMPLEMENTATION AND EVALUATION

The SmartAgriGo framework is tested for effectiveness using government-approved agricultural data and real-world crop and plant disease [2], [10]. The crop recommendation module is trained using organized soil and climatic data. These data are collected from trusted agricultural data sources. For plant disease detection, labeled leaf image data with various crop diseases are used. Weather factors incorporated into the system are tested using climate data to replicate real-world agricultural settings. The experimental setup is developed us-ing contemporary AI development tools. The crop recommen-dation models (SVM and Random Forest) are developed using Scikit-learn for supervised classification problems. The plant disease detection model using Convolutional Neural Networks (CNN) with Softmax activation functions is developed using TensorFlow. The CNN model is trained to predict leaf images into various disease classes, and Softmax outputs probability values for confidence measurement. The SmartAgriGo frame-work is assessed based on key performance indicators that are applicable to agricultural decision support systems:

1) Prediction Accuracy: This is the measure of the accuracy of the system in suggesting crops and identifying plant diseases.
2) Precision and Recall: This is the measure of the accuracy of the system in suggesting crops and identifying plant diseases. F1 score gives a balanced measure of precision and recall.
3) Confidence Score (Softmax Output): This is a measure of the probability distribution of the disease classes.
4) Explanation Reliability: This is a measure of the consistency of SHAP feature attribu-tion and LIME explanations.

The crop recommendation module applies SVM to deter-mine the best crop classes based on soil and weather variables. Random Forest improves classification accuracy by mini-mizing overfitting and better estimating feature importances. The plant disease detection model applies CNN to extract hierarchical visual features from leaf images. The Softmax layer transforms network outputs into probability distributions over disease classes, allowing confidence-based predictions. To provide transparency, SHAP is applied to interpret crop recommendations by attributing feature contributions. LIME is applied to identify infected leaf regions affecting CNN predictions. Before the implementation of the models, exten-sive preprocessing was carried out to ensure the consistency and quality of the data. In the crop recommendation system, missing data in soil properties was treated using statistical imputation methods, while outliers in nutrient data were normalized using Min-Max scaling. Normalization of features ensures that features like Nitrogen content and rainfall, which are measured on different scales, have equal contributions dur-ing the training of the model. The categorical labels of crops were processed using label encoding methods to transform them into machine-readable numerical form. The dataset was split in 80:20 ratio to avoid overfittig and ensure an unbaised assessment. In plant disease identification, leaf photos was resized to a fixed size appropriate for the input layer of CNN models. Image augumentation methods like rotating , flip the image, and brightness of the photo were made. Pixel value was normalized to range 0 to 1 to enhance the convergence of gradients during training. The CNN model was trained with Softmax activation function.

The optimizer was chosen for optimal gradient descent optimization. Early stopping criteria were added to avoid overtraining when the validation accuracy reached a plateau. To mimic real-world agricultural scenarios, the system was tested with different weather patterns and soil types.

The crop suggestions were tested with different climatic patterns to ensure robustness. Likewise, plant disease detection was tested with different image lighting conditions and background noise levels to mimic real-world agricultural settings. In addition, the explainability results were tested for qualitative results. SHAP values were examined to ensure that agronomically important features (such as high nitrogen content for rice plants) had higher contribution scores. LIME results were examined to ensure that the highlighted regions corresponded to actual diseased regions.

Metric	Algorithm	Result	Technical Justification
Crop Prediction Accuracy	SVM	>88%	Effectively separates crop classes in structured soil datasets.
Crop Prediction Accuracy	Random Forest	>92%	Ensemble learning improves robustness and reduces overfitting.
Disease Detection Accuracy	CNN + Softmax	>93%	CNN extracts spatial features; Softmax ensures multi-class probability classification.
Precision & Recall	Random Forest	>90%	Strong classification performance on labeled agricultural data.
Explanation Reliability	SHAP	High interpretability	Quantifies feature contributions using Shapley values.
Visual Explanation Accuracy	LIME	Clear localization	Highlights relevant superpixels influencing classification.
Inference Time	Optimized CNN	<150 ms	Lightweight architecture enables near real-time prediction.
Memory Efficiency	Quantized Models	~60% reduction	Reduced model precision decreases storage and computational demand.
Scalability	Hybrid Edge-Cloud	Efficient deployment	Edge performs inference; cloud handles training and retraining.

TABLE II Performance Metrics and Expected Outcomes of Proposed System

VI. EXPECTED RESULT

The expected outcome of the SmartAgriGo framework is a result of its ability to act as an integrated in-telligent agricultural decision-support system. The crop recommendation module takes structured inputs like soil nutrients, pH value, temperature, humidity, and rainfall to recommend the best crop recommendation. The inputs are a multidimensional feature vector that is processed by supervised learning algorithms. The predicted crop is the class label with the highest learned compatibility based on the agricultural data. The result theoretically shows the best compatibility between the soil fertility status and the crop nutrient requirements. The consistency of the predictions with varied environmental inputs shows the generalization ability of the system and proves its relevance to practical agricultural situations.

1) The disease detection module takes leaf image inputs and uses a Convolutional Neural Network model combined with a Softmax activation function. The CNN model iden-tifies hierarchical spatial features like texture, lesions, and color abnormalities that are common in plant diseases. The Softmax activation function normalizes the output of the CNN model to provide a probability distribution for different classes of diseases, thus enabling the model to classify diseases based on confidence levels. The disease name with the highest probability score is identified as the predicted class. The use of confidence levels improves the model's reliability by enabling the user to interpret the confidence level of the predicted output.
2) Apart from the predictive results, the framework also employs Explainable Artificial Intelligence methods to promote transparency. SHAP values are used to explain crop recommendation outcomes by determining the con-tribution of each soil and climatic factor to the final prediction result. This enables users to determine the influence of factors such as nitrogen content or rainfall on the recommended crop. In disease diagnosis, LIME provides localized explanations by pointing to the regions of the leaves that had the highest contribution to the prediction outcome. These methods improve the trans-parency of machine learning models and hence user trust, especially in agricultural settings where results have a direct effect on economic outcomes.
3) The web application layer is responsible for the inte-gration of all the predictive and interpretability modules and provides real-time feedback for user inputs. After the submission of soil information or leaf images, the system is able to process the information using backend AI models and provide predictions with low latency. The low latency of the application confirms the feasibility of its deployment. Real-time feedback of the application also ensures that farmers can take immediate actions regarding crop selection and disease treatment. The results confirm that SmartAgriGo is able to provide accurate prediction, explanation, and efficient system integration.

Sr.	Module	Input	Output
1	Crop Recommendation	Soil nutrients, pH, temperature, humid-ity, rainfall	Recommended Crop Name
2	Disease Detection	Crop leaf image	Predicted Disease Name
3	Explainable AI Output	Model prediction re-sults	Feature importance (LIME/SHAP)
4	Web Application Response	User input data	Real-time predic-tion result

TABLE III
EXPECTED OUTPUTS

VII. CONCLUSION

This research introduced SmartAgriGo, an Explainable Ar-tificial Intelligence (XAI)-based intelligent agriculture frame-work for transparent crop suggestion and plant disease identi-fication [8], [10]. The proposed framework combines super-vised machine learning models for structured soil and cli-matic data analysis, and Convolutional Neural Networks with Softmax activation for multi-class plant disease identification. Unlike traditional black-box agricultural prediction models, SmartAgriGo combines Explainable AI approaches, including SHAP and LIME, to improve transparency and trustworthi-ness. SHAP offers quantitative feature attribution for crop suggestion, and LIME offers visual explanations for disease identification. This combination fills the transparency gap in predictive models, which is essential in farmer-centric systems where predictions have a direct effect on economic outcomes. The probability outputs produced by the Softmax layer further improve the reliability of the decision by providing confidence levels for each classification outcome. In summary, SmartA-griGo provides a unified, scalable, and interpretable solution for smart agriculture. The proposed framework provides a solution for sustainable agriculture practices. The framework uses predictive analytics, deep learning, and explainability to promote the adoption of responsible AI in the agricultural sector.

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