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Smart Agriculture Advisor Using Machine Learning and Deep Learning

Dr. Om Prakash Samantray[1], Kona Sai Sanjana[2], Paila Rakesh[3], Pentakota Rahitya[4], Gummala Jayanth[5]
[1]*Associate Professor, Department of Computer Science and Engineering – Data Science Anil Neerukonda Institute of Technology and Sciences, Visakhapatnam, Andhra Pradesh, India*

Abstract: Agriculture is an important part of our economy and ensures food security. However, farmers often struggle to decide which crops to grow, what fertilizers to use, and how to manage pests effectively. These decisions are usually based on experience, which may not always lead to the best results. To address this issue, this paper introduces a Smart Agriculture Advisor. This web-based application uses Machine Learning (ML) and Deep Learning (DL) to help farmers make better decisions. The system includes four main features: soil classification, crop recommendation, fertilizer suggestion, and pesticide identification. Farmers can upload soil images, and a deep learning model identifies the soil type. Based on soil conditions, weather, and nutrient levels, the system recommends suitable crops. It also suggests appropriate fertilizers, identifies plant diseases from leaf images using convolutional neural networks (CNNs), and recommends suitable pesticides. By combining ML and DL techniques, the system provides accurate and practical guidance. It is user-friendly and helps farmers improve productivity, use resources efficiently, and promote sustainable farming practices
Keywords: Smart Agriculture, Machine Learning, Deep Learning, Soil Classification, Crop Recommendation, Convolutional Neural Networks (CNN)

I. INTRODUCTION

Agriculture is essential for ensuring food security and supporting economic growth, particularly in developing countries where many people rely on farming as their primary source of income. However, farmers face several challenges, including declining soil fertility, nutrient loss, unpredictable weather, improper crop selection, excessive fertilizer use, and pest infestations. These issues can significantly reduce crop productivity and increase financial risks. In many rural areas, farmers also have limited access to expert agricultural guidance and therefore depend on traditional farming practices that may not be suitable for changing environmental conditions. Recent developments in Machine Learning (ML) and Deep Learning (DL) provide promising solutions to these challenges. Machine learning algorithms can analyze structured data, such as soil nutrient levels and weather data, to generate useful recommendations. In contrast, deep learning models, such as Convolutional Neural Networks (CNNs), can process images to identify soil characteristics and detect plant diseases. This work proposes a Smart Agriculture Advisor, a web-based system designed to assist farmers through four key functions: soil classification, crop recommendation, fertilizer guidance, and pest detection. By integrating ML and CNN-based models, the platform offers an accessible decision-support tool that helps farmers make informed decisions and improve agricultural productivity.

II. RELATED WORK

A. Soil Classification

Soil classification is a fundamental component of precision agriculture because it helps determine appropriate crops, nutrient requirements, and irrigation strategies. Abeje et al. introduced a hybrid CNN–SVM approach for soil identification using a dataset of 1,800 soil images, achieving an accuracy of approximately 95% while classifying six different soil categories. Conventional techniques such as Decision Trees and Support Vector Machines generally depend on laboratory-based soil testing, which can be time-consuming and less accessible to farmers. In comparison, deep learning techniques that analyze soil images provide a faster and more scalable method for automatic soil classification.

B. Crop Recommendation

Crop recommendation models assist farmers in selecting crops that are most suitable for their soil conditions and local climate. Gosai et al. proposed a machine learning-based system that utilized parameters including nitrogen, phosphorus, potassium (NPK) levels, soil pH, temperature, humidity, and rainfall.

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Their research evaluated several algorithms such as Random Forest, Support Vector Machine, Decision Tree, and Naïve Bayes. Among these models, Random Forest and SVM demonstrated superior prediction performance. Despite these advancements, many existing crop recommendation systems focus mainly on predicting crops and do not incorporate other important agricultural decision-support features.

C. Fertilizer Recommendation

Machine learning techniques have also been applied to fertilizer recommendation in order to guide farmers on appropriate nutrient management. Akhilesh et al. conducted a comparative study using Decision Tree, K-Nearest Neighbors (KNN), and Random Forest algorithms with input features including soil type, crop type, temperature, humidity, and NPK nutrient levels. Their results indicated that the Decision Tree model achieved the highest prediction accuracy of 99.78%. However, most fertilizer recommendation models are designed as standalone solutions and are rarely integrated with broader agricultural advisory systems.

D. Pesticide Recommendation

Recent developments in deep learning have enabled the use of image-based disease detection systems for crop protection. Convolutional Neural Networks (CNNs) are widely applied to analyze plant leaf images in order to identify diseases and suggest appropriate pesticide treatments. Some studies also combine CNN models with traditional machine learning classifiers to further improve detection accuracy. Nevertheless, the majority of existing approaches concentrate only on disease or pest detection and lack integration with other agricultural services such as soil analysis, crop recommendation, and fertilizer management within a single platform.

III. METHODOLOGY

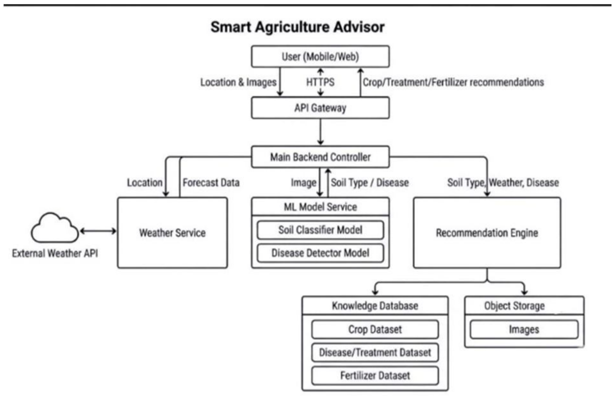

Fig.1 Proposed System Architecture

The proposed Smart Agriculture Advisor is designed using a modular, service-oriented architecture that combines machine learning models, real-time weather data, and a knowledge-based recommendation engine to provide intelligent farming support (Fig. 1). Users access the system through a web or mobile application by entering their location and optionally uploading soil or crop leaf images. All data is securely transmitted via HTTPS through an API Gateway, which manages authentication and routes requests to the backend. The Main Backend Controller acts as the central unit, coordinating different services based on user input. For location-based requests, it retrieves real-time weather information—such as temperature, humidity, rainfall, and wind speed—from an external weather API. For image-based tasks, uploaded images are processed by the ML Model Service, which includes a Soil Classifier and a Disease Detection model. The prediction results are returned to the controller.All collected data is then sent to the Recommendation Engine, which combines real-time inputs with information from a Knowledge Database containing crop, fertilizer, and disease treatment datasets. Based on this analysis, the system generates crop recommendations, fertilizer advice, and treatment suggestions. Uploaded images are stored in cloud storage for scalability and future model improvements. Finally, the recommendations are delivered back to the user through the API Gateway. The modular design ensures scalability, security, and efficient real-time decision support for smart farming applications.

A. *Implementation*

1) Soil Classification The soil classification module uses a deep learning–based image classification approach to identify soil types from uploaded images. The dataset, obtained from Kaggle, contains 1,600 labeled soil images divided into 80% training and 20% testing sets. A Sequential Convolutional Neural Network (CNN) was implemented using TensorFlow/Keras. The architecture includes convolutional and max-pooling layers for feature extraction, followed by fully connected dense layers for multi-class classification. A Softmax activation function is used in the output layer to predict the soil class. The model was trained for 25 epochs using the Adam optimizer with categorical cross-entropy loss and achieved a test accuracy of 83.48%. The predicted soil type is then used as input for the crop and fertilizer recommendation modules.
2) Crop Recommendation The crop recommendation module applies a supervised machine learning approach to predict suitable crops based on soil and environmental conditions. A Random Forest classifier was chosen due to its strong predictive performance. The dataset, sourced from Kaggle and supplemented with self-generated soil data, contains about 2,200 records covering 22 crop types such as rice, maize, banana, jute, and cotton. Input features include soil type, NPK values, temperature, humidity, rainfall, and wind parameters. Data preprocessing was performed using a Standard Scaler, and K-fold cross-validation was applied to improve reliability. The model achieved a mean cross-validation accuracy of 99.45%, with evaluation metrics of accuracy (0.9936), precision (0.9939), recall (0.9936), and F1-score (0.9936). The system outputs the top three crop recommendations with confidence scores.
3) Fertilizer Recommendation The fertilizer recommendation module predicts the most suitable fertilizer based on soil properties, crop type, and environmental conditions. The dataset, obtained from Kaggle, contains approximately 1,000 records with parameters such as temperature, humidity, rainfall, wind speed, soil type, and crop name. Categorical variables were converted to numerical form using label encoding. The dataset was split into 80% training and 20% testing data. Multiple models, including Random Forest and XGBoost, were evaluated using 5-fold cross-validation. Results showed that the Random Forest classifier achieved the best performance with an accuracy of approximately 98%. Therefore, Random Forest was selected as the final model. The module outputs a single fertilizer recommendation based on the input parameters.
4) Pesticide Recommendation The pesticide recommendation module detects crop diseases from leaf images and suggests suitable treatments. A custom Sequential CNN model was implemented using TensorFlow/Keras. The dataset, obtained from Kaggle (Rice Leaf Disease Dataset), contains 4,684 RGB images belonging to three classes: Leaf Smut, Bacterial Blight, and Brown Spot. The data was divided into 80% training and 20% validation sets. Images were resized to 224 × 224 pixels and normalized (1./255). Data augmentation techniques, including rotation, horizontal flipping, and zooming, were applied to improve generalization and reduce overfitting. The model was trained for 10 epochs with a batch size of 32 using the Adam optimizer and categorical cross-entropy loss function, achieving a validation accuracy of 96.37%. Based on the predicted disease class, the system provides a predefined pesticide recommendation using a rule-based mapping approach.

IV. EXPERIMENTAL RESULTS

A. *Soil Classification*

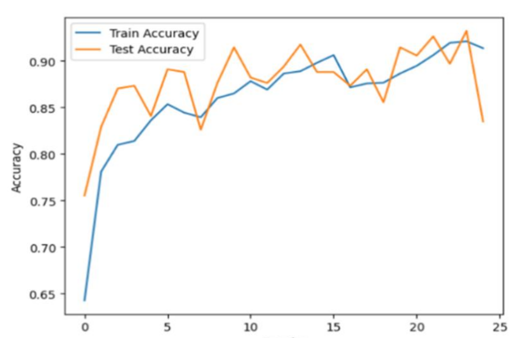

Fig. 2. Training and Testing Accuracy of the Soil Classification Model

The Fig.1 illustrates the training and testing accuracy of the CNN-based soil classification model over multiple epochs. The results show a gradual improvement in accuracy, indicating that the model effectively learns soil image features during training and achieves stable prediction performance.

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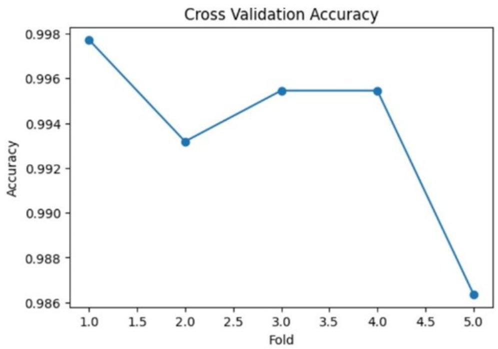
B. Crop Recommendation



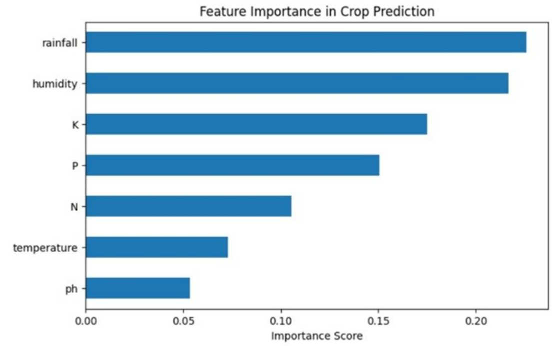


Fig. 3. Cross-Validation Accuracy of the Crop Recommendation Model Fig. 4. Feature Importance in Crop Recommendation Model

C. Fertilizer Recommendation

The confusion matrix Fig5 shows the performance of the XGBoost model in predicting the correct fertilizer type. Most values appear on the diagonal, indicating that the model accurately recommends the appropriate fertilizer for most cases.

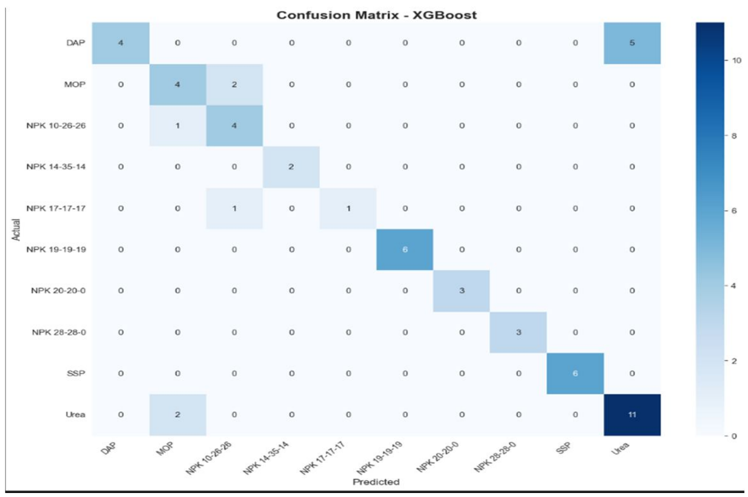
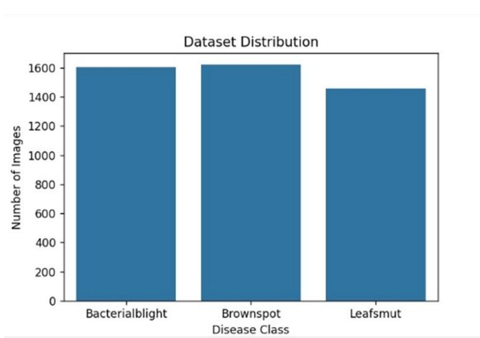


Fig.5 Confusion Matrix of XGBoost Model for Fertilizer Recommendation

D. Pesticide Recommendation



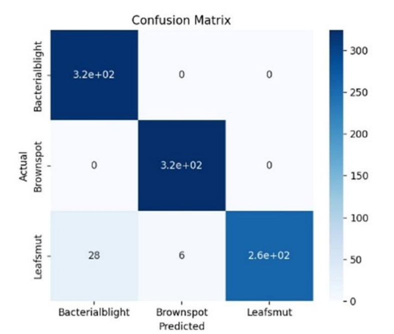


Fig.6 Dataset Distribution of the Pesticide Recommendation Model Fig.7 Confusion Matrix of the Model

V. CONCLUSION

This paper presents a Smart Agriculture Advisor system that integrates soil classification, crop recommendation, fertilizer recommendation, and pesticide recommendation into a single platform. Machine learning and deep learning techniques are used to analyze soil images, environmental conditions, and crop data to support agricultural decision-making. The experimental results show that the proposed models achieve reliable prediction performance. By combining multiple agricultural decision-support modules, the system helps farmers make informed choices, improve crop productivity, and promote sustainable farming practices.

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