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SMART AGRO AI: INTELLIGENT FORECASTINGFOR CROPS, FERTILIZERS, ANDPLANT HEALTH

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ABSTRACT

In the recent years, the agricultural sector has witnessed a significant technological advancement aimed at addressing longstanding challenges such as low productivity, soil degradation, climate variability, and widespread plant diseases. Despite these efforts, many farmers, particularly in developing regions, still rely on traditional methods, lacking access to intelligent systems that can guide them through scientific decision-making. Deep-Agro presents an innovative AI-powered solution that integrates modern web technologies, machine learning, deep learning, and real-time environmental data to assist farmers in making informed and timely decisions for crop selection, fertilizer application, and disease detection. Deep-Agro is designed as a web-based platform that bridges the gap between conventional agricultural practices and data-driven smart farming. The system offers models for crop and fertilizer recommendation, yield forecasting, plant disease detection, and farmer education. Machine learning models, including Random Forest, XGBoost, and Decision Trees are employed to analyze soil parameters such as nitrogen, phosphorus, potassium, and pH levels. These insights are used to recommend the most suitable crops and fertilizers tailored to specific regional and environmental conditions. In addition, Deep-Agro leverages Long Short-Term Memory (LSTM) networks and time-series data to predict crop growth and forecast potential yields. This helps farmers with pre-planning and logistical arrangements. A key highlight of the system is its Convolutional Neural Network (CNN)-based disease detection model, which uses image processing to identify leaf diseases at an early stage, enabling prompt and precise intervention. The platform integrates real-time weather data using APIs to account for dynamic environmental conditions such as temperature, humidity, and rainfall, which significantly influence the growth of crop.

Keywords: Crop Recommendation, Fertilizer Prediction, Plant Disease Detection, LSTM, CNN, Sustainable Agriculture, Agricultural Forecasting

I. INTRODUCTION

Historically, agriculture has been the foundation of many economies around the world, especially in developing and agrarian areas where a sizable section of the populace depends on farming as their main source of income. Despite its basic significance, the agricultural industry still faces enduring difficulties that have a negative impact on farmer livelihoods, sustainability, and productivity.

Among these challenges are unpredictable weather patterns, dwindling soil fertility, inadequate crop selection, excessive fertilizer use, pest invasions, and frequent crop disease outbreaks. Additionally, the absence of data-driven, real-time farming guidance results in less-than-optimal farming practices, which not only produce low yields and increased operating costs but also exacerbate environmental impacts like soil erosion, nutrient runoff, and greenhouse gas emissions. The agricultural industry still faces enduring difficulties that have a negative impact on farmer livelihoods, sustainability, and productivity.

The worsening effects of climate change make matters worse. Furthermore, crop diseases frequently go undetected until they worsen, resulting in significant losses. Farmers in many rural areas do not have access to timely, scientific tools or extension services that could help with the precise identification of such problems. Using real-time data analytics, machine learning, and image processing, Deep-Agro is an AI-powered smart agriculture platform designed to tackle these issues. It improves decision-making and resource optimization by providing farmers with insightful advice on crop selection, fertilizer use, and disease detection.

II. LITERATURE SURWAY

In order to overcome the difficulties associated with traditional farming, researchers have been looking more closely at the integration of artificial intelligence (AI) and data-driven methodologies in agriculture over the past ten years. Precision agriculture has been made possible by the development of smart farming technologies, which have increased crop yields and optimized resource use. The development of intelligent systems for

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particular agricultural tasks, such as crop recommendation, yield prediction, and plant disease detection has been the subject of numerous studies.

In [1], Patil and Thorat developed a crop selection system using decision tree algorithms that considers soil parameters and weather data. While effective in simple scenarios, the model lacked adaptability to diverse environmental conditions. Another study by Singh et al. [2] applied Random Forest and K-Nearest Neighbors (KNN) for crop prediction, reporting improved accuracy, but the system was not integrated with real-time weather data or disease diagnostics.

For fertilizer recommendation, a system proposed by Sharma et al. [3] utilized rule-based logic combined with soil nutrient values. However, the absence of machine learning limited the model's ability to learn from new data or scale across regions with different soil conditions.

III. METHODOLOGY

A systematic process that includes data collection, preprocessing, algorithm development, model training, and system deployment is used in the creation of Deep-Agro. To provide smart farming recommendations, the system combines cloud-based technologies, deep learning (DL), and machine learning (ML):

3.1. Data Collection: The platform is trained and run using data collected from various sources at https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset

Soil data are static inputs that are either manually supplied by farmers or obtained from publicly available agricultural datasets. These inputs include nitrogen (N), phosphorus (P), potassium (K), pH, and moisture levels.

- **Weather Data:** Real-time information gathered from https://openweathermap.org/, APIs such as temperature, humidity, rainfall, and wind speed.
- **Plant Disease Images:** The Convolutional Neural Network (CNN) model for disease detection is trained using labelled image datasets (such as Plant Village) using https://www.kaggle.com/code/atharvaingle/plant-disease-classification-resnet-99-2/input.
- **Historical Records:** To aid in forecasting and individualized advice, databases containing yield data and best practices for agriculture are kept up to date.

3.2. Data Preprocessing: Preprocessing is done on collected data to guarantee consistency and enhance model performance:

Tabular Data: Numerical fields undergo imputation and normalization.

Image Data: To improve training robustness, images are resized, normalized, and enhanced.

Label Encoding: For classification tasks, crop types and disease categories are encoded.

IV. MODELLING AND ANALYSIS

4.1 SYSTEM ARCHITECTURE

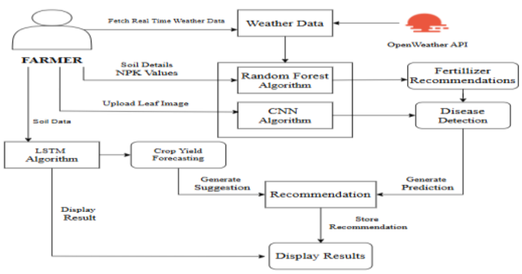

Figure 1: System Architecture

The operational workflow of the Deep-Agro system is designed to integrate user inputs, external environmental data, and internal historical datasets to generate precise, AI-driven agricultural recommendations.

4.1.1.User Input Submission:

The process begins when a farmer uses a web interface on a computer or mobile device to access the Deep-

Agro platform. The user provides vital inputs such as agricultural data, such as soil pH, crop preferences, geographic location and any apparent crop-related problems, as well as soil nutrient levels (such as nitrogen, phosphorus, and potassium). People with different levels of technical literacy can easily use the interface because it is made to be accessible and intuitive.

4.1.2. Fetching Real-Time Weather Data Analysis of Deep Agro:

Upon receiving the input, the system connects to external weather services—such as Open Weather APIs—to retrieve real-time meteorological data. Forecasts of rainfall, wind patterns, temperature, and humidity are among the data gathered. This dynamic environmental data plays a critical role in influencing crop selection and disease risk evaluation

4.1.3. Querying Internal Database:

To retrieve historical information pertinent to the user's location, the system simultaneously queries its internal repository. This comprises past crop yields, records of fertilizer applications, evaluations of soil quality, and chronicles of disease outbreaks. The system can adjust its forecasts to the local agricultural environment by gaining access to this contextual data.

4.1.4. Data Aggregation and Processing:

A unified dataset is created by combining all data streams, including user inputs, historical records, and real-time weather data. After that, this dataset is pre-processed and organized before being fed into the machine learning pipeline of the platform.

4.1.5.Machine Learning Model Prediction:

Machine learning models that have already been trained are applied to the pre-processed data. Convolutional Neural Networks (CNNs) are used for disease detection based on uploaded plant leaf images, while algorithms like Decision Trees, Random Forest, and XGBoost are used for crop and fertilizer recommendation models. In order to identify potential plant diseases and provide optimal recommendations for the best crop type and fertilizer combination, the models evaluate the input data.

4.2Core Components Description:

A collection of machine learning (ML) and deep learning (DL) models, each especially designed to address distinct aspects of agricultural intelligence, are used by the Deep-Agro platform. These models are intended to provide precise and useful information, such as forecasting yield, identifying diseases, and recommending crops and fertilizers:

4.2.1 Crop and Fertilizer Recommendation Model:

The primary objective of this model is to recommend the most suitable crops and the corresponding fertilizer formulations based on user-submitted soil data and real-time weather conditions.

Input features include:

- Soil nutrients (Nitrogen, Phosphorus, Potassium)
- pH level
- Moisture content
- Temperature and humidity (via weather API)
- Crop season (derived from time of year and region).

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Figure 2: crop recommendation model

Key Metrics:

- **OverallAccuracy**: 3+2+3/9 =8/9 ≈
- **Rice Accuracy**: 3/4=75%
- **Wheat Accuracy**: 23≈66.67%
- **Maize Accuracy**: 33=100%%

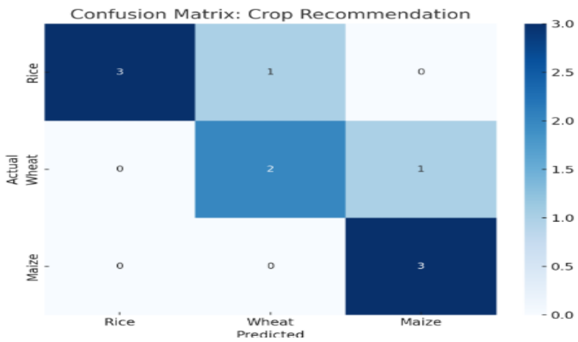

Figure 3: Confusion matrix of crop recommendation

The performance of the machine learning model (such as Random Forest or XGBoost) used for crop recommendation within the Deep-Agro platform is assessed by the confusion matrix that is displayed. Based on input features like soil characteristics, weather, and seasonal factors, the model seeks to categorize the best crop—rice, wheat, or maize.

4.2.2Yield Prediction Model:

Yield Prediction Model: This model uses time-series analysis to predict expected crop yields under specific soil and weather conditions. Temperature, average monthly rainfall, soil composition, crop cycle length, sowing date, and historical yield data for the area and crop are examples of input parameters. The model's foundation is Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN) that works well for simulating temporal dependencies.

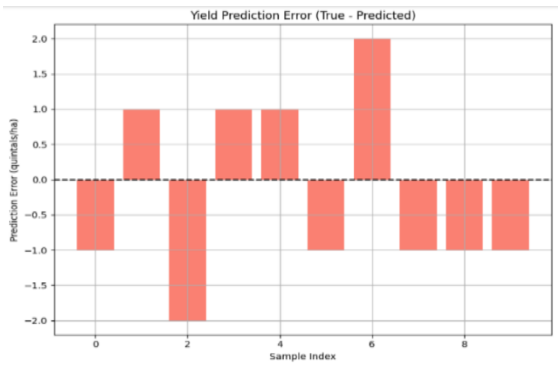

Figure 4: yield prediction model

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The architecture consists of a dense output layer, one or two LSTM layers, and dropout layers to reduce overfitting. Mean Squared Error (MSE) is used as the loss function in the training process, along with the Adam optimizer. Metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 score are used for evaluation. The anticipated yield is expressed in the final outputs.

4.2.3 Disease Detection Model:

Convolutional Neural Networks (CNNs) are used by Deep-Argo's Disease Detection Model to recognize plant diseases from uploaded leaf photos. After pre-processing the images (resizing, normalization), the data is fed into a CNN model that has been trained.

The disease name and suggested remedial measures, like applying pesticides or treating the soil, are output by the model, which classifies the disease using learnt visual patterns. This enables farmers to identify problems early, reduce crop loss, and increase yield by acting quickly**.**

This model analyses photo of crop leaves and finds visual signs of plant diseases to facilitate early disease detection. RGB photos of leaves and crop type metadata are accepted by the system. The Plant Village dataset, which comprises more than 50,000 annotated photos covering more than 30 crop-disease combinations, is used to train the model.

In order to extract spatial features, the CNN architecture consists of stacked convolution layers, Max Pooling layers, and ReLU activation. A flattening layer, fully connected dense layers, and a Soft max layer for multiclass classification come next.

The Adam optimizer and categorical cross-entropy as the loss function are important training parameters. Early stopping is used to avoid over fitting, and dropout layers are added for regularization.

Classification metrics like accuracy, precision, recall, F1-score, and confusion matrices are used to assess the model's performance.

4.3 INTERPRETATION OF RESULTS:

The CNN-based disease detection model's ability to distinguish between three plant conditions—Healthy, Leaf Curl, and Blight—is assessed in the confusion matrix. Correct classifications are indicated by diagonal values (2 for Healthy, 2 for Leaf Curl, and 3 for Blight), whereas incorrect classifications are represented by off-diagonal values.

Matrix Interpretation:

Actual \ Predicted	Healthy	Leaf Curl	Blight
Healthy	2	1	0
Leaf Curl	0	2	1
Blight	0	0	3

With a small amount of confusion between Healthy and Leaf Curl, the model detected blight with 100% accuracy and other classes with high accuracy. This illustrates how well the CNN model detects diseases early and accurately, which is essential for prompt intervention and better crop health management in the Deep-Agro system.

V. CONCLUSION

By combining machine learning, and artificial intelligence, the Deep-Agro project offers a thorough and creative response to contemporary agricultural problems. Building a smart farming platform that could help farmers with important agricultural decisions, such as crop and fertilizer recommendations, yield prediction, and disease detection, was the main goal. The system has demonstrated its ability to provide users with precise, timely, and pertinent insights by effectively implementing sophisticated algorithms like Random Forest, CNN, and LSTM.

The system guarantees inclusivity and offers value to even individuals with little technical expertise by integrating multilingual support and instructional materials. With the aid of deep learning and image processing, the disease detection model aids in early diagnosis, which may lower crop loss and increase yield.

By taking environmental factors into account, real-time weather integration improves decision-making even more. Furthermore, the utilization of backend frameworks and cloud storage guarantees data availability, security, and scalability across geographical boundaries.

The research can be further enhanced in the future by adopting cloud-based infrastructure that could guarantee high scalability, data security, and continuous availability. Furthermore, the platform can be deployed in different regions with different levels of digital maturity and internet connectivity as a multi-lingual support. AI chat bots can also be added to Deep-Agro for customer support.

In conclusion, Deep-Agro shows how AI can revolutionize agriculture, especially in areas where conventional approaches are inadequate because of resource waste, pest outbreaks, and climate volatility. Deep-Agro facilitates precision farming, lessens reliance on gut feelings, and promotes sustainable agricultural development by integrating several clever models into a unified and user-focused system.

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