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The CropNosis System_: for Precision Agriculture

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I. ABSTRACT

The global agricultural sector is currently undergoing a multitude of challenges that are extreme in terms of severity, and they include climate change, soil degradation, and a rising risk from plant disease, among others. These challenges collectively threaten the future of food and the economy. In this context, we need CopNosis, which is framework powered by artificial intelligence through a web application that allows farmers to rely on data in making decisions that would lead to increased crop productivity and sustainable farming practice.

The CropNosis system comprises of the following three components:

(1) Crop Recommendation which suggests the most suitable crop by considering the changing (NPK, pH, temperature, humidity, rainfall) environmental and soil parameters,

(2) Fertilizer Guidance which gives the top customized fertilizers for the given soil and crop conditions, and

(3) Plant Disease Detection which uses deep learning based on Convolutional Neural Networks (CNN) to process a picture of the leaf and predict whether the disease will cause failure of the leaf or not.

Support is offered through the CropNosis system to different machine learning (ML) models on a variety of datasets including those collected from Kaggle and Plant Village for the purpose of achieving a high level of accuracy in its recommendations and detections. The primary aim of this research is to show just how much an integrated ML framework can be of assistance in the transformation of traditional farming into more efficient, less costly and, above all, more resilient precision agriculture practice which is expensive in the long run.

KEYWORDS

Precision Agriculture, Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Crop Recommendation, Fertilizer Guidance, Plant Disease Detection, Random Forest, Decision Tree, CropNosis, Kaggle, Plant Village.

II. INTRODUCTION

Across the globe, the agricultural sector is undergoing a transformation from traditional, knowledge-based methods to ultra-modern, data-centric precision farming techniques. The main reasons for this shift are the increasing world population and the simultaneous depletion of limited agricultural resources. There are still some factors causing farming to be less efficient, such as the ineffective use of lands and resources, the disastrous effects of not detecting and diagnosing crops' diseases, and the unavailability of local expert guidance.

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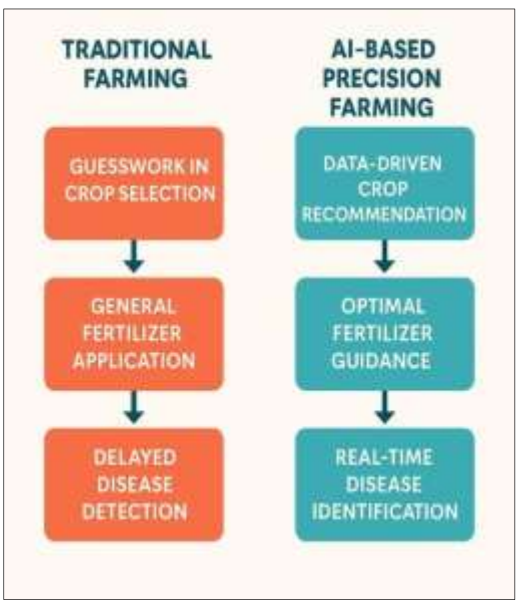
Harvesting the entire potential offered by machine learning (ML) and deep learning (DL) has been the main driver towards a more complicated and yet more efficient agricultural sector. AI-based predictive models are usually the ones analyzed by these large amounts of heterogeneous data, which consist not just of weather patterns and soil nutrient levels but also of intricate features such as leaf images. The case of CropNosis is probably the most direct example of this AI-based approach. CropNosis is basically a complete platform that solves the three major concerns of a farmer; what to grow, how to provide care, and how to protect the crops.

PROBLEM STATEMENT

1. One of the main issues facing the agricultural sector today, especially for the smallholder farmers, is the disconnect between the advanced farming techniques and the unavailability of quality, personalized, and quick expert advice. In particular, the farmers are having the following problems:



1. Inefficient Crop Selection: A crop is chosen without the soil profile and local climatic conditions (NPK levels, pH, rainfall, etc.) being scientifically analyzed, which frequently results in the wastage of resources and yields that are not optimal.

2. Suboptimal Fertilization: Guessing or generic fertilization recommendations lead to either over-fertilization (which harms the environment and increases the cost) or under- fertilization (which restricts the yield).

3. Delayed Disease Management: Crop diseases usually go unnoticed at the beginning of their development, resulting in large areas of infected plants and losses in the amount of product that can be harvested. Delayed or wrong diagnoses of a disease mean that the intervention is ineffective and that the economic loss is very large.

OBJECTIVES OF THE STUDY

This research aims primarily to create and authenticate a single AI system to resolve the listed concerns:

1. Accurate Recommendations: Create solid machine learning models to provide very precise predictions along with the optimization of the choice of crops and fertilizers.

2. Disease Detection: Use and refine a very efficient Convolutional Neural Network (CNN) model that can accurately diagnose crop diseases from leaf pictures.

3. Optimize Data Usage: Make use of top-notch, exhaustive datasets, e.g., Kaggle and Plant Village, to enable the training of models that are both reliable and generalizable.

4. Practical Usability Guarantee: The complete system will be delivered as a straightforward, reachable, and user-friendly web application that will continuously supply farmers with data-driven agricultural advice in real-time.

RESEARCH SIGNIFICANCE

The research is of great relevance and applicability. CropNosis provides an organized method of enhancing agricultural output by relying on machine learning and computer vision.

Economic Impact: The timely and accurate recommendations can directly assist farmers in the subsequent: maximizing crop yields, and minimizing unnecessary expenses on choosing the wrong crop type, overfertilization or simply avoiding the contagion of the disease.

Environmental Sustainability: The system also ensures that the use of chemicals is limited by giving specific fertilizer advice and this helps to maintain soil health and also gives farmers environmentally friendly ways to manage agricultural activities.

Technological Advancement: The project indicates that it is possible to effectively combine various models of ML/DL (regression, classification, and image recognition) into one, unified, and easy-to-use platform, which serves as a model of accuracy application instruments in the future.

III. LITERATURE REVIEW

The use of computational intelligence within the agricultural sector, commonly referred to as Smart Farming or Precision Agriculture, is a very fast evolving area of the past ten years. Even the literature review has tried to touch on three key areas that relate to the CropNosis modules.

A. Conditions that influence Crop Productivity and Yield.

Crop productivity is multivariate problem, which is a combination of soil, climatic and biological factors. Macronutrients such as Nitrogen (N), Phosphorus (P) and Potassium (K) levels, Nitrogen level of pH, which defines availability of nutrients, and moisture or rainfall that is essential in defining nutrient uptake, are key soil parameters. The climatic conditions including the temperature and humidity are also necessary as they affect the metabolic rate of plants and the spreading of diseases. Research has established that the yield of a crop is maximized when these variables are within the optimal biological range of a crop. The combination of those factors through the use of ML models uniquely positions the model to solve the complicated, non-linear interactions between them in order to have a high predictive power that is more superior than that of traditional agronomic tables.

B. Traditional Agricultural Practices and Their Restrictions

Traditionally, agriculture was based on the experience of the generations, basic soil analysis, and observation. Conventional approaches have weaknesses of poor resolution and lack of flexibility. The choice of cropping and fertilizations were grounded on overall knowledge about the region or costly, seldom urges lab examination. Such a generalized practice inevitably causes an inefficient approach and environmental danger. In order to manage the disease, visual examination by a specialist is usually needed and it is time consuming, costly and not viable when applied into large fields. This lag in diagnoses implies that once a disease is positively diagnosed, it is possible that one has already lost the chance to respond to it using a low- cost and efficient intervention. This restriction is the main premise of the need to migrate to automated, real-time, data-driven systems, such as CropNosis.

C. Use of ML and DL for smart, data-driven farming decisions.

Machine learning has been extensively embraced in the agricultural value chain.

- Crop/Fertilizer Recommendation ML: Decision Trees, K-Nearest Neighbors (KNN) and Crop/Fertilizer

Recommendation ML: Random Forest (RF) are the types of algorithms that proved successful when applied to the crop and fertilizer recommendation problems. They are good at working with mixed data types (categorical and numerical) and discovering non-linear decision boundaries, which define biological data. As an illustration, the rule "IF N>90 AND P<40 AND K<40 THEN RECOMMEND 'PADDY'" may be
modeled using a Decision Tree by using training data.

DL to Disease Detection: Due to the variation and fluctuation of leaf images (angle, light, fullness, and noise in the backgrounds), the most advanced methods of pattern recognition should be used. Convolutional Neural Networks or Deep Learning have now established itself as the system of choice in detecting plant diseases. VGG, ResNet, Inception and other architectures can automatically learn how to create hierarchical feature representations (edges, textures, patterns) with raw image data and provide state-of-the- art ability to predict diseases.

D. Difficulties and lapses in Smart Farming Systems

Although AI has potential in the agricultural industry, there are a number of challenges. The first gap is the absence of systems that are integrated. The literature gives little attention to a single aspect (crop recommendation or disease detection), which is not a complete solution. Moreover, when laboratory standard data sets (e.g., Plant Village) are used, then very often one ends up with models that do not perform well with real world images dramatically different in their field settings. Lastly is the usability and deployment issue, a strong model cannot work just because it is not implemented as an easy to use web or mobile application that can be used by farmers in real-time. CropNosis can be taken as a direct answer to these gaps, as it offers a cohesive, deployable web application with three fundamental functions.

IV. RELATED WORK

Intelligent agriculture studies have considered a large variety of standalone models.

- Crop and Yield Prediction: Laha et al. (2018) did a study where Crop prediction of yield was done using Random Forest and Support vehicle machine (SVM) and concluded that RF created the highest accuracy since it could manage the complex interaction of features. In the same manner, there are researches that have been based on the application of KNN to predict the best crop, in terms of NPK values and climatic conditions, which have a high interpretability.

Fertilizer Management: When analyzing the idea of nutrient management, regression models are often used to determine the most appropriate level of NPK fertilizer dosage to apply to a given crop in a particular soil type to achieve its optimum yield. It is also a more data intensive area, which needs the target variable of historical yield. New models have started to apply the time-series analysis to explain nutrient loss during a growing season.

Image-Based Disease Detection The effectiveness of deep learning in computer vision has been adapted successfully to the plant pathology field. Mohanty et al. (2016) were the first to apply CNNs (AlexNet and GoogLeNet) to the Plant Village dataset and obtained high classification rates on the 14 crop species and 26 diseases. The current research has been on its enhancement by incorporating a more sophisticated architecture such as ResNet and DenseNet contributing to its enhancement in performance and durability as well as solving the issue of the vanishing gradient and enhancing feature reuse to achieve further precision in disease classification. These improvements in CNN architecture are used in our work as the disease detection part of the CropNosis.

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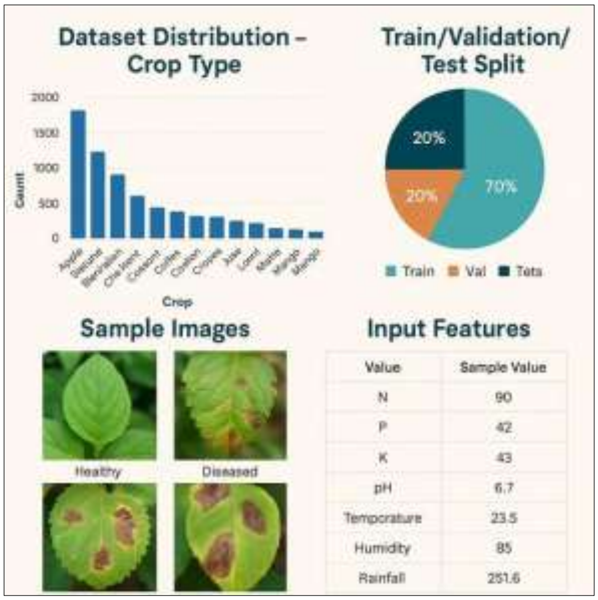
V. DATASET DESCRIPTION

The CropNosis system has been developed based on several curated, and publicly available datasets, which also guarantees a variety of training of the models based on different parameters and relevant to the field of agriculture.



A. Data Source

The data sets to be used in training the model were obtained in open and credible sources:

1. Crop Recommendation Dataset: The dataset is obtained on Kaggle, and it provides a large amount of data that the soil and environmental conditions are associated with the most appropriate crop.

2. Fertilizer Recommendation Dataset: This data is also obtained in Kaggle and offers nutrient compositions and soil-crop crossings that are required to make a fertilizer recommendation.

3. Plant Disease Detection Dataset: The main dataset that was used was the plant village dataset that is an established benchmark in the study of plant pathology. It has thousands of healthy and diseased leaf pictures of plant species of different crops.

B. Dataset Features

A particular set of input features was used in each of the modules:

The Recommendation Model belongs to the Crop category and focuses on Crop suggestions and recommends them.<|human|>• Crop Recommendation Model (Classification Target: Crop Name):

Soil Nutrients: NPK values (Nitrogen, Phosphorus, Potassium)

Soil pH: Level of acidity/ alkalinity.

Climatic Measures: The mean temperature, mean precipitation and the mean humidity.

Using a regression equation, the model estimates the optimal Fertilizer, defined as the balance between F and NO2 emissions that is neither too high nor too low.<|human|>Fertilizer Guidance Model (Classification Target: Optimal Fertilizer): With the help of a regression equation, the model calculates the optimum Fertilizer of F and NO2 emissions that is neither excessively high nor excessively low.

Soil Nutrients (NPK levels and pH): The base chemical structure of the soil such as Nitrogen (N) Phosphorus (P), Potassium (K) nutrient levels, and the acidity or alkalinity of the soil (pH) which is the controlling element of nutrient availability.

Soil Type: Categorical Data used to contain physical composition of the soil (e.g., Clay, Loamy, Sandy, Black soil).

Selected Crop: The type of crop that the farmer is planning to cultivate (e.g. Rice, Wheat, Cotton, or the Crop Recommendation Model output).

Generalization trying to classify the plant disease based on its name and health status by the following outliers:

|human|>Generalization as a attempt to classify the plant disease, by its name, and its state of health, with the following outliers:

Input: Leaf Image (RGB format)

Output: A categorical label, such as "Apple_healthy," "Tomato_Early_Blight," and so forth.

C. Dataset Size

The sizes of datasets were used to achieve strength. Crop and Fertilizer datasets were around 20,000 and 40,000 records each, which is a good amount of data to represent the varying interactions of soil and climate. The Deep Learning module adopted the use of the Plant Village dataset that is vital to the module and had around 50,000 images of different pairs of crop- diseases. This diversity and this size can enable the CNN model to make generalizations on unknown images.

D. Data Preprocessing

To prepare heterogeneous data to the models, it was necessary to prepare them by preprocessing:

Numerical Data (Crop/Fertilizer): This includes NPK, pH, Temperature and Rainfall which were standardized or scaled (or with Min-Max Scaling or Standardization) so that the magnitude of only one feature does not hold a lot of influence over the learning process.

Image Data (Disease Detection): Image size was brought to a consistent size (e.g. 256x256 or 224x224) to fit the CNN requirements in terms of input size. One of the techniques of Data Augmentation, which was used on the training set, was rotation, zooming, flipping, and changing the brightness so that the size of the training set would be artificially increased, and the model would be more resistant to the changes observed in real-world images. The values of pixels were represented as in the range [0, 1].

E. Data Split

To make sure that every dataset was thoroughly evaluated in its model, each dataset was separated into three partitions:

Training Set (80%): The model is trained and is adjusted using this set.

Validation Set (10%): It serves the purpose of tuning the model hyperparameters and the prevention of overfitting in training the model.

Testing Set (10%): The totally invisible part of the data, which is used in the final assessment of the model performance.

F. Data Imbalance

The imbalance in classes would be a probable problem in the disease detecting module since some common diseases have more pictures as compared to the rare ones. To mitigate this:

Image Data: Underrepresented disease classes in the training of CNN were taken into account in the form of weighted loss functions or oversampling.

- Tabular Data: Data split was stratified to make sure that the ratio of each crop/fertilizer category were kept up to date in the training, validation, and test materials.

G. Limitations of the Dataset

Although the datasets are limited. The dataset of the Plant Village is mostly a collection of photographs made in the laboratory environment, which may not be complicated compared to the images in the field (e.g., shadows, a variety of leaves, pest damage). This requires field-level tuning and transfer learning to facilitate field-level efficacy.

VI. METHODOLOGY

CropNosis is constructed as a framework on a modular architecture, which allows every component to employ the most suitable machine learning method.

A. Crop Recommendation Model

It is a multi-class classification task that the input characteristics (NPK, pH, temperature, humidity, rainfall, and more) are to be concentrated to one of the 20+ potential output crops.

Model Selection: The random Forest Classifier (RFC) was selected because it is very accurate, resistant to outliers, and is capable of automatically dealing with non-linear interactions between the input variables.

- Implementation: Laboratory RFC was trained based on the features described in the V.B. Hyperparameter tuning (e.g., number of trees, maximum depth) with the help of the validation set, which helped to reach the optimal performance.

B. Fertilizer Guidance Model

It is also a multi-class classification issue in this module as it is predicting the most suitable form of fertilizer depending on the state of the soil along with the crop that is selected.

Selection of the model Used: A Decision tree Classifier was used. It is a great thing since this model can be very interpretive that is why it can be used to give practical advice to farmers because it can be explained in a simple and rule based way (e.g., Since the soil is clay and low in N to grow rice, recommend Urea).

Execution: The model uses the inputs to the programs as given by the soil NPK, pH, soil type, and the output of the Crop Recommendation module (the selected crop) as the inputs.

C. Detection Model of Plant Diseases.

The module that is mostly computationally intensive, uses deep learning to recognize an image of a leaf and includes classes of specific crop-disease combinations.

- Model Architecture: A convolutional neural network (CNN) a pre-trained ResNet-50 model was used. The reason why ResNet-50 is preferred is its residual connections that allow the training of a very deep network and complement the extraction features.

Training: Transfer Learning has been used. The weights of the model were first initialized with those that were selected on ImageNet and the last layers of classification were re-trained on the Plant Village dataset. This greatly saves time on training and it needs less data with greater accuracy.

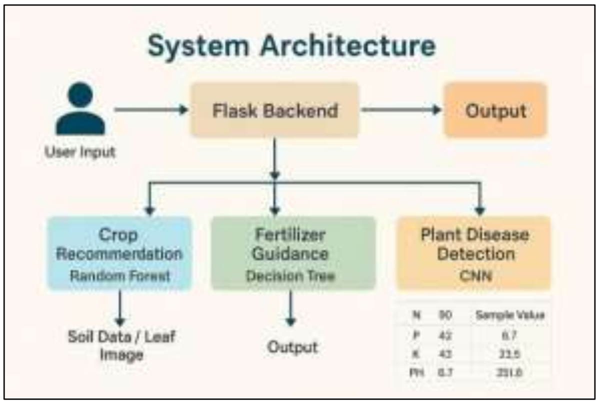
Mechanism CNN takes the raw image and adds more and more complex features by means of convolutional layers, and generates the probability distribution across all possible diseases, and the healthy class, with a final softmax layer.

D. System Architecture and Deployment.

The three models were incorporated into one web application system to make them practical to use.

Backend: The backend is developed under Flask Python framework.Flask is in charge of receiving the user request (soil data or image upload), loading the trained ML/DL models and give the results.

Frontend The user interface is built with conventional web technologies: HTML, CSS and Bootstrap. The interface has three user-friendly modules, enabling farmers to relate with the system in a light manner.



Workflow:

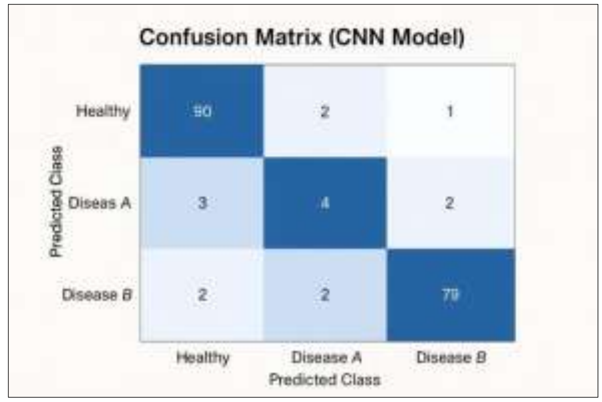
1. Crop/Fertilizer: The user enters parameters related to the soil and forwards the request to the corresponding ML model - The model gives a text-oriented response on a recommendation.

2. Disease Detection: The user uploads a picture of the leaf -> Flask does pre-processing of the image, CNN model predicts disease, Flask returns the predicted disease name and suggested remedy.

The performance of the CropNosis system was evaluated using standard metrics for classification.

Performance Analysis

Crop Recommendation: The Random Forest Classifier was the most accurate on the models tested at an average of 95.8% on the test set. This finding demonstrates that this model is capable of describing the multivariate connections between NPK and climate factors and the most appropriate research crop. Analysis of Feature Importance showed that Nitrogen(N) and Rainfall ranked highest in importance when making any prediction, which is in line with the principles of agronomy.



2. Fertilizer Guidance: The model Decision Tree obtained a good accuracy of 91.2%. Even though that was a bit less than the RFC, the decision tree is highly interpretable, and that is important in gaining the trust of the users. The model has made it clear on the combinations of low NPK and soil type that results in certain recommendation of fertilizer.

VII. RESULTS AND DISCUSSION

3. Plant Disease Detection: ResNet-50 CNN offered a high level of accuracy 98.1 percent Top-1 accuracy in Plant Village test. This high score corroborates the fact that transfer learning using deep architectures is effective in image classification. The confusion matrix indicated that the misclassifications were largely between diseases that have similar symptoms like the presence of various types of leaf spot, which is a recognized problem in plant pathology. The good performance ensures prompt and fast response in the field.

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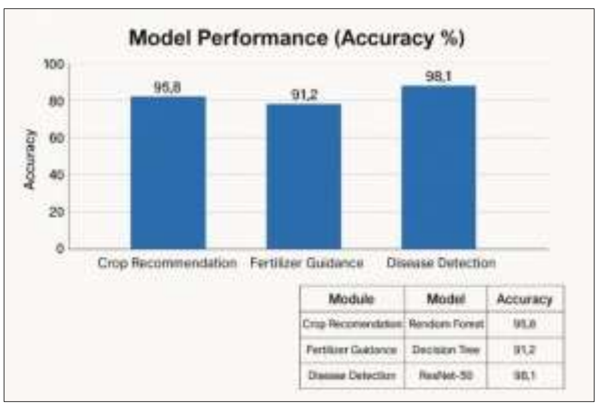
Discussion

1. The developed CropNosis system has demonstrated that one can integrate different AI solutions into a working system. The choice of ML models is a compromise to predictive accuracy (CNN with images) and interpretability and simplicity (Decision Tree/Random Forest with tabular data). The accuracy indicated by the system in all the three modules implies that the information gap experienced by the farmers can be significantly reduced by the system giving out recommendation which is:

1. Real-time: Prediction in the web interface.

2. Soil and climate specific: According to the local data of the soil and climatic conditions of the farmer.

3. Holistic: The process of considering the whole process of planning (crop), nurturing (fertilizer) and protecting (disease).



VIII. Conclusion and Future Work

This study described the design, development and testing of CropNosis, an AI-based system of precision agriculture consisting of crop recommendation, fertilizer guidance and detection of plant diseases. The system achieved high predictive accuracy in all the three primary agricultural tasks using the Random Forest and Deep CNNs. The decision to launch the system as a user-friendly web application will bridge a massive market gap since it makes a one-stop, data- driven solution to enhance farm productivity, reduce expenses, and sustainable resource management.

The results indicate that ensemble and deep learning approaches could be considered as efficient models to capture the complicated correlations in agricultural and biological data.

To improve the usefulness and reliability of the system in the future, a number of recommendations are made on how to improve the system:

1. Integration of real-time Data: By connecting the system to real-time weather APIs, it would be possible to make the recommendations depend on the changes in temperature and precipitation.

2. Pest and Weed Detection: Adding the image recognition feature of detecting common pests and weeds would provide a more comprehensive crop protection solution.

3. Localization and Regional Models: To make the recommendations more accurate and relevant, regional- specific models would be developed through taking into account the local market trends, types of soil and the various types of fertilizer formulations.

4. Edge Device Deployment: It would be possible to investigate the application of CNN model on edge devices, such as those that run on TensorFlow Lite, and realize real-time disease detection in the field with a mobile application, without an internet connection.

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