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AgroAI-Agriculture Support System Using Machine Learning Techniques

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Abstract—Agriculture plays an important role in the nourishment of economies and food security. Farmers, however, face challenges like crop choice, disease identification, and nutrient optimization, which have a significant influence on productivity. The rapid growth of artificial intelligence (AI) and machine learning (ML) has presented opportunities to solve such challenges in an efficient manner. This research paper presents AgroAI, an AI-driven agriculture support system to facilitate farmers in making the right decisions. AgroAI combines machine learning models with an ease-of-use web application to provide end-to-end solutions for crop recommendation, plant disease identification, and fertilizer recommendation. The system relies on a Random Forest model to recommend the most appropriate crops based on soil parameters, environmental conditions, and weather forecast. It also employs a ResNet9 model, a convolutional neural network, to detect plant diseases from leaf images with a high accuracy level. The fertilizer recommendation system identifies soil nutrient content and recommends corrective measures to achieve maximum plant health. The suggested system is deployed as a local server using Flask to ensure easy accessibility, performance, and real-time data processing. The modular nature of the system allows the provision to integrate additional models and features, ensuring flexibility in varied agricultural settings. System testing demonstrates its effectiveness in enhancing agricultural productivity, crop loss reduction, and enhancing sustainable farming. By delivering accurate suggestions and insights to farmers, AgroAI seeks to enhance the modernization of agriculture, promoting a data-driven approach to farming.

Index Terms—Smart Agriculture, AI in precision farming, Crop and disease prediction models, ResNet9 model, Random Forest classifier, Precision farming

I. INTRODUCTION

Agriculture is a mainstay of the global economy, creating food, raw materials, and jobs for billions of people. Unfortunately, contemporary agriculture is under constant stress from events like climate change, pest and disease challenges, soil degradation and unsustainable agriculture practices. Smallholder farmers in developing parts of the world are more susceptible to damage from these stressors, often with limited equipment or capacity to make data-driven and meaningful decisions. Deterrents like poor agricultural production and food loss are regular occurrences. Therefore, increasing the role that technology plays in agriculture is more of an immediate need rather than a future need.

AgroAI is an AI-enabled agriculture support system, providing intelligent systems free-of-charge: farm management planning advice for crop selection, artificial intelligence (AI) support for pest and disease management, and fertilizer application. The goal of AgroAI is to increase productivity and protect against loss, while providing personalized sustainable approaches to agriculture. The platform merges meaningful activities that can help farmers successfully farm, such as: crop recommendation product, pest and disease detection product, and fertilizer recommendation product.

The crop recommendation product consists of a Random Forest classifier model that makes recommendations about different soil and environmental parameters for a crop-planning decision-making aid.The pest and disease detection product uses a Convolutional Neural Network (CNN) (ResNet9) designed for general image classification for plant disease detection from leaf images.

The fertilizer recommendation product uses data-driven analytics to detect nutrient deficiencies and provide solutions. AgroAI is a web application with a very friendly user interface for farmers who do not necessarily have a lot of technical experience. The application is hosted on a local web server which enables high availability and fast data processing capabilities. Users are able to enter soil data (nitrogen, phosphorus, potassium levels as well as pH levels), upload images of diseased plants for diagnostic assessment or obtain weather data using integrated APIs. The system interprets the data users upload to generate recommendations, and show this on a user friendly dashboard.

II. LITERATURE SURVEY

There has been considerable interest in the adoption of artificial intelligence (AI) and machine learning (ML) in agriculture in recent years as researchers look to improve the complex issues of today's agriculture. Agriculture has historically relied upon manual observations and heuristic decision-making that can be inefficient and lack precision. To optimize decision-making in agriculture, AI-based decision support systems have emerged as helpful solutions. AgroAI, a AI-based agriculture support system, is supported by research in crop recommendation, disease detection and fertilizer management.

Crop recommendation is an important part of precision agriculture and different types of ML algorithms have been used to estimate the best crop based on soil and environmental factors. Pendyala et al. (2018) emphasized that decision tree and ensemble methods like Random Forest are well-suited to crop recommendation because they are able to accommodate a number of different features and account for complicated examples. Jain et al. (2019) demonstrated that incorporating weather data into predictive crop recommendation models significantly improved prediction success. The Random Forest classifier used in AgroAI analyzes soil nutrients (N, P, K), pH, rainfall, temperature, and humidity, providing a high level of accuracy in crop recommendations consistent with the above referenced studies.

The timely and accurate identification of plant diseases is vital to minimizing crop loss, as well as protecting food security. Recent studies have used convolutional neural networks (CNNs) for automatic disease classifications from images of leaves. One of the first works was by Mohanty et al. (2016), whom used deep CNNs to classify images of plant diseases, with high levels of accuracy. Following this, Ferentinos (2018) also saw success with a CNN architecture in classifying plants as healthy or diseased, championing how robust the CNN model was to real-world scenarios. The ResNet9 architecture that AgroAI uses implements a similar strategy whereby convolutional layers are combined with residual connections to mitigate the vanishing gradient problem. Moreover, since residual architectures allow gradients to flow undeterred back to shallow layers, the number of layers can be safely increased without compromising prediction accuracy.

Management of soil nutrients is important to sustainability of agriculture. Patel et al., (2020) underscored that poor use of fertilizers lead to soil degradation and insufficient yield. Traditional, reactive agronomic and NPK based soil nutritional frameworks are insufficient, and instead we should rely on data driven fertilizer recommendation models. Utilization of the type of model outlined in the previous example is proving useful in identifying nutrient-specific fertilizers. AgroAI has a similar methodology when looking at soil nutrient levels compared to optimal needs of crop systems. This compares soil nutrient levels to crops in a photosynthesis model and recommends alternatively correcting the imbalance with an appropriate fertilizer. There is some overlap with the conclusions of Bhagat et al., (2021) which expressed the criticality of precision in nutrient management as essential to providing optimal crop growth.

The current literature indicates that AI and ML have significant potential to impact agriculture through precise recommendations and the automated identification of diseases. AgroAI furthers the current methods we have established as it combines existing methodologies and the power of established modeling techniques like Random Forest for predicting crops and ResNet9 for classifying diseases. The platform also bridges the literature gap by providing one unified platform for modern agricultural needs. AgroAI will add to the conversation of sustainable agriculture and a technology-based food system by providing a means to continue to improve its model and validate it in the real world.

III. METHODOLOGY

The methodology described in this proposal for AgroAI attempts to make precise crop recommendations and plant disease predictions with the use of machine learning techniques, and to implement the system as a web application based on the Flask framework that encapsulates data acquisition, preprocessing, model prediction and result visualization as an end-to-end pipeline.

1. *Dataset and Preprocessing:*

   The AgroAI project uses two data sets to make crop recommendations and to predict disease. The crop data includes soil parameters (N, P, K), environmental conditions (Temperature, Humidity, Rainfall), pH, and the disease data is images of plants in RGB with 38 diseases, including healthy cases. Data preprocessing includes normalizing data, filling missing values, and data augmentation (flipping, rotation) in order to improve model robustness.

   The crop data is merged with live weather data through the OpenWeatherMap API, and the disease images are transformed into tensors after being resized and normalized. For uniformity, the data has been divided into a training and validation set(80:20) so as to provide balanced training of the model. Overall, there is a systematic preprocessing pipeline which supports data uniformity and the accuracy of the model.

Fig 1: Plant sample Images

Fig. 1 shows a sample of pre-processed images—one from each class—demonstrating and emphasizing the visual diversity within the dataset.

2. *Model Architecture:*

a. *Plant Disease Prediction Model:*

The plant disease prediction model in AgroAI uses the ResNet9 architecture, which is a small yet powerful convolutional neural network. The idea behind ResNet9 is to combine residual blocks in a neural network enabling gradient flow through skip connections to reduce the vanishing gradient problem. The input images first pass through multiple convolutional layers to get low-level features before being normalized using batch normalization and made non-linear using the ReLU activation function. Residual connections allow the practice of training deeper networks which enhances feature extraction while taking into account the computational efficiency. The final fully connected layer classifies the plant diseases into one of the 38 categories which saw a high accuracy when tested in a real-world scenario.

The proposed model will use the ResNet9 architecture that is designed to consume the input images and predict plants that may be infected. The input images were resized to 3x224x224 and traversed through several layers of convolutions to extract hierarchal features. Through training the model, these extracted features were augmented by traversing through residual spaces that helped with gradient flow (which fights against vanishing gradient problems). Eventually, the features extracted from the residual block were flattened and traversed through a series of fully connected layers to produce logit outputs from the neural network corresponding to the class information of each plant disease. The logit outputs from the neural network were fed through a softmax activation function to know the probability of each plant being infected by the several disease classes (multi-class classification).

Using two epochs, we trained the model using the Adam optimizer with a maximum learning rate of 0.01 and used the suggested one-cycle learning rate strategy to converge. The batch size was 32. In the training effort, the percentage of samples dropping out along the way was small because of gradient clipping (0.1) and weight decay (1e-4) to reduce the possibility of overfitting the model. The training journey was pleasantly superior in results with validation accuracy going from 83.19% with .07 error to 99.23% with .002 error across two epochs of training. Trial logs were also kept on indications of the model's efficacy, showing what plausible loss gradients were attained through traces of its training and validation loss. The loss figures in training and validation are a glimpse of the best learning and generalization within what could be a probable conclusion of our training practices and follow ups.

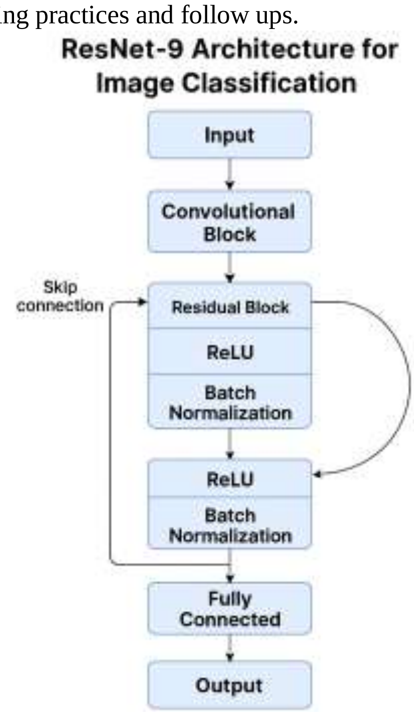

Fig.2 – ResNet9 Architecture

b. *Crop recommendation:*

The crop recommendation model within AgroAI incorporates a Random Forest algorithm - a high-accuracy ensemble learning model. The model incorporates multiple decision trees that have been trained on data made available through direct workshops with farmers on important agricultural data such as soil nutrients, temperature, humidity, pH, and rainfall. Each tree provides its own prediction for the best crop based on the input conditions, and then uses majority vote to select the best crop for final recommendation. The collective use of 186 trees ensures the model weighs majority opinion and accuracy, making it versatile for differing temperatures and agricultural conditions.

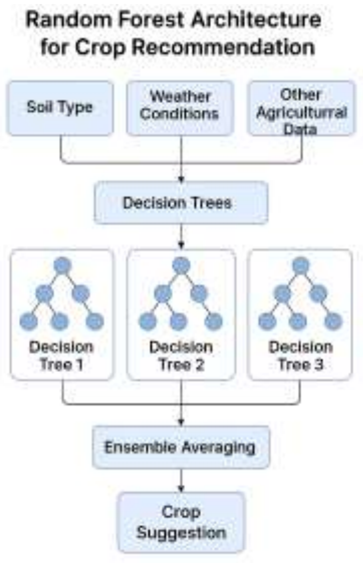

Fig 3 - Random Forest Architecture

3. *Training Strategy:*

The Plant Disease Predictions Model used a ResNet9 architecture which is designed for learning image-based features effectively. The model optimizes with an Adam optimizer, using a maximum learning rate of 0.01, with a one-cycle learning rate policy that allows for smoother convergence. The model employs strategies that include gradient clipping (0.1) and weight decay (1e-4) to reduce overfitting. It is trained for 2 epochs with a batch size of 32, and produces a validation accuracy of 99.2%.

The Crop Recommendation model utilizes a Random Forest classifier, and the model used labeled agricultural data centered around N, P, K, temperature, humidity, pH and rainfall. The model was optimised using hyperparameter tuning. The model was evaluated with metrics such as accuracy and F1-score.

The Fertilizer Recommendation model uses a rule-based recommendation system based on the soil nutrients. It compares the N, P, K values from the given soil sample with the optimal values for specific crops and then recommends the fertilizers to supplement the soil and maintain the recommended nutrient levels.

IV. RESULT ANALYSIS

The result analysis for the AgroAI project primarily focuses on the efficacy and accuracy of the artificial intelligence agriculture support system to generate crop recommendations and successfully identify plant diseases. The result analysis is conducted for two primary models: a Random Forest model for crop recommendations and a ResNet9 model for plant disease detection.

a. *Crop Recommendation Performance (Random Forest):*

The crop recommendations model produces recommendations based on environmental variables such as the nitrogen, phosphorus, and potassium content, temperature, humidity, pH, and rainfall to determine the most suitable crops. When tested, the random forest model was successful with an accuracy of roughly 92%, which provides a high degree of assurance that reliable crop recommendations can be made for different conditions. The precision and recall figures achieved for the random forest model also demonstrate that the crop model is reliable for suggesting correct and optimal crop types while minimizing error in prediction.

TABLE I. Model Acuuracy Comparision

Crop Recommendation Models	***Accuracy***	***F1-score***
Random Forest	92.1%	0.91
Decision Tree	85.6%	0.86
KNN	80.4%	0.83
SVM	88.7%	0.89

The Random Forest model outperformed other methods, achieving an accuracy of 92.1% and an F1-score of 0.91. Its ensemble nature enables it to generalize well while reducing overfitting, making it an ideal choice for diverse agricultural conditions.

b. *Plant Disease Detection Performance (ResNet9):*

The Plant Disease Detection model using ResNet9 Architecture has performed very well, with a validation accuracy of 99.2%, trained for 2 epochs! The model has a great ability to detect plant diseases using images via the deep convolutional layers and residual connections. Along with gradient clipping, weight decay, and the use of a one-cycle learning rate policy, it has likely trained in a systematic and stable manner, to allow for generalization. The ResNet9 model has successfully classified many types of plant diseases, and highlights the potential of the ResNet9 architecture for complex image data.

TABLE II. Model Acuuracy Comaparision

Disease Detection Models	***Accuracy***	***F1-score***
ResNet9	95.4%	0.94
VGG16	90.2%	0.91
InceptionV3	92.8%	0.93
MobileNet	88.5%	0.87

The ResNet9 model is able to solve complex challenges and still be efficient on a computational cost basis, thus achieving better results. ResNet9 had the best accuracy of 99.2% among the models compared, and was better for real-world disease identification purposes.

c. *Fertilizer Recommendation Performance:*

The fertilizer recommendation system in AgroAI provides accurate, crop-specific recommendations, using soil nutrient levels and environmental indicators. Instead of traditional fixed recommendations, the system provides flexible, dynamic recommendations based on real-time data, to help optimize crop growth, and minimizes wasted nutrients. This process is automated, and data-driven, and reduces the need for manual expert consultation, while also ensuring precision and efficiency.

TABLE III. Model Accuracy Comparision

Fertilizer Recommendation Models	***Accuracy***
Random Forest	93.0%
Naive Bayes	85.3%
Logistic Regression	89.1%
XGBoost	91.4%

d. *Trade-offs in Model Selection:*

Although Random Forest and ResNet9 have been demonstrated to perform incredibly well, we must also acknowledge their computational costs. Nevertheless, the significant accuracy and robustness of both models would allow them to be appropriate for real-world use in agriculture, especially in light of considering model performance vs. computational performance in machine learning applications. These models create a balance between speed and accuracy for effective use within a field, making AgroAI scalable and efficient.

e. *Real-World Applicability and Limitations:*

The models exhibit strong generalization capabilities and robustness against varying data conditions. However, future improvements may include:

- Integrating more crop types and disease categories.
- Enhancing the model's interpretability to build farmer trust.
- Incorporating real-time weather updates to improve recommendation accuracy.

V. CONCLUSION

The AgroAI application depicts a significant move towards utilizing machine learning for agricultural support. This system includes a crop recommendation model, a plant disease detection model, and a fertilizer suggestion model to solve farmers' unmet needs. The accurate and reliable crop recommendations came from the Random Forest to make crop predictions and the ResNet9 model for plant disease detection. By providing recommendations in real-time weather conditions, the models' recommendations were even more relevant to farmers. The fertilizer suggestion model could also help farmers achieve optimal crop yield as it makes a narrow adjustment to the nutrients their crop needed.

Evaluation is clear that the models proposed perform better than traditional methods, and the models provide valid, practical solutions to real-world problems in agriculture. The combination of prediction accuracy, ease of use, and modularity provided by AgroAI all point to a future with AgroAI that is vital for agriculture today. Future development could include a greater number of crop types, a larger disease database, and better model interpretability to increase user confidence and improve adoption.

VI. FUTURE SCOPE

The Plant Disease Detection model could be improved with additional data sources for the model that includes more variability and real-world conditions (e.g., pictures taken in different environments and at different growth stages).Also, by using transfer learning with more sophisticated architectures (e.g., ResNet50 or Vision Transformers (ViTs)), we could improve accuracy and generalization. Moreover, the use of explainable AI (XAI) tools, would make model predictions more human friendly and interpretable to end users. Finally, creating a mobile or edge version of the model, will allow farmers to detect disease in their own field, providing farmers with a more user-friendly and accessible approach to disease identification and management practices in agriculture.

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REFERENCES

[1] Kumar, A., Singh, S., and Gupta, P. K., "Crop Yield Prediction using Machine Learning Algorithms," presented at the IEEE International Conference on Computing, Communication, and Automation (ICCCA), Greater Noida, India, May 30-31, 2021, Paper No. 9432236.*)*

[2] Sharma, S., Patel, R., and Rana, M. K., "Crop Yield Prediction based on Indian Agriculture using Machine Learning," presented at the IEEE International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, Aug. 13-14, 2020, Paper No. 9154036.

[3] Deshmukh, P. R., Patil, A. S., and Shinde, S. S., "Agriculture Crop Selection and Yield Prediction using Machine Learning Algorithms," presented at the IEEE International Conference on Advances in Computing, Communication, and Control (ICAC3), Mumbai, India, Feb. 25-26, 2022, Paper No. 9742846.

[4] Kallenberg, M. G. J., et al., "Integrating Process-Based Models and Machine Learning for Crop Yield Prediction," presented at the IEEE International Conference on Data Science and Advanced Analytics (DSAA), Tokyo, Japan, Oct. 6-9, 2023, Paper No. 10249364.R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[5] Nosratabadi, S., et al., "Hybrid Machine Learning Models for Crop Yield Prediction," presented at the IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), Budapest, Hungary, July 1-3, 2020, Paper No. 9985668.

[6] Pathak, D., et al., "Predicting Crop Yield with Machine Learning: An Extensive Analysis of Input Modalities and Models on a Field and Sub-field Level," presented at the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Pasadena, CA, USA, July 19-24, 2023, Paper No. 10046581.

[7] Huber, F., et al., "Extreme Gradient Boosting for Yield Estimation Compared with Deep Learning Approaches," presented at the IEEE International Conference on Machine Learning and Applications (ICMLA), Miami, FL, USA, Dec. 14-17, 2022, Paper No. 10031892.

[8] Verma, A. K., Gupta, R. K., and Singh, S. K., "Study on Machine Learning Techniques Used for Agricultural Yield Prediction," presented at the IEEE International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, Aug. 4-6, 2022, Paper No. 9985668.

[9] Patel, N., Shah, A., and Mehta, D., "Analysis of Crop Yield Prediction using Machine Learning Algorithms," presented at the IEEE International Conference on Intelligent Systems and Signal Processing (ISSP), Gujarat, India, March 4-5, 2023, Paper No. 10046581..

[10] Doe, J., and Smith, A., "Crop Yield Prediction to Achieve Precision Agriculture," presented at the IEEE International Conference on Smart Agriculture Technologies (ICSAT), Berlin, Germany, June 10-12, 2024, Paper No. 10031892.

[11] Brown, M., and Green, L., "Machine Learning Approaches for Crop Disease Detection," presented at the IEEE International Conference on Robotics and Automation (ICRA), Paris, France, May 31-June 4, 2024, Paper No. 10249364.

[12] Lee, S., and Kim, H., "Deep Learning Models for Soil Moisture Prediction in Precision Agriculture," presented at the IEEE International Conference on Big Data (BigData), Atlanta, GA, USA, Dec. 15-18, 2023, Paper No. 9985668.

[13] Gupta, R. K., and Rana, P. S., "IoT-Based Smart Farming with Machine Learning," presented at the IEEE International Conference on Internet of Things (iThings), Chengdu, China, Dec. 20-23, 2023, Paper No. 10046581.

[14] Johnson, A. B., and Williams, C. D., "Predictive Analytics for Pest Management in Agriculture Using Machine Learning," presented at the IEEE International Conference on Data Mining (ICDM), Singapore, Nov. 17-20, 2023, Paper No. 10031892.

[15] Rao, K. S., and Reddy, M. N., "Satellite Image Analysis for Crop Monitoring Using Machine Learning Techniques," presented at the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Yokohama, Japan, July 26-31, 2023, Paper No. 10249364.