AI in Agriculture (An Ensemble Stacking Approach with Web Application for Crop, Fertilizer, and Disease Recommendation)

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***Abstract*—The web-based system for crop recommendation, fertilizer prediction, and plant disease detection from leaf images using ensemble machine learning is being presented in this paper. The models take into consideration soil, weather, and image data to recommend accurate and practical solutions to the farmers through an easy-to-use portal.**

***Keywords*—Ensemble stacking, Image feature extraction, Soil and weather parameters, Machine learning inference API**

I. Introduction

Precision agriculture increasingly works in lines of data analysis, and this system augments crop yield while minimizing losses due to diseases. This system introduces a fully integrated web application capable of crop recommendation, fertilizer prediction, and plant disease detection. The system employs ensemble stacking techniques and classical machine learning techniques to give enhanced prediction accuracy. Recommendations for crops and fertilizers are prepared on soil nutrient content and weather parameters, and plant disease detection is achieved through feature classical extraction from leaf image classes. The system combines these modules into a simple-to-use web portal so that the research gap of fragmented agricultural decision-making tools can be addressed and to provide farmers with actionable insights into crop selection, fertilizer management, and disease control.

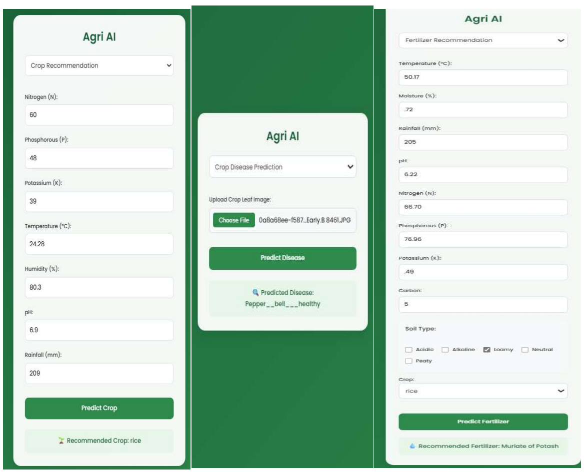

Fig. 1. Screenshorts of hosted webapplication
(https://github.com/shelby2770/AI-in-Agriculture)
(https://agri-ai-325y.onrender.com/)

II. Dataset Description

A. Crop Recommendation Dataset

The crop recommendation module utilizes a dataset [2] containing 2,200 samples, each representing a unique set of soil and environmental conditions. The dataset includes the following features: Nitrogen (N), Phosphorous (P), and Potassium (K) content (all in mg/kg), temperature (°C), relative humidity (%), soil pH, and rainfall (mm). The target variable, label, specifies the recommended crop for each set of conditions. All entries are complete, with no missing values, and the data types include both integer and floating-point values for the features, and categorical values for 22 the crop label .

B. Fertilizer Recommendation Dataset

The fertilizer recommendation [3] module is based on a dataset of 3,100 entries. Each record includes soil and environmental features: Temperature (°C), Moisture (%), Rainfall (mm), pH, Nitrogen, Phosphorous, Potassium, and Carbon content. In addition, categorical features such as Soil type and Crop type are provided, along with the target variable, Fertilizer, and an additional Remark column. All features are non-null, and the dataset supports 10 fertilizers prediction based on both soil and crop context.

C. PalnetVillage Dataset

For plant disease detection, the system uses the PlantVillage [1] image dataset (with 20k+ images of 3 leaf plants and its 12 type of diseass), organized into directories by disease and crop type (e.g., Tomato_Bacterial_spot, Potato___Late_blight, Pepper__bell___healthy). Each directory contains numerous leaf images representing either healthy or diseased states for various crops. This structure enables supervised learning for multi-class disease classification using image-based features.

III. Methodology

A. Data Preprocessing and EDA

For both the crop and fertilizer datasets, preprocessing began with checking for missing values and ensuring data completeness. Outliers in numerical features such as nutrient levels, temperature, humidity, pH, and rainfall were capped using the interquartile range (IQR) method to reduce their impact on model training. Categorical variables, including crop and fertilizer labels, were encoded using label encoding. Soil type in the fertilizer dataset was converted to a one-hot encoded format. All numerical features were standardized using StandardScaler to ensure uniformity across variables. Exploratory Data Analysis (EDA) included boxplots to visualize outlier distributions, histograms for feature distributions, and correlation heatmaps to examine relationships between variables. These steps ensured the datasets were clean, balanced, and suitable for machine learning.

For the disease detection task, the PlantVillage image dataset was organized by class folders, each representing a specific crop-disease combination or healthy state. Images were resized to a uniform 128x128 pixels for consistency. Feature extraction was performed using Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and color histograms to capture texture and color information relevant for disease classification. The extracted features were then concatenated to form the final input for classical machine learning models. EDA involved visualizing sample images from each class and inspecting the distribution of extracted features, ensuring the dataset was well-structured for robust image-based classification.

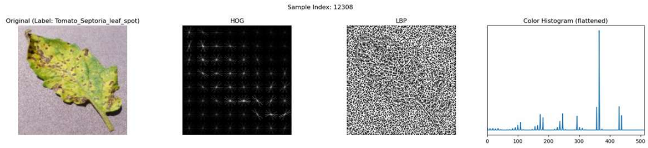

Fig. 2. Features extracion of a leaf image (imgae data preprocessing)

B. *Model Training*

For both crop and fertilizer recommendation, several classical machine learning algorithms were evaluated, including Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Decision Tree, Random Forest, and Gradient Boosting. To further enhance predictive performance, a stacking ensemble was implemented, combining multiple base learners with a meta-learner. The datasets were split into training and testing sets, and all features were standardized prior to training. For disease detection, classical models such as Random Forest, Logistic Regression, and KNN were trained on features extracted from leaf images using HOG, LBP, and color histograms.

C. *Evaluation*

Model performance was assessed using metrics such as accuracy, F1-score, precision, recall, and confusion matrices, with the best-performing models selected for deployment.

IV. Results

Crop Recommendation: The stacking model for crop recommendation achieved an accuracy of 1.00 (100%), with a macro average F1-score of 0.99 and a weighted average F1-score of 1.00 on the test set. The confusion matrix and classification report show near-perfect precision and recall across all crop classes, indicating highly reliable predictions .

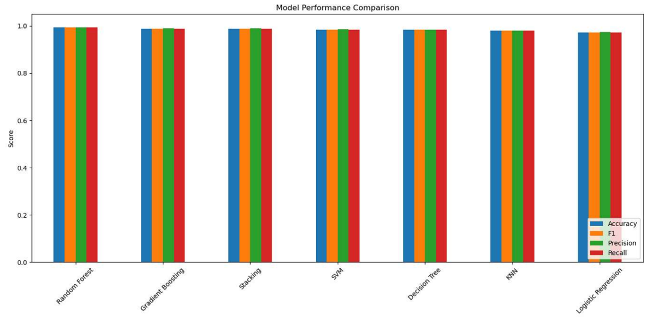

Fig. 3. Multiple models performance of Crop Recomendation

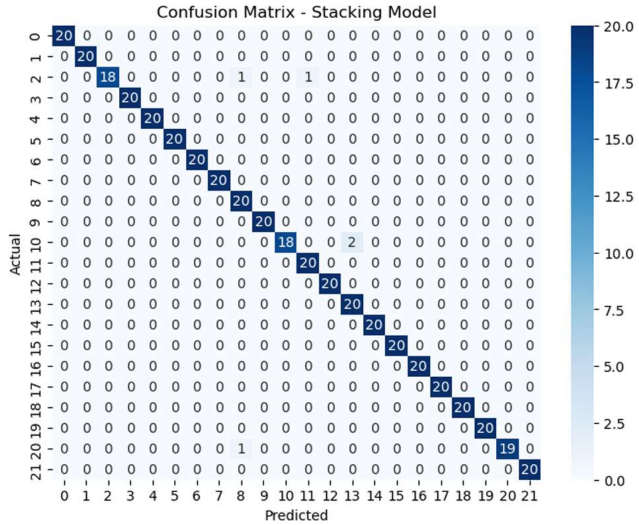

Fig. 4. Confusion Matrix of Stacking Model

Disease Detection: For plant disease detection, the Random Forest model reached an overall accuracy of 0.90 (90%), with a macro average F1-score of 0.83 and a weighted average F1-score of 0.89. The ROC curves for each class demonstrate high AUC values, and the feature importance plot highlights HOG features as the most significant for classification. The confusion matrix and classification report confirm strong performance across most disease categories, with some variation in recall for specific classes.

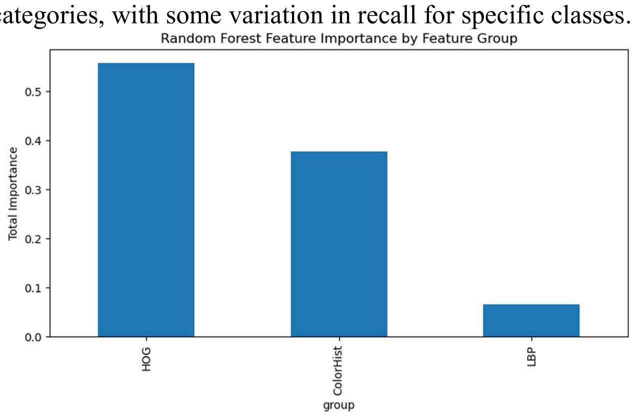

Fig. 5. Random Forest Feature Importance for image feature extraction

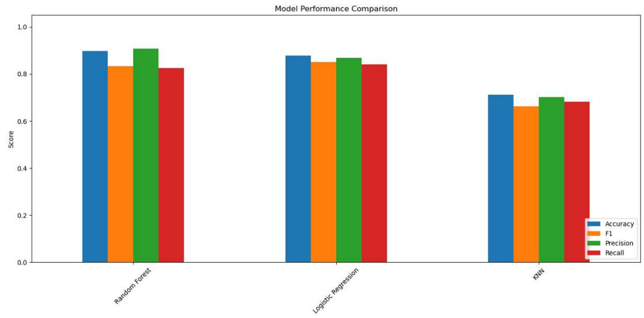

Fig. 6. Multiple models performance of Disease Detection

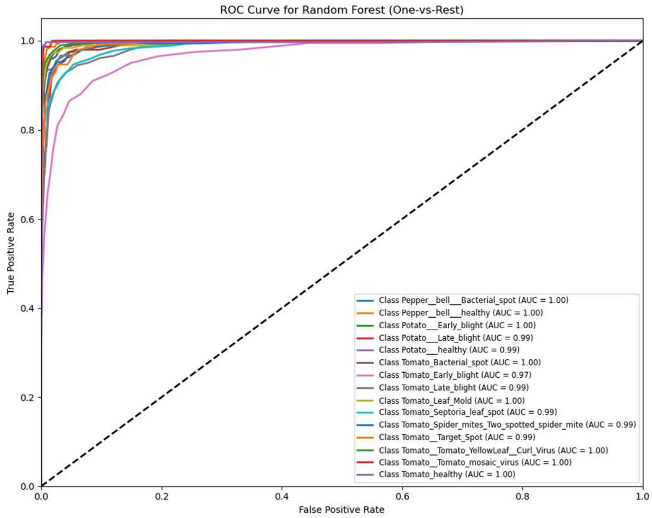

Fig. 7. ROC Curve for Random Forest

Fertilizer Recommendation: The stacking model for fertilizer recommendation achieved an accuracy of 0.99 (99%), with both macro and weighted average F1-scores of 0.99. The confusion matrix and classification report indicate excellent precision and recall for all fertilizer classes, confirming the robustness of the ensemble approah.

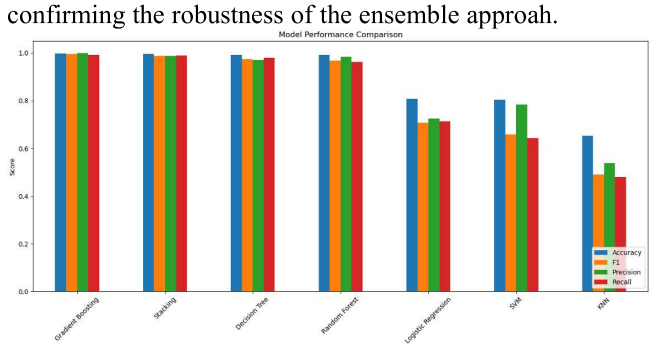

Fig. 8. Multiple models performance of Fertilizer Recomendation

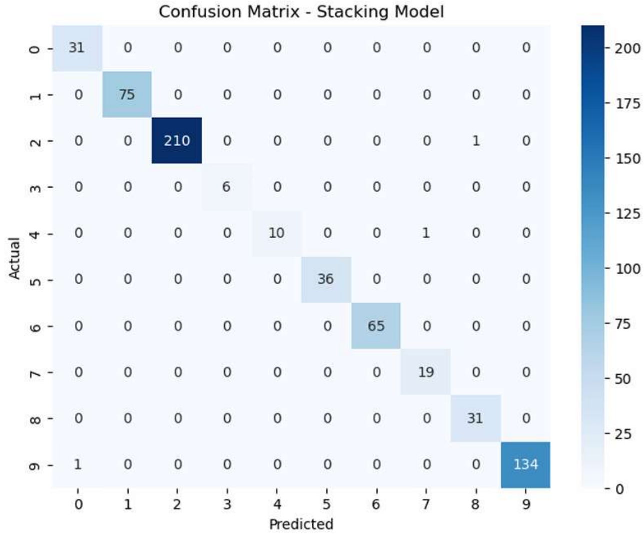

Fig. 9. Confusion Matrix of Stacking Model

V. Conclusion

This work shows that by employing stacking ensemble techniques with classical machine learning and image-level feature extraction, it is possible to obtain very accurate crop, fertilizer, and disease recommendations from one web application. The system operated with near-perfect accuracy for crop and fertilizer predictions and good performance in plant disease detection, therefore providing way of a platform for farmers with data-based, practical means. The modules are combined in an intuitive portal, thus filling the gap in the available comprehensive agricultural decision tools and realizing great opportunity for impacting precision agricultural practices.

VI. Limitation

Crop Recommendation: The crop recommendation models achieved 100% accuracy on the provided dataset, primarily because the dataset contains only 2,200 rows and four columns have unique feature (2200) combinations. As a result, the models essentially memorized the training data, leading to perfect performance on internal tests but likely poor generalization to new, unseen data. Additionally, the correlation heatmap revealed no significant relationships between most features, suggesting limited predictive power and potential overfitting.

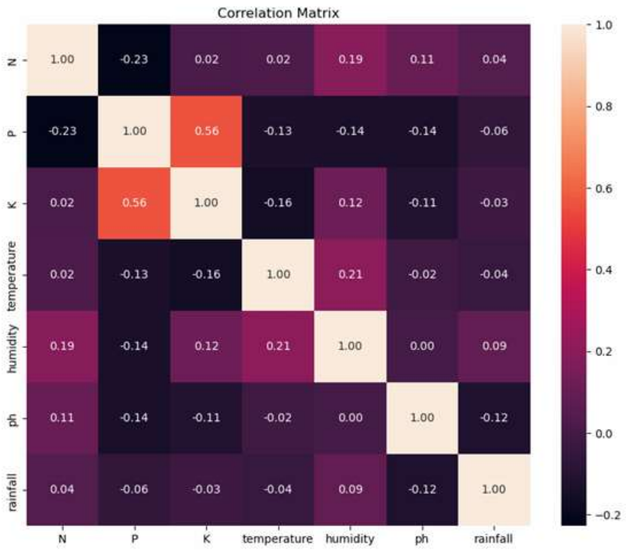

Fig. 10. Correlation Matrix of Crop Dataset

Fertilizer Prediction: For fertilizer prediction, tree-based models performed well by capturing complex patterns in the 3,100-row dataset, while other algorithms struggled. This indicates that the dataset's structure is better suited to models like Random Forest, but may not generalize well to different data distributions or larger, more diverse datasets.

Disease Detection: The image-based disease detection models, which rely on classical feature extractors (HOG, LBP, color histograms), showed reasonable performance but produced several incorrect predictions. Accuracy could be significantly improved by adopting deep learning approaches, such as convolutional neural networks, which are better suited for complex image classification tasks.

VII. Future Recommendations

To address these limitations, future work should focus on collecting larger and more diverse datasets, especially for crop recommendation, to improve model generalization. For fertilizer prediction, exploring feature engineering and hybrid models could enhance robustness. For disease detection, implementing deep learning techniques and augmenting the image dataset would likely yield better accuracy and reliability. Additionally, external validation on real-world data is recommended for all modules to ensure practical applicability.

References

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