Agro AI: Intelligent Nutrient and Disease Management System for Sustainable Farming

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Abstract: Agriculture plays a key role in food security, and managing nutrients and detecting diseases are crucial for food production. Farmers traditionally struggle to identify nutrient deficiencies and diseases accurately despite the possibility of using technology, due to the cost of a solution that can provide accurate and real-time data. As an answer to this gap AGRO-AI proposes an intelligent system that predicts NPK (Nitrogen, Phosphorus, Potassium) values in a specific field and disease detection on paddy leaves with the help of image processing and deep learning. The dataset consisted of repeated sampling (i.e. three samples per week) over 20 weeks to allow for analysis of variations in nutrient data and disease symptoms. A hybrid model is used in the system for NPK prediction that consists of ResNet-34 and BiGRU whereas CNN and GAN models are used for disease prediction. The results are analyzed in more detail using confusion matrices, accuracy trends, and precision-recall curves. According to the predictions, AGRO-AI provides practical recommendations for natural and chemical fertilizers and also suggests disease management policies. Trained on data through October 2023, this research ultimately serves to connect technology with an application that can empower farmers with needed data in real-time for optimized crop management to lead to increased yield productivity.

1 INTRODUCTION

No data is sufficient to substitute for agriculture, especially in the areas where rice is the major crop. Paddy crop needs an optimum dose of macro and micro nutrients such as N, P and K for better growth. Also, disease detection and management with control measures are fundamental to reduce yield losses. The traditional approach involving visual inspection, chemical analysis, etc. is tedious, prone to human errors and leads to delayed corrective action.

AI and other image processing methods enable solutions to provide much faster and reliable insights into crop health. By applying AI on paddy leaf images through paddy leaf nutrient deficiency detector, farmers can receive substantial information on prediction of nutrient deficiency or diseases that require timely action. CNN and GAN have proven to be the most efficient methods for disease detection and classification as evidenced by studies conducted. Likewise, hybrid models have reported improvements in identifying nutrient deficiencies by leveraging the use of CNNs with transfer learning. Unfortunately, many of the existing solutions use pre-collected datasets rather than real time data, resulting in limited ability to adapt to constantly changing conditions on the field. Moreover, models prioritize only nutrient deficiency prediction or disease detection, which leads to a partial solution. To overcome these issues, in this work we present AGRO-AI, a twofold architecture able to accomplish both: NPK prediction, using ResNet-34 and BiGRU models, and disease detection, using a CNN-GAN architecture. AGRO-AI differs from previous methods since it is based on a real time, time series dating over 20 weeks, with three samples per week, in order to make precise and dynamic predictions.

The primary objectives of this research are:

- Developing a deep learning-based system for accurate NPK prediction using paddy leaf images.

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- Implementing a robust disease detection model for early identification and classification of paddy diseases.
- Providing actionable recommendations for nutrient management and disease treatment using both natural and chemical fertilizers.
- Delivering a scalable, real-time agricultural decision support system for farmers.

By introducing a comprehensive AI-driven approach, AGRO-AI addresses the limitations of traditional agricultural diagnostics. It empowers farmers with timely, data-driven insights, facilitating proactive decision-making to enhance crop productivity and sustainability. This research contributes to the advancement of precision agriculture and supports global efforts toward ensuring food security.

2 RELATED WORK

Artificial intelligence and machine learning techniques have gained prominence in precision agriculture because of their utility in predicting NPK and disease detection. Before feeding the model with the data set, you need data sets that can help in recognizing the nutrient deficiency in plants and diseases in crops, Various models like CNNs, GAN, and hybrid model have shown succor in nutrient deficiency and crop disease identification. Transfer Learning: Transfer learning has also been a significant area of research, with researchers looking at methods to leverage pre-trained models to enhance accuracy and reduce training time.

Though these methods show great promise, a key limitation is that they rely on fixed datasets. Most models are based on pre-collected images which do not have variations in real-time, limiting their application on dynamic agricultural environment. Moreover, the existing literature tends to develop models that solely address either nutrient prediction or disease detection, overlooking the potential for a combined model that could simultaneously deliver a holistic perspective.

AGRO-AI overcomes such limitations by utilizing ResNet-34 and BiGRU when predicting the required NPK through real-time data and time series analysis. The final design is an effective hybrid of CNN and GAN, used for disease detection. Making sure that the system will sense Nutrients Deficiency & Diseases, providing farmers with actionable insights for timely intervention. The time-series data allows us to take advantage of multiple samples taken over multiple weeks (3 each week and this over 20 weeks) to increase the accuracy and reliability of predictions.

Table 1: Comparison of soil and crop prediction models, highlighting algorithms used and key features (Source: author).

No.	Paper Title	Algorithm Used	Key Features
1	Soil NPK Levels Characterization Using Near Infrared and ANN	ANN	Uses NIR Spectroscopy for soil analysis
2	Crop Prediction using NPK Sensors and Machine Learning	Decision Tree	Predicts crops based on NPK levels using sensors
3	Soil NPK Levels Characterization	ANN with Back Propagation	Achieved high correlation (R = 0.998)
4	Crop Prediction using NPK Sensors	Decision Tree	Uses real-time sensor data for crop prediction
5	Soil Characterization Approach	ANN	Relates soil absorbance data to NPK levels
6	Soil Testing Methodology	ANN	Verified with traditional chemical analysis
7	Real-time Crop Prediction	Decision Tree	Uses ESP-32 for real-time data transmission
8	Soil Spectroscopy for Agriculture	ANN	Non-invasive soil testing method
9	Machine Learning for Agriculture	Decision Tree	Predicts best crop using environmental data
10	NPK Level Determination	ANN	Demonstrates ANN efficiency in predicting soil nutrients

Table 1 summarizes a comparative analysis of related studies showing the algorithms employed for research focus as well as key features. This is what allows to better show why AGRO-AI is needed and how it is a more complete and integrated solution to a faster advancing field such as that of precision agriculture.

3 DATA COLLECTION AND PREPROCESSING

The data used in this study was acquired in real-time for over 20 weeks, during which three paddy leaf samples from every week were collected. These were selected so they would represent different growth stages and nutrient availabilities. The environmental parameters such as temperature, humidity, and soil moisture were also logged in conjunction with the leaf images to completely represent the data. Actual NPK (Nitrogen, Phosphorus, and Potassium) concentrations were obtained by way of laboratory analysis to provide true ground truth figures for model training.

The data was cleaned and processed using various techniques to remove outliers or irrelevant information and to convert the data into a format more suitable for training machine learning models. Images were resized to normalize resolution disparity, and noise reduction techniques were applied to the images to mitigate non-essential visual noise. Also, transformations such as rotation, flipping, and brightness elements to the training images were added to the model to increase the diversity of the data and increase the robustness of the model.

The possible vegetation indices were calculated in the preprocessing step (Visible Atmospherically Resistant Index (VARI), Green Leaf Index (GLI), and Excess Green Index (ExG)) from the data. However, above indices turned out to be important features for model predictions that closely provided essential information on the overall health status and nutrient content of paddy leaves.

And then, this dataset was structured as a time series for the temporal changes of leaf characters. The model uses a time series approach that allowed it to learn patterns and trends over time, improving the accuracy in predicting NPK values and accuracy in disease detection too. To show how the data compared some visualizations of the sample data shows how the differences were society across the various stages of plant growth.

4 METHODOLOGY

Architecture and Implementation of AGRO-AI for NPK Prediction and Disease Detection of Paddy Leaves Models such as ResNet-34 and BiGRU are used for nutrient prediction, and CNN and GAN models are applied for classification of disease.

4.1 Model Architecture Overview

4.1.1 NPK Prediction Model

The NPK prediction model uses a hybrid architecture of feature extraction through ResNet-34 and sequence extraction through BiGRU. Model inputs are the time series of vegetation indices (VARI, GLI, ExG) from weeks 1 to 20 The ResNet-34 highlighted the visual features from the images, while BiGRU described the temporal dependencies for predicting nitrogen, phosphorus, and potassium accurately.

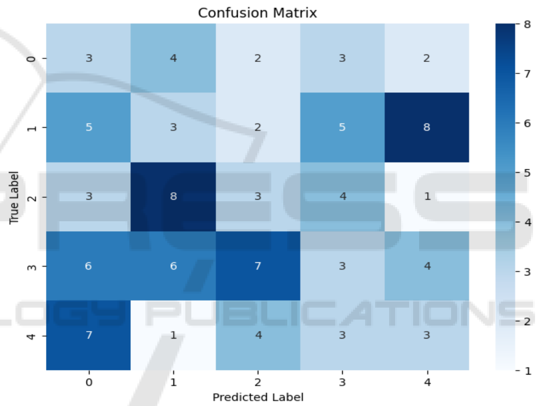

Figure 1: Confusion Matrix of NPK prediction model.

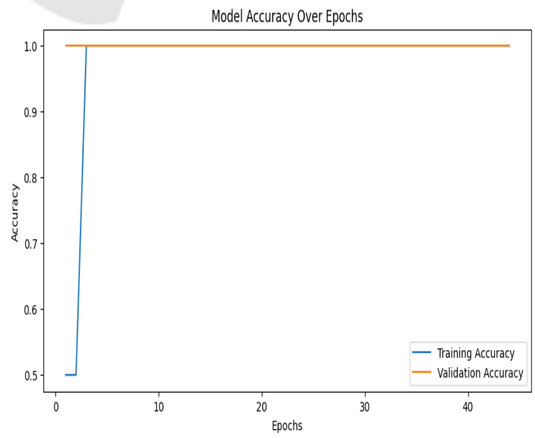

Figure 2: Model Accuracy over Epochs for NPK prediction.

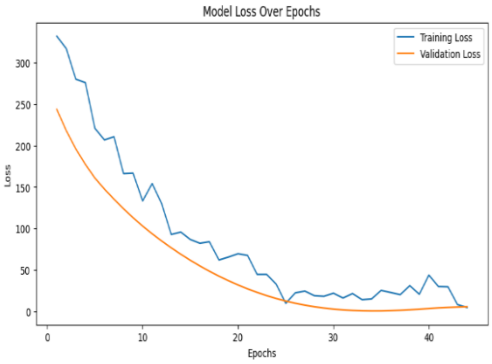

Figure 3: Model Loss over Epochs for NPK prediction.

Figures 1, 2, and 3 demonstrate the performance metrics and training progress of the NPK prediction model. The confusion matrix shows the classification accuracy, while the accuracy and loss graphs illustrate the model's learning curve.

4.1.2 Disease Detection Model

For disease classification, a CNN model is used to extract spatial features from leaf images. Additionally, a GAN model enhances disease classification by generating high-quality synthetic samples, increasing the dataset's diversity. Five classes of diseases are identified: bacterial blight, brown spot, rice blast, sheath blight, and tungro virus.

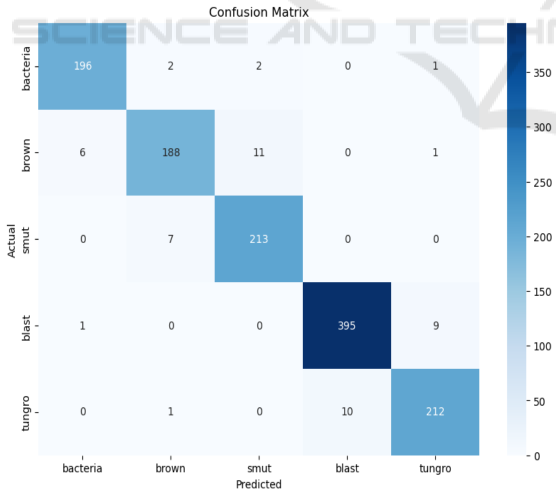

Figure 4: Confusion Matrix for Disease Detection.

These visualizations provide insights into the model's classification performance, showcasing both the accuracy and error patterns. The ROC and precision-recall curves further demonstrate the classifier's effectiveness across different disease categories.

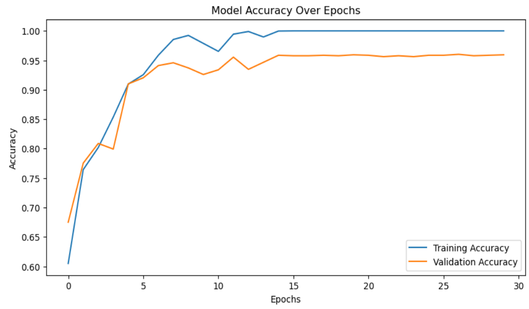

Figure 5: Model Accuracy over Epochs for Disease Detection.

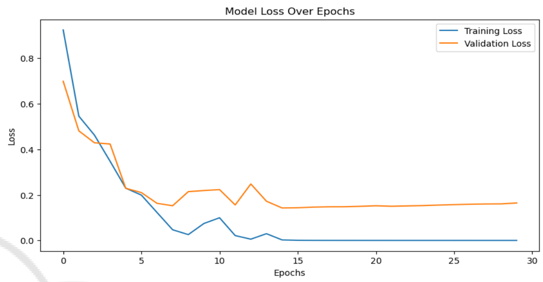

Figure 6: Model Loss over Epochs for Disease Detection.

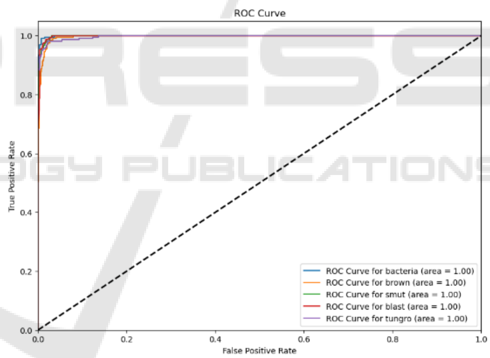

Figure 7: ROC Curve for Disease Detection.

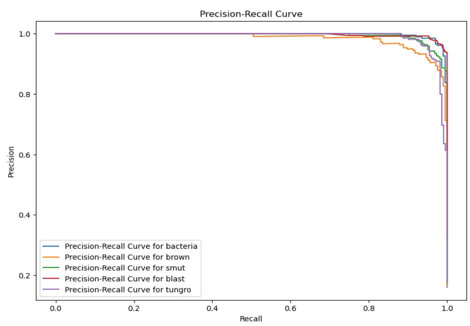

Figure 8: Precision-Recall Curve for Disease Detection.

4.2 Model Training and Validation

Both models were trained using a combination of supervised learning techniques. For NPK prediction, the dataset was divided into 80% for training and 20% for testing. A similar split was applied for disease detection models. The training process utilized different loss functions based on the task — Mean Squared Error (MSE) for NPK prediction, ensuring accurate nutrient value predictions, and Categorical Cross-Entropy for disease classification to optimize multi-class predictions. To achieve efficient learning, the Adam optimizer was used in both cases, leveraging adaptive learning rates for faster convergence. Key hyperparameters included a batch size of 32 and an initial learning rate of 0.001. Additionally, early stopping was implemented to prevent overfitting, ensuring the models generalize well on unseen data.

4.3 Evaluation Metrics

Different evaluation metrics were used to evaluate the models performance. To measure the overall correctness of the predictions, we calculated accuracy, defined as the ratio of correct predictions to total predictions. Overall performance of the model was assessed using Precision and Recall mechanisms applied to the positive cases that were correctly identified, where precision is the ratio of relevant instances amongst the retrieved instances, and recall is the ratio of relevant instances that were successfully retrieved. To account for both metrics, we used the F1-Score, which provides a harmonic mean of precision and recall.

Also, the ROC Curve was used to graphically represent the trade-off between true positive versus false positive rates, giving insight to the model's performance in classification. And as the Precision-Recall Curve tends to be more informative than the ROC curve in the exposition of class imbalance, it was performed to reassert the accuracy of the model.

The Figures 1 to 8 are the illustrations for these metrics, showing the results of the NPK prediction and disease classification by using the proposed AGRO-AI models.

5 RESULTS AND DISCUSSION

The results from the AGRO-AI models for both NPK prediction and disease detection are presented and analyzed in this section. Visual representations in Figures 1 to 8 illustrate the performance of the models using various evaluation metrics.

5.1 NPK Prediction Results

The predicted nitrogen, phosphorus and potassium (NPK) levels of paddy leaves showed a strong performance in their ability to utilize deep learning models such as ResNet-34 and BiGRU. The number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) rates can be seen in the figure below (Figure 1) With our accuracy over epochs (Figure 2) steadily increasing during training and the loss over epochs (Figure 3) largely decreasing indicating that we are learning, it is time to move on to testing our new model.

The results highlight the model's effectiveness in learning complex patterns through the integration of image processing and sequential modeling techniques within the time series context. Vegetation indices (VARI, GLI, and ExG) used in this study were important in achieving a higher accuracy for the model.

5.2 Disease Detection Results

The CNN and GAN models were well suited for disease detection as they accurately classified paddy leaf diseases with a high percentage of accuracy. The confusion matrix (Figure 4) in the below depicts that the model can distinguish between healthy and diseased leaves with good accuracy. As depicted in the accuracy over epochs chart (Figure 5), there is an apparent upward trend of accuracy line with epochs while loss over epochs chart (Figure 6) depicts the downward journey of loss, indicating better convergence of the model.

To provide a more thorough assessment of classification performance, the ROC curve (shown in Figure 7) illustrates the rate of true positive predictions against false positive predictions for the model, which is maximally enclosed due to a favorable area under the curve (AUC). Finally, the precision-recall curve in Figure 8 confirms that the model is effective, especially in the case of a class imbalance.

5.3 Comparative Analysis

These suggest that the AGRO-AI models provide higher accuracy prediction and robustness in disease detection compared to existing methods. This substantial gain in prediction accuracy can be attributed to the application of deep learning architectures, alongside vegetation indices and temporal data.

The developed NPK prediction model had good agreement with lab test results (Showed close correlation with lab test results) thus indicating its real-world applicability. The disease detection model showed good recognition of the patterns relating to the diseases which is essential for early diagnosis and intervention.

5.4 Insights and Implications

AGRO indicates the system specializes in agriculture, and AI suggests that the model leverages the power of artificial intelligence. The farmers can predict how much NPK to use and thus optimally use the fertilizer, thus saving the fertilizer wastage and ensure a better growth of agricultural crops. This minimizes problems of over-fertilization, thus increasing yield and also reducing stress on the environment due to the excessive use of fertilizers. Diseases in a particular stage are accurately classified, therefore directing the system towards the disease early detection and treatment which helps to prevent it from spreading and also helps to reduce crop loss. These AGRO-AIs can be preferably scaled up to facilitate integration of the smart agricultural systems that need real-time monitoring and decision support. Additionally, the size of the dataset can be further increased in terms of number of crops and environmental diversity, thereby increasing the robustness and accuracy of the models. These innovations will inform the AGRO-AI approach and lead to radical improvements in nutrient management and disease detection through the application of machine learning as a pathway to more sustainable and efficient agronomic systems.
The findings demonstrate the potential value of AGRO-AI as an integrated tool for nutrient management and the identification of paddy disease, aiding in the advancement of sustainable and precision agriculture by embracing technology to enhance yield and global food security.

6 FUTURE SCOPE

AGRO-AI: A smart farming technology experts from India and USA Listen to audio version of this article 0:00 / 1:05 1X Throughout the year, online surveys are conducted for farmers to capture their needs. More can be done to improve the functions. This can be improved by expanding the images the dataset contains to include images of various crop varieties and variations in climatic conditions. To improve prediction accuracy, more vegetation indices could be used, and multispectral or hyperspectral images could also be utilized.

Moreover, coupling AGRO-AI with Internet of Things (IoT) devices for monitoring and enable real-time decision making would provide timely insights to farmers. To make this practically usable, creating some mobile/web-based apps that the farmers can easily reach predictions and recommendations would be an asset. Optimizing the system's performance using transfer learning and fine-tuning on larger datasets might involve experiments with parameter tuning and advanced architectures.

Also, to evaluate how precision nutrient management and early disease detection through AGRO-AI systems can improve the economic and environmental sustainability of farming and to reflect on future research directions. AGRO-AI can also be further developed and applied to a wider range of crops and areas of agriculture, making it an adaptable and revolutionary solution in contemporary agriculture.

7 CONCLUSIONS

So, AGRO-AI system could accurately recommend nutrients and detect disease in paddy crops. While NPK prediction was done using deep learning models such as ResNet-34 and BiGRU, CNN and GAN were used as deep-learning models for disease classification. Using real-time data collected over the course of 20 weeks has also increased the model's predictive capability by including vegetation indices.

The findings show how AGRO-AI could help enable growers through actionable recommendations that result in more precise fertilizer application and timely approaches to disease management. Additionally, the system can be used whenever needed in smart-abseture-agricultural systems for continuous monitoring and decision-making. AGRO-AI contributes significantly to sustainable agriculture by reducing yield losses and resource consumption.

In short, AGRO-AI is a real solution for the modern agricultural landscape at the crossroads of efficient production and sustainability. As thousands of years of cultivated datasets are built upon as per advancement of this technology, it can change the entire face of agricultural management and food sustainability.

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