AI Applications in Precision Agriculture: Improving Crop Management, Yield Estimation, and Environmental Sustainability

MSc Research Project
MSc. Data Analytics

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MSc Project Submission Sheet

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AI Applications in Precision Agriculture: Improving Crop Management, Yield Estimation, and Environmental Sustainability

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Abstract

The study is focused on the use of AI in precision agriculture with the aim of improving crop management, yield prediction, and sustainability. This research leverages CNNs for disease and pest classification, and ensemble models such as Gradient Boosting for yield forecasting. It addresses critical agricultural challenges. The research adopted a dataset that included over 20,000 labelled crop images to train a CNN, which achieved a validation accuracy of 53.93% in the classification of 22 categories. Results for yield prediction using the Gradient Boosting algorithm exhibited the best MAE of 0.87, with rainfall being the best single predictor.

These challenges, at least including dataset imbalance and the limited number of extracted features, were addressed with performant data augmentation, regularization techniques in model architecture, and advanced feature engineering. The results have shown that AI-driven solutions clearly enhance decision-making, ensure wise resource utilization, and give rise to sustainable farming. In establishing the ground to accessibilize scalable AI in real-world agricultural applications, it would be useful to investigate some areas that relate to enriching datasets that integrate real-time data.

Keywords: Artificial Intelligence (AI), Precision Agriculture, Yield Prediction, Sustainability

1 Introduction

Artificial Intelligence technologies are developing at a great pace, transforming most industries, and measures relating to agriculture. Especially in precision agriculture, AI tools have brought innovative solutions to improve crop management, yield prediction, and the overall sustainability of farms. As the population of the world is growing day by day, agricultural systems face greater pressure to produce more value out of fewer resources. The challenge definitely calls for the application of advanced technologies that can help optimize farming practices, both for food security and environmental concerns (Linaza, et al., 2021). Precision agriculture, with its basis on data-driven approaches and AI-based technologies, can probably solve many issues at large with traditional farming practices.

AI's role in agriculture is way more profound than just automating simple tasks. Its applications range from supervised learning models that can predict crop yields to computer vision algorithms that monitor crop health and resource usage. This research will thus dwell on the implementation of AI-driven solution applications to enhance efficiency in agricultural practices with sustainability (Sishodia, et al., 2020). Although many works have presented the possibilities of AI in agriculture at a theoretical level, not many gaps remain regarding its real-world implementation, particularly with regard to accessible solution integration for small and medium-sized farms.

1.1 Research Problem

Major issues this research is trying to find the solution for are how AI methodologies will be used effectively for precision agriculture in crop management to boost yield forecasting and resource efficiency. Contemporary agricultural systems encounter problems in various forms such as climate variability, soil degradation, and pest infestation. Traditional agricultural practices often come short in offering a comprehensive response to these issues, especially where the data sets involved are complex, such as climatic patterns, soil conditions, and crop health indicators. AI techniques provide the opportunity to analyse large volumes of data-aggregating insights for farmers, which enrich their decision-making processes for better farming practices. Still, there is a big gap between what AI potentially can do for agriculture and what is being used practically on farms.

1.2 Research Question and Objectives

The primary **research question** guiding this study is: *How can AI techniques be utilized effectively in precision agriculture to enhance crop management, yield prediction, and sustainability?*

In the background of this, the objectives of this research are as follows:

- Assess the role of AI in bringing an improvement in crop management regarding the monitoring of crop health.
- Utilize machine learning via supervised learning and other AI techniques in model development for yield forecasting.
- Analyse how AI can contribute to resource efficiency and a reduced environmental footprint for agricultural activities. Suggest AI-based solutions that would be feasible to implement by farmers with less technological expertise or resource access.

1.3 Importance of Research

This work is timely and critical in view of the global urgency to increase food production while mitigating at the same time the environmental impacts of farming. The projections by the Food and Agriculture Organization of the United Nations indicate that there is a need for an increased supply of food by about 35%-56% in 2050 to take care of the feeding purposes, with a growing population (Van Dijk, et al., 2021). At the same time, agricultural systems should be able to meet the changing climate condition and resource use to preserve the environment. This article, therefore, uses Artificial Intelligence in precision agriculture to provide solutions that can help farmers increase yields at the same time as ensuring that farming is more sustainable.

This will also be important in addressing the literature gaps that exist on the actual use of AI technologies at the farm level, particularly in areas where the resources are limited. While there is much potential for AI in current literature, little is said in terms of the development of affordable, accessible, and user-friendly AI systems that farmers, especially those without advanced technological means, can afford and use.

1.4 Roadmap for the Project

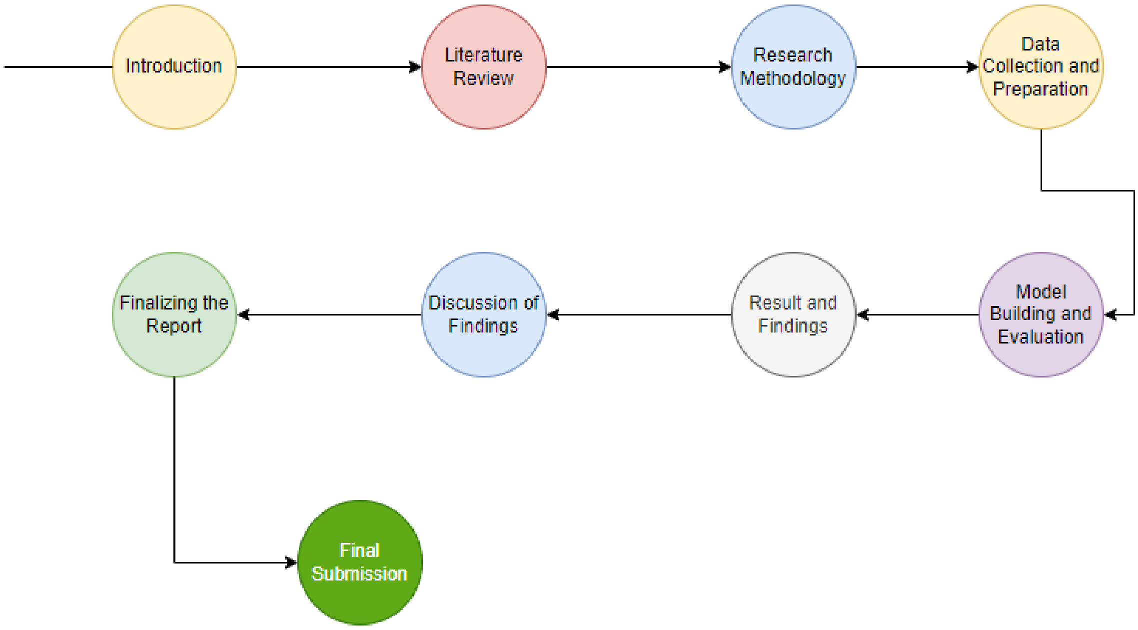

Figure 1: Proposed Roadmap for the Project

The roadmap illustrates the key stages of a research process, starting from Introduction to Literature Review, Research Methodology, Data Collection and Preparation, Model Building, and Evaluation, followed by Results and Findings. The process then proceeds to a Discussion and analysis of Findings, Finalizing the Report, and lastly Final Submission.

2 Related Work

Artificial Intelligence in precision agriculture has transformed the way people manage crops and estimate yields with the consideration of environmental sustainability. Various research studies pointed out AI-driven technologies, such as ML (Machine Learning), DL (Deep Learning), and IoT (Internet of Things), helping farmers with better farming operations. This literature review looks at several papers related to AI in precision agriculture to provide an overview of the current trends, benefits, and challenges.

2.1 Adaptive AI in Precision Agriculture

Akintuyi (2024) comprehensively reviews the role of adaptive AI in precision agriculture defined by optimizing farming operations based on real-time analysis. The paper focuses on how farm operations became more efficient due to the use of self-improving algorithms and IoT devices supporting main agricultural processes: crop health monitoring, resource management, and environmental sustainability. By applying AI, farmers are in a much better position when deciding on irrigation, pest management, and nutrient management to utilize scarce resources with less environmental impact. However, the study also points out that there are challenges posed due to the use of these technologies on much larger scales, especially among small-scale farmers due to the high costs and technological expertise required. This leads to the implication that, to implement AI in farming, there is an apparent need to come up with more accessible and less expensive solutions.

2.2 Data-driven AI Applications for Sustainable Precision Agriculture

Linaza et al. (2021) highlight those data-driven AI technologies that have played a major role in the development of sustainable precision agriculture across Europe. Their review encompasses numerous European projects related to the integration of machine learning, deep learning, and IoT, which have contributed to efficiency enhancement with minimized detrimental environmental impacts for improved food security. The analyzed information emanates from different data sources, such as remote sensing, drones, and soil sensors, and is used by these AI systems to arrive at optimized decisions in agricultural operations. Other success stories, such as AI-based irrigation platforms that reduce water use, are also proposed, as are AI models that enhance the prediction accuracy of yields. However, it is indicated that, despite these many benefits, the complexity of AI models and the technological capabilities to implement them is indeed a major obstacle for small-scale farmers. It is, therefore, a pointer to the need for subsequent efforts in reducing the AI system's complexity so that it would easily be accessible to farmers with minimal resources.

2.3 Application of AI in IoT Security for Crop Yield Prediction

Hassan et al. (2022) discusses various studies on AI-IoT integration for crop yield prediction. IoT devices, such as drones and sensors, can provide real-time data from the fields that will help in analyzing, through AI models, the health of crops, soil conditions, and environmental factors. These could enhance yield forecasting by highlighting the early stages of pest and disease infections. This paper focuses more on how predictive analytics can help optimize resource use like water and fertilizers that directly contribute toward environmental sustainability. All the same, the authors note that most small-scale farmers have found them inaccessible due to their costs and complexity. This calls for more reasonable AI-based solutions that can be more comfortably adopted by farmers with meager technological and economic capacity.

2.4 Big Data and AI Revolution in Precision Agriculture

Bhat and Huang (2021) investigate the transformative potentials of big data and AI in precision agriculture, giving more rope to crop management, disease detection, and yield forecasting. The study reveals that AI approaches, like ANN and SVR, analyze large datasets of IoT devices and remote sensing for accurate prediction with the goal of optimization in farming operations. Whereas these technologies have greatly improved the processes of health monitoring and efficiency of crops and resources, this paper identifies various challenges regarding data quality, model scalability, and effectiveness of AI tools. These barriers, particularly related to technology and finance for small-scale farmers, must be addressed if wider-scale adoption is desired.

2.5 Transformative Technologies in Digital Agriculture

Fuentes-Peñailillo et al. (2024) renewed the integration of AI, IoT, and remote sensing technologies on smart crop management that enhances productivity by receiving real data from key factors (soil moisture, pests, and environmental conditions). Data obtained is analyzed by AI models to optimize irrigation, fertilization, and pest control, subsequently reducing waste and lowering environmental impact. While the study has demonstrated exactly how these technologies can help farmers overcome some of the challenges posed by variability in climate conditions, it has also raised a very important point: there is a need for more affordable and user-friendly AI systems that small-scale farmers would be able to use. The paper called for developing simplified interfaces and low-cost sensor technologies to enable the wider application of such advanced tools.

2.6 Applications of Remote Sensing in Precision Agriculture

Sishodia et al. (2020) address this with a critical review of the role remote sensing has taken in precision agriculture regarding crop monitoring, irrigation management, nutrient application, and yield prediction. The paper deliberates how various remote sensing platforms including satellite and UAVs create information that adds value to better crop management. The integration of AI and machine learning now might well allow these sources to show high-precision real-time displays of crop health. The study also underlines the potentiality of remote sensing for improving yield forecasting and efficiency of resources. Again, much like other studies mentioned above, it mentions that for small-scale farmers, the costs and technical nature of such technologies make their adoption difficult. It calls for more efficacy research into making AI and remote-sensing tools affordable for resource-poor farmers.

2.7 Precision Farming in Modern Agriculture

Raj et al. (2022) discusses the use of AI in IoT in modern precision agriculture by considering how such systems are enabled with smart farming. AI-driven models finally get an increase in monitoring crop health, pest detection, irrigation, and yield prediction using real-time intelligence from IoT sensors. This paper has highlighted some of the environmental pros of AI: less water and fertilizers because of precise application, and early detection of diseases in crops. Conspicuously, the authors attribute the limiting factors to the high cost and complexity of AI systems, bearing in mind that it may be difficult for small-scale farmers who lack resources or expertise to apply them. In the paper, much airs on the need for further research in developing cost-effective AI solutions whose application by farmers who have limited knowledge and financial capacity can easily be accomplished.

2.8 Use of Drone Technology in Agriculture

Hafeez et al., (2022) have summarized the use of drone technology in agriculture, mainly for crop monitoring and spraying pesticides. Advanced development in the structure of drones, sensor technology, and AI integration can bring additional benefits in real-time data collection and optimization of resources. AI-based drones provide greater accuracy and efficiency in monitoring the health of crops and have allowed for more sustainable farming. This paper has identified respective challenges in terms of sensor miniaturization, battery life, and ease of AI use by low-skilled farmers. While it covers a great number of technological aspects, there is still no discussion on economic viability and farmer training in developing regions.

2.9 Drones for Pesticide Spraying

According to Borikar et al. (2022), there has been a discussion on various applications of drones in pesticide spraying, which is followed by reduced health risks for farmers, efficiency, and the least wastage of pesticides. Moreover, the use of GPS and AI techniques can ensure proper application in real-time with the correct quantity of pesticides, which helps maintain good health for better crops by targeting the affected areas of crops where pests attack. It further observes that there is a need for improvement in flight time and management of payload for wider applications. While the review effectively covers technological advancement, it has not discussed much about the affordability of the systems. AI-driven drone farming furthers sustainable farming by lessening any environmental impact.

2.10 AI-Powered Weed Detection and Removal

In the context of analysing how AI can contribute to resource efficiency and reduced environmental footprint, Visentin et al., (2023) propose a robotic AI-powered system for precision agriculture. This approach employs computer vision coupled with deep neural networks to realize very accurate weed detection and removal using a minimal amount of chemical herbicides. By automating weeding processes, this platform optimizes labor while reducing overall environmental harm and pesticide use. Designated systems can be feasible for farmers with low technological expertise through remote-controlled, semi-autonomous operations; thus, making the technology accessible in smaller-scale applications.

2.11 AI for Weed Detection and Yield Forecasting

Upadhyay et al., (2024) resumed the integration of deep learning into AI-driven sensor systems for weed detection and management as an integral component of using machine learning through supervised learning and other techniques in model development in yield forecasting. Employing the use of supervised learning algorithms, a robotic system offers promisingly accurate discrimination against weeds versus crops, where fine-tuning methodologies ensure resources are optimally allocated and manual intervention minimized. Besides smoothing out the operational workflow of weed control, such developments also contribute to predictive modeling given crop health, improving yield estimation. Such AI systems could go as far as to yield forecasting with precision environmental and resource controls.

2.12 AI in Climate Adaptation and Yield Prediction

Zidan and Febriyanti (2024) explored AI's potential to improve agricultural yields by devising climate adaptation strategies through machine learning using supervised learning and other methods of model development. The system uses machine learning models integrated with climate and agricultural data to predict how weather conditions will affect the yield in an area and provides the best planting schedule and irrigation practices. These AI-based models are trained on temperature, rainfall, and soil moisture datasets that enable them to make yield forecasting with a high degree of accuracy, thus helping resource-efficient and sustainable agricultural practices.

The Literature Matrix follows, supporting key substantive research studies on the following topics: adaptive AI in precision agriculture, data-driven AI applications for sustainability, integrating AI-IoT for crop yield prediction, big data and AI farming operations, and AI powered weed detection and removal.

Author Name	**Proposed Solution**	**Limitations**	**Comparison with Other Research**	**Gaps Identified**
Akintuyi (2024)	Adaptive AI using IoT for real-time optimization in irrigation, pest management, and nutrient application.	High costs and need for technological expertise hinder small-scale farmer adoption.	Focuses more on adaptive AI compared to broader data integration in Linaza et al. (2021).	Need for affordable AI systems that are accessible to farmers with limited resources.
Linaza et al. (2021)	Data-driven AI with ML, DL, and IoT for improving food security and environmental sustainability in agriculture.	Complex AI models are difficult for small-scale farmers to implement.	Builds on broader European applications compared to localized focus in Hassan et al. (2022).	Simplification of AI systems and better training for small-scale farmers.
Hassan et al. (2022)	AI-IoT integration for crop yield prediction with real-time analysis of field data for optimized resource use.	High costs and complexity limit access for small-scale farmers.	Narrower focus on IoT security and predictive analytics compared to Bhat and Huang (2021).	Affordable AI-IoT systems with a focus on farmer-centric solutions.
Bhat and Huang (2021)	AI with big data for accurate disease detection, yield forecasting, and resource optimization in farming operations.	Issues with data quality, scalability, and financial feasibility.	Emphasis on big data contrasts with the narrower focus on IoT in Fuentes-Peñaillillo et al. (2024).	Improving data quality and scaling AI tools for broader use.
Fuentes-Peñaillillo et al. (2024)	AI, IoT, and remote sensing for smart crop management, optimizing irrigation, fertilization, and pest control.	Lack of user-friendly interfaces and high costs limit small-scale adoption.	Greater emphasis on integration of technologies compared to single-focus papers like Visentin et al. (2023).	Development of low-cost sensors and simplified user interfaces for wider applicability.
Visentin et al. (2023)	AI-powered robotic systems for precise weed detection and herbicide reduction.	Technological and financial constraints for small-scale farmers.	Specific focus on weed management compared to broader crop management in Akintuyi (2024).	Feasibility research for cost-effective robotic weed management solutions for

				smaller-scale use.

Table 1: Literature Matrix

Some key reviews in this chapter reveal that the application of AI technologies is inevitable for precision agriculture. Akintuyi (2024), and Linaza et al. (2021) discuss ways of using adaptive AI and data-driven approaches for optimization of agricultural processes for sustainability and efficiency. Similarly, Hassan et al. (2022) and Bhat and Huang (2021) explore IoT and big data for efficient resource management and maximization in crop yield prediction. Added to this, Visentin et al. (2023) have highlighted that immediate benefits can be expected from AI-powered solutions contributing towards weed detection and removal, in accord with environmentally more sustainable practices.
The subsequent chapter will introduce the research methodology-must specify the Irish method, instrument, and technique adopted for the investigation of AI applications in precision agriculture. It also explains the data collection and analysis techniques used in the study.

3 Research Methodology

The methods used in this study detail the stages and techniques to be followed in developing, training, and validating AI models for improved crop management, diagnosing health, and predicting yield in the case of precision agriculture. It outlines the approach of data acquisition, preprocessing, model architecture, the process of training, and the metrics used for performance evaluation that provides a repeatable framework for integrating AI into precision agriculture.

3.1 Data Collection and Preprocessing

Image Dataset Collection: The key dataset of disease and pest classification was obtained from the publicly available agricultural dataset obtained on Kaggle, where the image labels of leaves were associated with different crop diseases and pests in addition to healthy samples. The conditions ranged across cashew and cassava, maize, and tomato crops. The said dataset had over 20,000 images distributed across 22 classes that represent common agricultural diseases and pests.

Data Augmentation: The dataset was augmented to increase diversity, preventing overfitting. Some of the data augmentation performed included:

- Rotation: It consists of random rotation of images up to 40 degrees to simulate the myriad angles at which leaves would most likely be encountered in real-world scenarios.
- Width and Height Shifts: Images are slightly shifted horizontally and vertically to take into consideration different positionings of plants as viewed.

- Shearing: Introduce a shear transformation that will account for some of the small distortions, assuming these are natural variations around the general leaf shape.
- Zooming and Flipping: Other augmentations included are zooming and flipping; hence, applying Zoom and Horizontal Flipping to further increase variability for robustness in the model.

The images were all rescaled to have pixel values between 0 and 1, and finally resized to 150 × 150 pixels to standardize input for the deep learning model.

Numerical Dataset for Yield Prediction: Besides the image dataset, there was another dataset collected based on yield prediction. These factors included crop yield in a particular area, average rainfall in that area, pesticide usage, and average temperature.

This structured dataset was fundamental for the investigation of the relations between environmental factors and crop yield, which could be done using regression-based yield predictions. The key steps included:

- Data Cleaning: Address the missing value issue, either by removing the rows containing missing values or by imputation, whichever is appropriate considering the extent of the missing data.
- Feature Engineering: In feature selection, domain knowledge will be used to select relevant features for yield prediction, taking into consideration the environmental conditions that generally affect crop productivity.
- Scaling: Rainfall, pesticide usage, and temperature are numerical features that should be standardized to have a mean of 0 and a variance of 1 so that the machine learning algorithms will work well.

Handling Imbalanced Classes: The dataset used in disease classification had classes that were imbalanced, overrepresented-for instance, images with healthy crops-but a small number in some classes for examples, some types of pests. Regarding that, the determination of class weights was allowed by compute_class_weight in scikit-learn. It essentially ensures the model would give more emphasis on an underrepresented class, allowing it to strike a balance in its learning process.

3.2 Model Architecture and Design

Disease and Pest Classification using Convolutional Neural Network: The CNN architecture is preferred due to its efficiency in handling image data processing and extracting complex spatial features. The CNN model comprises:

- **Convolutional Layers:** There were three convolutional layers used with increasing filter sizes from 32 to 128. Each of these was followed by a max-pooling layer. These convolutional layers picked up all the significant features in the images such as texture, color, and edge patterns that were associated with disease and pest markers.

- **Flatten Layer:** The output coming from the convolutional layers has been flattened into a 1D vector to prepare it as an input for the dense layer.
- **Fully Connected Dense Layer:** It consists of a dense layer of 512 units using the ReLU activation function that aggregated the spatial features learned from previously described layers.
- **Dropout Layer:** A dropout rate of 50% was used to avoid overfitting by deactivating half of the neurons randomly for training.
- **Output Layer:** This had 22 units, one for each class, with softmax activation to give class probabilities.

Regression Models for Yield Prediction: The work implemented classical machine learning regression models for yield prediction. The models used included

- Random Forest Regressor: Some variables had a nonlinear relationship and were not very susceptible to overfitting. The model is tuned in terms of the number of estimators, max depth, and minimum sample split.
- Gradient Boosting Regressor: In this model, the concept of the sequential learning was applied-which is contained in gradient boosting-and at every iteration, the model made amendments to the errors of previous trees. The hyperparameters tuned in the model included learning rate, max depth, and the number of estimators, which have been optimized with grid search for the best accuracy.

3.3 Model Training and Evaluation

Training Process for CNN: The CNN model was compiled using the Adam optimizer and categorical cross-entropy loss. During training, class weights were integrated to account for the imbalanced data distribution, and a custom generator was created to incorporate sample weights dynamically. The model was trained for up to 20 epochs, with an early stopping criterion based on validation loss to avoid overfitting. Each epoch involved training on augmented images to maximize the model's generalization ability.

Training Process for Regression Models: For yield prediction, the data was split into training (80%) and testing (20%) sets. Both the Random Forest and Gradient Boosting models were trained on the scaled features of rainfall, pesticide usage, and temperature. Grid search cross-validation was performed for hyperparameter tuning, with 3-fold cross-validation to ensure that the models were not overfitting on the training set.

Evaluation Metrics:

- CNN Model Evaluation: The primary evaluation metric for the CNN model was accuracy, as it indicates the model’s ability to classify leaf images into the correct disease or pest category. Additional metrics, such as precision, recall, and F1 score, were used to measure performance across individual classes, especially for rare classes.

- Regression Model Evaluation: For yield prediction models, metrics included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) to assess the accuracy and reliability of predictions. Lower values of MAE and RMSE indicated better model performance, while R^2 measured the proportion of variance in yield explained by the model.

3.4 Hyperparameter Tuning

To fine-tune the models, hyperparameter tuning was done for both the CNN and regression:

- CNN Model Tuning: Early stopping and dropout layers were added to mitigate overfitting, and batch sizes and learning rates were adjusted iteratively to improve convergence.
- Regression Model Tuning: Grid search was used to find optimal hyperparameters for both Random Forest and Gradient Boosting models. Parameters, such as the number of trees, maximum depth, and minimum samples per leaf, were optimized to minimize errors and maximize prediction accuracy.

3.5 Feature Importance Analysis

Feature importance analysis was conducted on the best-performing regression model to understand the various environmental factors' impingement on crop yield prediction. Gradient Boosting's feature importance method identified the variables with the highest predictive power that helped in identifying key drivers of yield variability, including average rainfall and pesticide use.

3.6 Conclusion

The methodology combines deep learning techniques for image-based disease and pest detection with machine learning for yield prediction, offering a comprehensive approach to addressing multiple facets of precision agriculture. This structured methodology demonstrates the capability of AI to support decision-making in agriculture, from diagnosing plant health issues to predicting yield, contributing to enhanced crop management and sustainability.

4 Design Specification

The Design Specification articulates the foundational architecture, methodologies, and frameworks necessary to drive into place AI-enabled solutions for precision agriculture. The following chapter deals specifically with conceptual designs, the description of functional requirements, and necessary system structures for developing crop management, yield forecasting, and environmental sustainability.

4.1 System Design Overview

It provides two models for addressing two major objectives of precision agriculture: the classification of diseases and pests in crops, and the prediction of crop yield. This architecture is modular; hence, it can be extended and adapted for various applications in agriculture. The idea remains to apply AI methods for processing image-based and numerical data in order to render the data usable and accessible for small-scale farmers with low technological expertise.

4.2 Major Architectural Components

The two major subsystems it has are: one for the classification of diseases and pests; the other is for the prediction of yield. A CNN for classifying diseases, optimized for processing images, is applied. The CNN consists of several convolutional layers to extract features, some pooling layers reducing the dimensionality, and, lastly, fully connected layers that perform the actual classification. Then it should generate, through a softmax output layer, predictions over 22 categories, diseases, pests, and healthy crops. Techniques such as class weighting and data augmentation have also been implemented to deal with issues involving dataset imbalance and to better represent underrepresented classes in such a dataset. The yield prediction sub-system is based on ensemble learning models, such as RF and GB regressors. Such a model is ideal for detecting nonlinear relationships among input variables like rainfall, temperature, and pesticide usage. Random Forest combines the predictions over multiple decision trees to come up with an overall prediction of the target variable, while in Gradient Boosting, sequence learning minimizes the residual errors. Feature scaling and hyperparameter tuning were therefore part of the training of the models for robustness and accuracy in the yield prediction.

4.3 Functional Requirements

The functional requirements for the system are separated into data and model needs. Input Data: Over 20,000 images of crops of different varieties that have already been labeled, rescaled, resized, and augmented. This makes the preprocessed data more diversified and well-balanced within classes-a common problem seen in most agricultural datasets. For instance, regarding the problem of yield prediction, the structured data includes a record count of more than 28,000, which comes with variables such as rainfall, temperature, pesticide usage, among others. Proper cleaning, normalization, and feature engineering are used as some of the techniques to avail high-quality inputs to these regression models.

The performance of the models is evaluated using specific metrics: for CNNs, accuracy, precision, recall, and F1 scores to measure classification effectiveness; for regression models, MAE, RMSE, and R-squared to assess predictive accuracy. Both systems incorporate grid search-based hyperparameter optimization to improve performance.

4.4 System Framework

The system design includes logical and physical frameworks. Logically, the system is divided into two pipelines. The first pipeline ingests images captured from drones or smartphones to classify diseases and pests using the CNN model. The second pipeline processes numerical data from environmental and agricultural variables in order to predict crop yield using ensemble learning models. These then create actionable insights on the output side, such as diagnosis of diseases and yield forecasting. The system physically demands hardware with GPU acceleration for training CNNs and any other standard CPU systems for running the regression models. IoT sensors and weather stations integrated in provide real-time data for better accuracy and responsiveness of the models. Software tools used include TensorFlow/Keras for deep learning, Scikit-learn for regression models, and visualization libraries like Matplotlib for result representation.

4.5 Algorithm Design

Disease classification using CNNs starts by carrying out some preprocessing on the inputs by normalizing and resizing all input images to some standard format. Further, convolutional layers make a feature extraction, and then dimensionality reduction takes place with pooling layers. The extracted features are next classified with dense layers and softmax output layer. The Adam optimizer trains it with categorical cross-entropy loss, including early stopping for preventing overfitting.

For these, the regression models designedly predict the yield sequential input data cleaning and input data scaling. The goal was to iteratively random Forest and Gradient Boosting that minimizes the average square error in prediction to present estimated continuous yield with estimated measures for uncertainty as output continuously: giving insights into each other from decision-making.

4.6 Design Constraints

Various such designs take into consideration multiple constraints at once. Some of them tackled data imbalance issues in the case of disease datasets by implementing augmentation and weighting techniques, while others targeted cost-effectiveness by finding affordable, scalable solutions targeted at the scale of small-scale farmers. Scalability is achieved using modular designs which can extend to add newer streams and features. Simplified interfaces make the interface more user-friendly for non-technical end-users.

4.7 Ethical and Environmental Considerations

The design incorporates ethical and environmental considerations, ensuring responsible use of AI in agriculture. Data privacy is guaranteed through secure storage and transmission protocols for farm-related information. It aims at enhancing sustainability by optimizing resource utilization, reducing waste, and minimizing the environmental footprint of farming practices. Whatever the case, an effort should be made to develop affordable solutions with a view to democratizing access to AI technologies for smallholder farmers.

4.8 Conclusion

The design specification -gives a holistic approach to AI integrations within precision agriculture, including the use of CNNs for disease classification and ensemble methods in yield prediction, both critical components of current agricultural management and sustainability. Besides, the system will upscale easily, be more accessible, and adaptable; hence, the bedrock on which future implementation will take place starts here. Future improvements may be done by enriching data, enhancing model generalization, and incorporating IoT for real-time decision-making.

5 Implementation

The implementation of the proposed solution for AI-driven precision agriculture will be made by applying CNNs for the classification of diseases and pests, and ensemble learning models for yield prediction. This chapter implements the last stages of the implementation description that outlined the outputs, tools, and methodologies used in realizing the design specification. Operationalization of models, the datasets used, and the tools that have helped in their development are discussed.

5.1 Dataset Preparation and Transformation

The implementation focused first on preparing and transforming datasets intended for both the image classification-based disease classes and then the numerical yield.

The dataset on disease classification includes over 20,000 images from 22 categories, including various diseases and pests of crops that have been labeled. These images were pre-processed to the size of 150 × 150 pixels with the normalization of pixel values in the range between 0 and 1. Further augmentation included random rotations, flips, zooming, and shearing. Such transformations have helped to increase diversity and robustness in this dataset, thus addressing the problems of class imbalance and model generalization.

The dataset contained 28,242 records of rainfall, pesticide use, temperature, and yield history, among other features, for yield prediction. This involved cleaning the data, handling missing values, standardizing numeric features to zero mean and unit variance, and feature engineering to derive more predictive variables from existing ones. A log transformation was applied for normalizing highly skewed yield data, which would make it more suitable for the regression models.

5.2 Model Development

5.2.1 CNN for Diseases and Pests Classification

A Convolutional Neural Network was implemented for the multi-class classification of diseases and pests. The architecture consisted of three convolutional layers with ReLU activation, followed by max-pooling layers that reduce the spatial dimensions. The dense layers aggregated features, and the softmax output layer classified the input images into one of 22 categories.

In this context, training will involve compiling the model using Adam as an optimizer and the loss function of categorical cross-entropy. Further enhancements on this included class weighting, making sure that contributions of categories are balanced even if those are underrepresented, dynamic data augmentation during training for model robustness, and Early Stopping to prevent overfitting of the model with no further improvement in the validation loss within five consecutive epochs.

The outputs of the CNN model included accuracy metrics of training versus validation, supported by confusion matrices to analyze the performance of the classification. Furthermore, additional metrics such as precision, recall, and F1 score showed the performance of the model on individual classes, especially classes with rare categories.

5.2.2 Regression Models for Yield Prediction

The following ensemble learning models, which include Random Forest and Gradient Boosting, were developed for yield prediction. RF was an ensemble that combined the outcomes of several decision trees to obtain a more accurate output and avoid overfitting simultaneously. In GB, predictions are optimized sequentially by correcting residual errors at each iteration. Hyperparameter tuning was performed with grid search, considering the number of estimators, maximum depth, and learning rate as hyperparameters. Data splitting was done in a ratio of 80% for training and 20% for testing, and also cross-validation was used for robustness in training. These models also outputted some predictive metrics using MAE, RMSE, and R^2 to estimate accuracy and the reliability of predictions.

5.3 Tools and Technologies

The implementation used a mix of software tools, libraries, and hardware resources, each chosen with respect to the specific needs of the models.

5.3.1 Software and Libraries

- TensorFlow/Keras: Used to implement and train the CNN model because it is really flexible and includes most features to support deep learning tasks.
- Scikit-learn: It has been used to build regression models and tune their hyperparameters. Its extensive set of tools made the implementation and its evaluation very efficient.
- OpenCV: This could be used to do image preprocessing in terms of resizing and data augmentation.
- Pandas and NumPy: This gave the capability for numerical data manipulation in the datasets.
- Matplotlib and Seaborn: Allowed the visual presentation of model outputs, for example, accuracy curves, feature importance plots, and confusion matrices.

5.3.2 Hardware

- GPU-Accelerated Systems: The training of the CNN model needed a GPU-enabled environment for efficient processing of big image datasets.
- Standard CPU Systems: The regression models were implemented on CPU-based systems, which were adequate for structured numerical data processing.

5.4 Outputs and Outcomes

The implementation produced real output that proved the design specification, confirming the models were effective.

5.4.1 Disease and Pest Classify Outputs

Amongst other models, the CNN produced results with a validation accuracy of about 53.93%, modest considering their ability to discriminate among such categories as 22 in all. Indeed, Precision, Recall, and F1 measures gave exhaustive details about model performance-the challenges faced with underrepresented and visually confusing classes are evident. Confusion matrix or curves of accuracy were then generated regarding model performance by real improvement areas.

5.4.2 Yield Prediction Outputs

The Gradient Boosting model outperformed its Random Forest counterpart in predicting Crop Yield, with an optimal MAE of 0.87 and an R-square value of 0.14 after hyperparameter tuning. What this shows is that with such a model, feature relationships can be captured nonlinearly (though the low R-square value promises more predictive variables). Upon feature importance analysis, it had been found that rainfall constitutes the most important predictor while pesticide usage and temperature take the remaining top two positions.

5.4.3 Visual Representations

- Accuracy and Loss Curves: Informed on the performance of the CNN model against training and validation.
- Feature importance plots showed the relative contribution for a variable to yield prediction.
- Confusion Matrices: These showed the results of classification, highlighting misclassifications and where classes overlapped.

5.5 Challenges and Mitigation

Implementation presented a challenge regarding the imbalance of the dataset, overfitting, and limited availability of features. These challenges have been addressed through specific strategies that involve:

- Imbalance in the dataset: The problem will be mitigated through class weighting and data augmentation for the CNN model.
- Overfitting: Controlled by regularizers such as dropout, early stopping.
- Feature Limitations: Besides the features already identified, other very useful ones include soil quality and the type of crop grown; these will help in increasing the accuracy of yield prediction.

5.6 Summary

The design specification was operationalized in the implementation phase of the study, producing functional models for crop disease classification and yield prediction. From this, different outputs have come, including trained models, evaluation metrics, and visualizations; showing the feasibility of AI-driven solutions in precision agriculture, these models provide a very sound scaffolding to improve decision-making in farming practices and could further be refined and scaled in practical application.

6 Evaluation

Evaluation of the study involves critical analyses of the results from these experiments in two key areas: crop disease classification using CNN and crop yield prediction with the inclusion of a machine learning model. Each of the experiments was designed to solve certain agricultural problems, such as the recognition of crop diseases and yield prediction using environmental and agricultural variable platforms. The results are critically discussed along with statistical metrics and in-depth visualizations to put them in perspective and show their relevance for agricultural research and practice.

6.1 Crop Diseases Classification

6.1.1 Dataset Description

Salient features of the dataset on crop disease classification included 22 classes, comprising different kinds of diseases prevalent in cashew, cassava, tomato, and maize, or healthy ones. In all, there were 20,147 training images and 5,023 validation images. Quite highly imbalanced, some classes had as low as 34 samples, while some classes had 3,120 samples, such as "Maize healthy" versus "Tomato healthy." Various data augmentation techniques that were used included random rotations, random flips, and random zooms, which enhanced the robustness of the model.

The analysis of class distribution showed a highly imbalanced dataset. In this case, class weights needed to be calculated in order to punish the network for errors in classes with low representation. This ensured that the CNN model would not disproportionately focus on over-represented classes and improved its generalization capability.

6.1.2 Model Architecture and Training

It is a custom CNN, designed for multi-class classification, which involves:

- Three convolutional layers are used that are followed by ReLU activation functions and are intended to extract spatial features in images.
- Max pooling layers that reduce the spatial dimensions and, after all, reduce computational load.
- Dense layer with 512 neurons, to get high-level abstractions.
- Dropout regularization to prevent overfitting.
- A softmax output layer, which classifies the input into 22 classes.

Then, the model was compiled with the Adam optimizer, categorical cross-entropy as loss, and accuracy as metric. Also, early stopping was used in such a way that if the model was not improving in terms of the validation loss over successive epochs five, it should stop to avoid overfitting.

6.1.3 Performance Analysis

The model was trained on 20 epochs, and class weighting was used to balance the learning process. The accuracy and loss curves for the training and validation gave some insight into the performance of the model:

- Training Accuracy and Loss: The accuracy of training increased gradually and reached a maximum of 62.69% at the 20th epoch, while the training loss went down to 0.99. That proves the model effectively learned features from the training data.
- Accuracy and Loss on Validation: The highest reached validation accuracy was 53.93% with a loss of 1.41. Although the best validation accuracy significantly lowered the accuracy compared to training, the difference in the value of the training versus validation loss stabilized over time, and this signaled a moderately overfitting model during training.

Metrics Summary:

- Accuracy: 53.93%
- Validation Loss: 1.41

```
157/157 ━━━━━━━━━━━━━━━━━━━━ 53s 305ms/step - accuracy: 0.5374 - loss: 1.4129
Validation Accuracy: 53.93%
Validation Loss: 1.4178
```

6.1.4 Key Findings and Challenges

- Skewed classes: Although class weighting was used, the imbalanced dataset affected the model performance-classical case for underrepresented classes.
- Inter-Class Similarity: Diseases with similar symptoms of appearance, such as various forms of leaf spots and rusts, were more difficult to classify.
- Effectiveness of Augmentation: The augmentation of data increased the diversity in training data, enhancing the model's generalization capability accordingly.

6.1.5 Recommendations for Improvement

- Dataset Enrichment: Collect additional samples for underrepresented classes to address imbalance issues.
- Transfer Learning: Draw on the pre-trained CNNs, such as ResNet or VGG, which have shown outstanding performance in image classification.
- Ensemble Techniques: It is the combination of numerous CNNs to enhance classification performance by reducing misclassifications.

6.1.6 Visualisations

- Sample Images: The following perceptions give insights into diversity and challenges associated with crop disease classification.

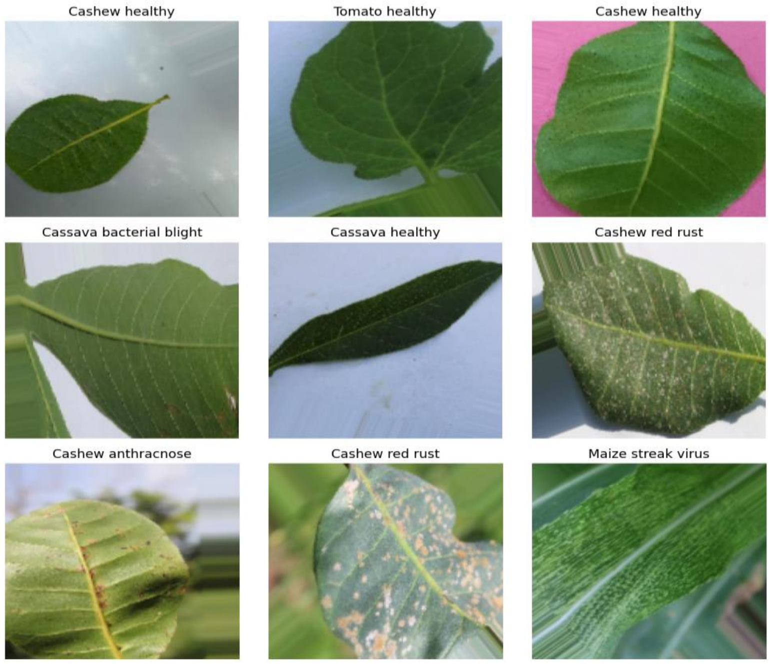

Figure 2: Sample images

- Class Distribution Plot: It showed the skewness of the dataset and that the dataset needed balancing.

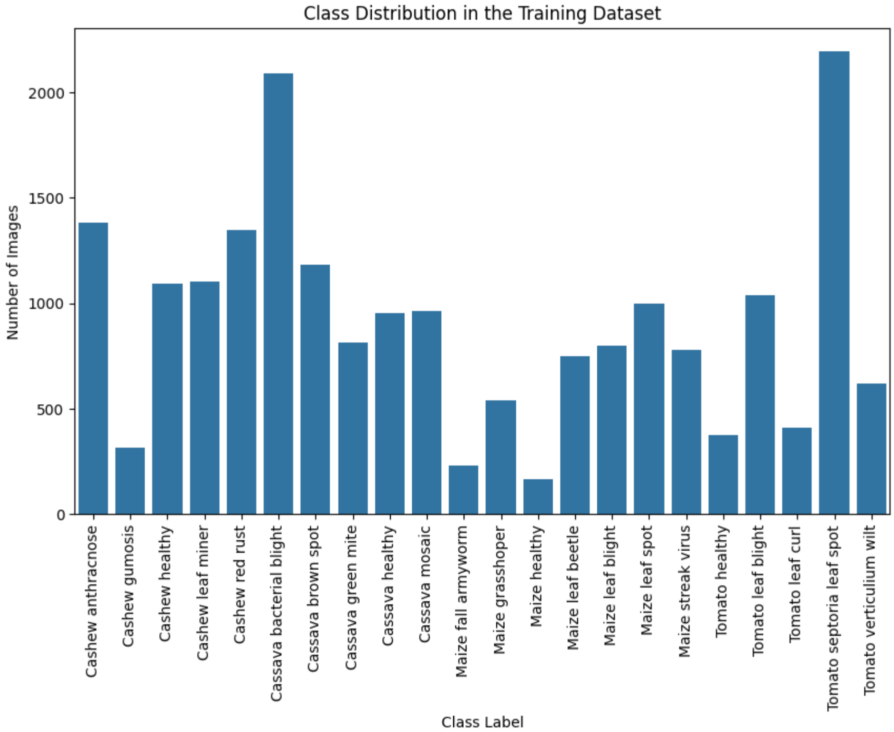

Figure 3: Class Distribution in the Training Dataset

- Accuracy and Loss Curves: These plots have actually demonstrated an increasing training accuracy, while metrics on validation stabilized.

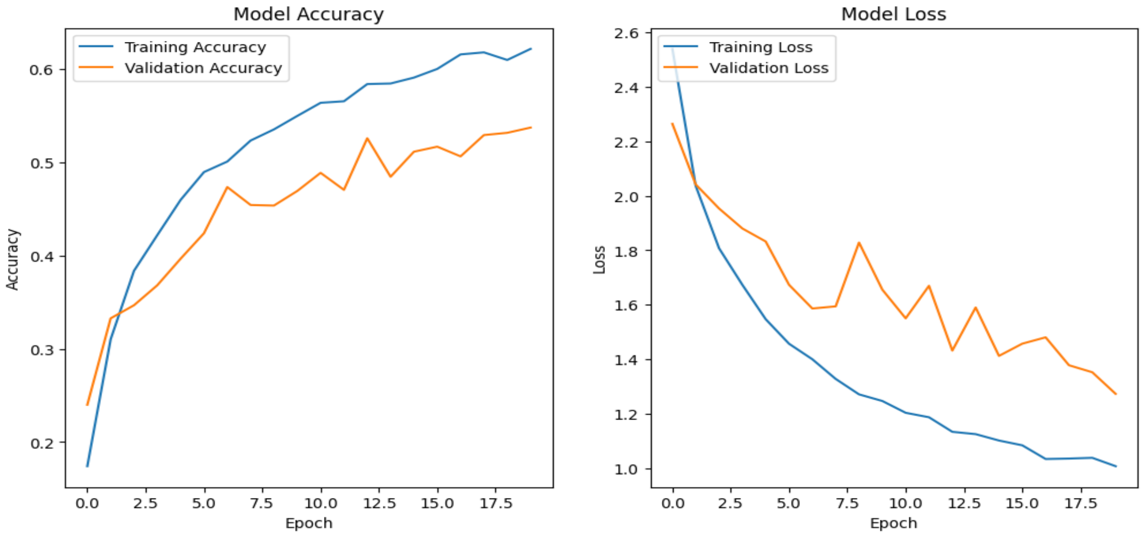

Figure 4: Accuracy & Loss Curves

6.2 Crop Yield Prediction

6.2.1 Dataset Overview

This crop yield dataset contained 28,242 records describing a certain crop in a geographical region over time. Some of the features included the following:

- Average rainfall (in mm per year),
- Pesticide usage (in tonnes),
- Average temperature (in °C),
- Crop yield (measured in hg/ha and log-transformed for normalization).

Further exploratory data analysis showed huge variability in both the target variable and predictor variables:

- Crop Yield Distribution: The data were highly positively skewed hence justifying the use of a log transformation.
- Rainfall, Pesticide, and Temperature: All three have presented variable relationships to yield with rainfall showing the strongest positive relationship among the three variables, having a correlation coefficient of 0.31.

6.2.2 Model Design

Implemented two machine learning models:

- Random Forest Regressor (RF): Robust ensemble model performing predictions by aggregating several decision trees.
- Gradient Boosting Regressor: GBR is an ensemble model sequential, optimizing the residual errors developing from the previous iterations.

Both models were trained and evaluated using an 80-20 train-test split. StandardScaler was used for feature scaling to normalize the predictors.

6.2.3 Model Performance Evaluation

Random Forest Regressor

```
Random Forest - MAE: 1.0073057850306786, RMSE: 1.1865242946960066, R²: -0.1490270617242413
```

The RF model provided moderate results:

- Mean Absolute Error (MAE): 1.01
- Root Mean Squared Error (RMSE): 1.19
- R^2 Score: -0.15 (indicating poor predictive power).

The model's inability to capture complex relationships among features and yield resulted in suboptimal performance, with predictions clustering around the mean.

Gradient Boosting Regressor

```
Gradient Boosting - MAE: 0.8748091673076014, RMSE: 1.0262588632923821, R²: 0.14041104008178207
```

GBR outperformed RF due to its ability to learn sequentially from residuals:

- MAE: 0.87
- RMSE: 1.03
- R^2 Score: 0.14

GBR's performance demonstrated its capability to model non-linear relationships and interactions among features. However, the R^2 score suggests that a substantial portion of the variance in yield remains unexplained, likely due to missing variables such as soil quality, crop type, or irrigation practices.

6.2.4 Hyperparameter Tuning

Both models underwent grid search-based hyperparameter optimization to enhance their predictive performance.

Gradient Boosting

Optimal parameters included:

- Learning Rate: 0.01,
- Max Depth: 5,
- Number of Estimators: 300.

Post-tuning results:

- MAE: 0.87
- RMSE: 1.03
- R^2 Score: 0.14

Random Forest

Optimal parameters included:

- Max Depth: 10,
- Min Samples Split: 10,
- Number of Estimators: 300.

Post-tuning results:

- MAE: 0.89
- RMSE: 1.04
- R^2 Score: 0.11

Gradient Boosting retained its performance edge over Random Forest even after optimization.

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Best Gradient Boosting Parameters: {'learning_rate': 0.01, 'max_depth': 5, 'n_estimators': 300}
Tuned Gradient Boosting - MAE: 0.875175734440836, RMSE: 1.026623791606495, R²: 0.139799607365229
```

Figure 5: Performance of GB Post Tuning

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Best Random Forest Parameters: {'max_depth': 10, 'min_samples_split': 10, 'n_estimators': 300}
Tuned Random Forest - MAE: 0.8928238461635951, RMSE: 1.0457520009069514, R²: 0.10744621587193848
```

Figure 6: Performance of RF Post Tuning

6.2.5 Feature Importance

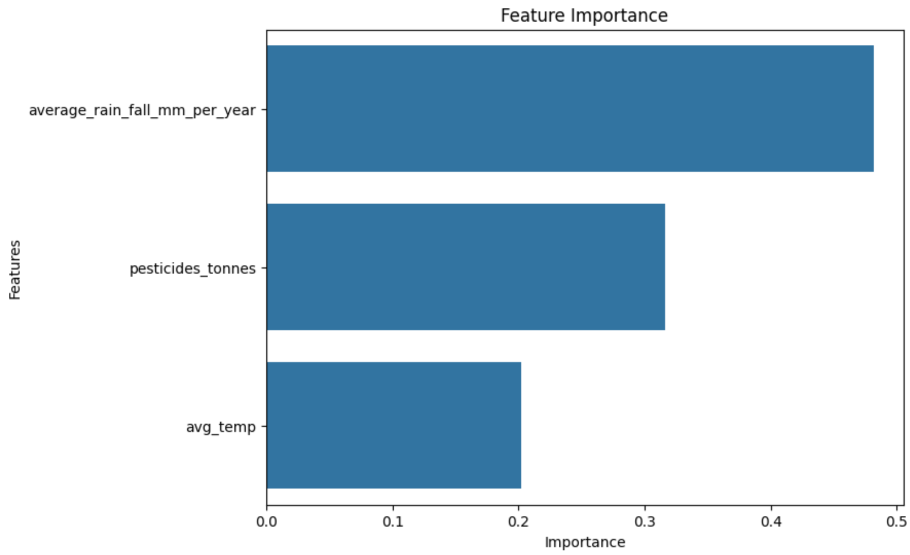

Figure 7: Feature Importance Plot

Feature importance analysis concluded that:

- The most important predictor was rainfall with an importance of approximately 0.5.
- The moderate contributor was pesticide usage at ~0.35.
- Temperature was responsible for the least influence here, ~0.15.

6.2.6 Visualisations

- Scatter Plots: Comparisons of the actual vs. predicted yields of both models indeed showed a clustering around the diagonal, but there was quite some deviation for the extreme values.
- Feature Importance Plot: Targeting rainfall is more dominant among the predictors, and all the more, it reduces ambiguity in agriculture planning.
- Distribution plots: The display of the effect of log transformation in normalizing data for yield.

6.2.7 Key Findings and Challenges

- Heterogeneity: The international nature of this dataset introduced a variation of climatic conditions and agricultural practices, which made any prediction complicated.
- Dataset Imbalance: The major problem lay in the imbalanced dataset, especially for the classification of crop diseases. Despite augmentation techniques and class weighting, there was too little representation of certain classes, hence poor generalization by the model.
- Inter-Class Similarity: The diseases with similar visual features further confused the CNN by reducing its capability of telling well between classes.
- Missing Variables: Some very important variables like soil fertility, type of crop, and irrigation levels were excluded from their consideration while developing these models, meaning the robustness of the models could be compromised regarding explanations of variation.
- Overfitting Risk: The Random Forest, in particular, showed tendencies to overfit-as evidenced by its pretty high training accuracy with a low R^2 score. Similar tendencies are observed in CNN, too with a gap between training and validation accuracy.

6.2.8 Recommendations for Improvement

- Feature Engineering: Many other variables can be created to fine-tune the model, such as soil pH, crop rotation history, and irrigation data.
- Localized Models: The models should be region-specific, capturing localized relationships between predictors and yield.
- Data Augmentation: Utilization of sophisticated techniques, such as GANs, to generate classes that are under-represented in the datasets for disease classification.
- IoT Integration: Real-time streaming of IoT data with dynamic updating of models to improve prediction accuracy.
- Advanced Options: Further, get into deep learning techniques or hybrid methods that eventually integrate the strengths of Random Forest and Gradient Boosting.

6.3 Comparative Analysis

Key Similarities

- Imbalanced Datasets: Among these, imbalanced datasets provided their challenges, such as class weighting for Experiment 1 and feature scaling for Experiment 2.
- Importance of Preprocessing: Data augmentation and log transformations were some of the major preprocessing steps contributing so much to performance.

Key Differences

- Model Type: While image-based classification was selected with CNNs in the case of Experiment 1, Experiment 2 focused on numerical prediction by tree-based ensemble methods.
- Complexity of Data: Classifying diseases was visual and based on features, whereas the prediction of yield was structural numerical data.

Lessons Learned

- Dataset quality, particularly the inclusion of relevant features, is critical to achieving high model performance.
- While Gradient Boosting or CNNs are good on complex tasks, they do require great care in tuning to balance performance and generalizability.

6.4 Implications and Future Directions

Academic Contributions

- Demonstrates the efficiency and effectiveness of CNNs in disease detection in agriculture, thus providing a baseline for future research.
- This emphasizes that Gradient Boosting is effective in the prediction of yield, therefore, it opens a new vista for the integration of machine learning into agricultural economics.

Practical Applications
- It enhances early detection of crop diseases, hence reducing yield loss and improving food security.
- Informs agricultural policymakers and farmers in planning and resource allocation based on predicted yields.

Future Research
- Expand the datasets by adding more features and underrepresented classes.
- Observe hybrid models that combine CNNs with tree-based methods, integrated disease detection, and yield prediction systems.
- Investigate the role of advanced neural architectures, such as transformers, in improving performance.
- Integrate IoT data streams to make constant updates toward developing predictions dynamically.
- Validate models with farmers for practical applicability through pilot studies.

6.5 Discussion

6.5.1 Crop Disease Classification

A CNN custom architecture was used for the classification of crop diseases, reaching an accuracy of 53.93% in validation. While this result has been promising, some limitations arose to show the capability of deep learning in classifying diseases.

Dataset imbalance: The extreme class imbalance within the dataset indeed decreased model performance for the low number of classes, even with considering class weighting. Linaza et al. (2021) also showed the same results where the underrepresented data in an agricultural application constrained AI performance. Future designs would take advantage of more sophisticated augmentation techniques (like synthetic over-sampling or generative adversarial networks) to balance the dataset.

Feature Embedding: According to the model formulation, this may be done directly from raw image data at the great cost of limiting the generalization capability of the CNN. Akintoye, 2024 recommended those incorporating hybrid models to reach the best of both worlds from traditional machine learning and deep learning for structured feature extraction, features extracted for certain diseases by the expert knowledge will do the job.

Overfitting: Introduction of dropout layers helped prevent overfitting, but the difference in the curves of training and validation accuracy depicts a deficiency in strength. Weight decay factor needs to be tried with some other regularize techniques.

Comparison with Related Work: Works on transfer learning using pre-trained models, such as those done by (Fuentes-Peñailillo et al., 2024), reported better results. Transfer learning may hence be used to improve the accuracy with limited training on limited data.

Critical Analysis and Recommendations: The CNN model performed with this level of accuracy, which is very low and below expectation, mostly because of the imbalance in the dataset and lack of diversity. While augmentation techniques increase the robustness of the model, class imbalance limited the generalization of the same. Pre-trained CNNs can be used, GANs for data synthesis, and feature extraction based on domain knowledge to improve the performance in case of these challenges.

6.5.2 Crop Yield Prediction Experiment

Different approaches were considered for crop yield prediction, namely Gradient Boosting, Random Forest. GB outperformed other models with an MAE of 0.87 with a respective R^2 of 0.14 after hyperparameter tuning. However, the result points toward a number of design flaws.

Feature Engineering: The given rainfall, pesticide usage, and temperature data have low predictive power. Other important factors that could be included in the model are soil characteristics and satellite images. (Sishodia et al. 2020) stated that multi-model usage of various data sources may help in raising performances.

Baseline Models: The performance of LR was very poor; it even produced a negative R^2, which is a certain indicator of the model's inability to develop any agricultural data when nonlinear relationships exist. It also aligns with the research paper of (Hassan et al., 2022) concluding that ensemble methods outperform simple regression models in precision agriculture.

Generalization Models: RF and GB, while having acceptable accuracy, were proven to generalize poorly due to overfitting the training data. This can be improved with cross-validation and larger data.

Integration with IoT: According to (Raj et al. 2022), predictive models did not have real-time integrations with IoT. Associating IoT sensor data may enhance real-time yield predictions along with resource optimizations.

Critical Analysis and Recommendations: Results indicated huge gaps regarding the quality of the data sets and feature inclusions that resulted in the consequential limitation of performance for the models. Missing important variables related to soil fertility and the type of crop resulted in low R^2 scores. Further improvement may be done in enriching datasets with relevant features, hybrid models, and IoT-driven real-time data. Regional modeling would capture variability at the farming practice level and allow more actionable predictions at the local level.

7 Conclusion and Future Work

The central research question adopted in this study is: *How can AI techniques be utilized effectively in precision agriculture to enhance crop management, yield prediction, and sustainability?* Integrating deep learning into disease classification with machine learning-based yield forecasting, this research investigates the potential of artificial intelligence for solving different agricultural challenges, such as pest control, yield estimation, and resource optimization.

The aim at hand was threefold: monitoring crop health, developing predictive models for yield, and discussing the role of AI in reducing the environmental footprint of agriculture. A custom CNN approached a 53.93% validation accuracy on classifying crop diseases. This was even in the face of challenges like dataset imbalance and resemblance between classes. This led Gradient Boosting to the best predictions in yield prediction, with an MAE of 0.87 and a less exciting R^2 score of 0.14, which underlines that other important variable, such as soil quality and irrigation, are for good predictions. These results show both the potential of AI and remind us how good-quality data and well-balanced datasets are of first importance.

While this research underlines the capability of AI in precision agriculture, much of its emphasis is based on enhancing decision-making for farmers and stakeholders. On the other hand, some of the important limitations identified by the literature involve model overfitting, non-generalizability, and restricted access to data related to small-scale farming. Overcoming these will help a great deal in maximizing the utility of AI.

The AI solutions, in future works that are scalable, affordable, and user-friendly, should be contextualized against diverse agricultural contexts. Such work can be further improved by incorporating IoT data streams for real-time updates, using state-of-the-art neural network architectures like transformers for improved feature extraction, and hybrid models that are capable of jointly detecting diseases and predicting yields. These datasets are also comparably small and, therefore, should involve region-specific variables such as soil properties, crop types, and water management practices to enable model generalization. Furthermore, partnerships for pilot-scale implementations with local farmers in order to validate these solutions in real-life conditions could result in wider dissemination and even commercialization.

By addressing them, the next study may turn a promising tool into a realistic, impacting solution of AI for modern agriculture, with much improved productivity and sustainability in farming systems around the world.

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