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The Effective Use of Artificial Intelligence in Improving Agricultural Productivity in Nigeria

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ABSTRACT
This research investigates the potential of Artificial Intelligence (AI) to enhance agricultural productivity in Nigeria, addressing critical challenges such as climate variability, limited access to modern farming techniques, and the need for sustainable practices. Employing a mixed-methods approach, the study integrates qualitative and quantitative methodologies, including surveys, interviews with small-scale farmers, and data analysis of agricultural outputs. Key findings reveal that AI applications, such as predictive modeling for crop yields, Pest prevention, disease detection, and resource optimization, significantly improve farming efficiency and sustainability. The research highlights the importance of tailored AI solutions that consider local agro-ecological conditions and farmer capacities. Furthermore, it identifies barriers to AI adoption, including data availability and cultural variability, which may hinder the widespread implementation of these technologies. The implications of this study underscore the necessity for comprehensive training programs and supportive policy frameworks to facilitate the integration of AI in agriculture, ultimately contributing to food security and economic stability in Nigeria. This research not only provides actionable recommendations for stakeholders but also contributes to the broader discourse on sustainable agricultural practices in Nigeria.

Keywords:
Artificial Intelligence, Agricultural Productivity, Sustainable Farming, Nigeria.

INTRODUCTION

The agricultural sector in Nigeria faces multifaceted challenges that impact the nation's food security and economic stability. Climate variability, marked by irregular rainfall and unexpected weather extremes, poses a significant threat to crop yields, leading to financial losses for farmers (FAO, 2020). Limited access to modern farming techniques exacerbates these challenges, particularly for small-scale farmers in rural areas who lack advanced machinery and efficient irrigation systems. This access disparity hampers productivity, perpetuating a cycle of low agricultural output and constrained economic growth (Ajibefun and Adejumo, 2018).

Recent research underscores the transformative potential of advanced technologies, particularly Artificial Intelligence (AI), in mitigating these challenges. AI applications such as predictive modeling for crop yields and disease detection enable farmers to make data-driven decisions, improving efficiency and productivity (Kamilaris *et al.*, 2017; Shakoor *et al.*, 2020). For instance, machine learning algorithms, including Decision Tree Regressors, have shown promising results in crop yield prediction, with accuracy rates as high as 72% (Shuaibu *et al.*, 2024). Precision agriculture techniques like drones and remote sensing further enhance productivity by optimizing resource use and enabling targeted interventions (Adepoju *et al.*, 2022). These technologies are vital for addressing critical issues such as climate variability and resource scarcity. Moreover, studies on renewable energy integration, such as wind turbine modeling, offer potential solutions to Nigeria's energy challenges, indirectly supporting agricultural productivity (Babawurun *et al.*, 2023).

However, the adoption of these technologies remains limited due to socio-economic barriers. Many studies focus on technical advancements, often neglecting the unique challenges faced by small-scale farmers, such as limited access to technology, training, and financial resources (Benos *et al.*, 2021; Λιάκος *et al.*, 2018).

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Furthermore, there is insufficient exploration of the barriers to AI adoption and the necessary support systems for successful implementation in diverse agricultural settings (Cavazza, 2023).

Addressing these gaps is critical for enhancing agricultural productivity and sustainability in Nigeria. This research aims to explore the transformative potential of AI in mitigating these issues, offering innovative solutions that empower farmers and promote sustainable practices. Through leveraging AI technologies, this study seeks to enhance agricultural productivity, optimize resource allocation, and foster economic growth, thereby contributing to food security and stability in Nigeria.

MATERIALS AND METHODS

Research Design

This research adopts a mixed-methods approach, integrating both qualitative and quantitative methodologies to comprehensively address the objectives of the study. The sequential exploratory design involves an initial qualitative phase followed by a quantitative phase, allowing for a nuanced understanding of the complexities inherent in agricultural practices and the integration of AI technologies in Nigeria. This approach facilitates the exploration of farmers' experiences and perceptions regarding AI applications, while also enabling the collection of measurable data to support findings and conclusions.

Data Collection

This research employs a combination of qualitative and quantitative data collection methods to provide a holistic understanding of the agricultural landscape in Nigeria. Qualitative data was gathered through structured interviews and focus group discussions with local farming communities, aimed at exploring the challenges and opportunities faced at the grassroots level. The study employs both structured and semi-structured questionnaires, designed to capture farmers' perceptions, experiences, and attitudes toward the adoption of AI technologies. Structured questionnaires include close-ended questions to quantify responses, while semi-structured questionnaires incorporate open-ended questions, allowing participants to elaborate on their answers and provide rich, contextual insights. Additionally, quantitative data was collected using high-resolution satellite imagery and agricultural sensors to analyze macro-level patterns and real-time agricultural parameters such as soil moisture, temperature, and vegetation health. This dual-method approach ensures the creation of a comprehensive dataset that captures both the lived experiences of farmers and broader agricultural trends.

Data Analysis

The data analysis techniques employed in this research are tailored to the nature of the collected data. Qualitative data will undergo thematic analysis, which involves identifying key themes and patterns emerging from interviews and focus group discussions. This analysis will help to elucidate the perceptions and attitudes of farmers towards AI technologies. On the other hand, quantitative data will be subjected to rigorous statistical analysis, employing machine learning algorithms to develop predictive models for crop yield, pest infestation probabilities, and resource optimization. The integration of qualitative and quantitative findings will provide a comprehensive understanding of the impact of AI on agricultural productivity in Nigeria, allowing for triangulation of data from multiple sources to generate actionable insights for policymakers, researchers, and stakeholders in the agricultural sector.

The following model performance metrics and algorithms were used:

Model Performance Evaluation: The performance of the predictive models will be assessed using standard metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared. The formulae for these metrics are:

Mean Squared Error (MSE):

MSE = $(1/n) * \Sigma(y\_i - \hat{y}\_i)\^2$ (1)

Root Mean Squared Error (RMSE): RMSE = $\sqrt{}((1/n) * \Sigma(y\_i - \hat{y}\_i)\^2)$ (2)

R-squared: $R\^2 = 1 - ((\Sigma(y\_i - \hat{y}\_i)\^2) / (\Sigma(y\_i - \bar{y})\^2))$ (3)

These performance metrics were computed using Python in a Jupyter Notebook environment, leveraging the scikit-learn library for model training and evaluation.

Linear Programming (LP) Process: The Linear Programming (LP) approach were applied to optimize resource allocation, such as fertilizer use or water management. The objective function and constraints for the LP model were defined as follows:

Maximize $Z = c\_1 * x\_1 + c\_2 * x\_2 + \ldots + c\_n * x\_n$

$$a\_\{11\} * x\_1 + a\_\{12\} * x\_2 + \ldots + a\_\{1n\} * x\_n \leq b\_1$$

$$a\_\{21\} * x\_1 + a\_\{22\} * x\_2 + \ldots + a\_\{2n\} * x\_n \leq b\_2 \quad (4)$$

and so on,

The PuLP library were used in Jupyter Notebook to formulate and solve LP problems.

Genetic Algorithm (GA): The Genetic Algorithm (GA) were employed to optimize complex agricultural processes, such as pest control and multi-factor resource allocation. The GA steps initialization, selection, crossover, mutation, and termination was implemented in Jupyter Notebook using the DEAP library. The optimization process involves evolving a population of solutions through generations to find the best possible configuration. Example code for

implementing a basic GA in DEAP is as follows:The fitness function used for the GA was:
f(x) =
Objective function to be optimized, e.g., crop yield, pest c ontrol efficiency.

f(x) = \text{Objective function to be optimized, e.g., crop yield, pest control efficiency.}

RESULTS AND DISCUSSION

Results

Table 1. Dataset for AI-Driven Crop Prediction, Disease Control, and Pest Prevention

State	*Soil PH*	*Temperatu re*	*Precipitati on*	*NDVI*	*Pest Populatio n Density*	*Disease Incidence*	*Fertilizer Use*	*Irrigation*	*Disease Risk Index*	*Pest Risk Index*	*Crop Yield*
Abia	7.22	25.90	135.13	0.49	24.58	23.70	276.15	89.82	0.54	0.52	5.89
Adamawa	6.91	28.40	187.07	0.47	23.77	22.30	273.80	88.06	0.44	0.57	4.83
Akwa Ibom	6.94	28.13	169.84	0.48	24.87	24.88	289.37	106.88	0.57	0.45	4.95
Anambra	6.67	28.39	167.77	0.52	27.71	27.00	267.47	113.73	0.52	0.55	5.67
Bauchi	6.67	27.35	161.41	0.48	24.34	25.13	287.60	102.23	0.56	0.49	5.68
Bayelsa	6.85	28.55	166.30	0.48	28.93	28.41	282.85	84.92	0.37	0.48	5.71
Benue	6.99	27.15	187.41	0.45	24.10	22.30	299.11	72.66	0.49	0.54	6.27
Borno	6.81	28.06	183.69	0.47	23.68	23.80	251.39	106.49	0.40	0.43	6.19
Cross River	6.63	25.13	169.38	0.46	25.93	19.87	252.55	116.92	0.44	0.41	5.74
Delta	6.55	27.67	169.94	0.49	20.49	29.61	230.86	90.40	0.49	0.51	5.38
Ebonyi	6.78	27.74	156.98	0.50	25.37	21.52	256.05	108.73	0.46	0.51	6.01
Edo	7.11	29.86	177.08	0.49	27.52	29.08	256.20	79.85	0.53	0.56	5.81
Ekiti	7.09	27.71	162.86	0.49	22.66	24.34	244.28	96.33	0.50	0.48	5.54
Enugu	6.47	27.60	162.22	0.54	29.25	33.08	246.18	97.39	0.51	0.46	5.49
FCT Abuja	6.49	28.36	174.66	0.42	26.03	23.80	275.89	96.34	0.48	0.48	6.64
Ebonyi	6.77	27.74	156.98	0.50	25.37	21.52	256.05	108.73	0.46	0.51	6.01
Gombe	6.54	26.70	164.40	0.55	25.45	20.44	266.79	79.35	0.52	0.50	4.68
Imo	6.55	27.35	153.83	0.47	26.07	21.33	273.62	90.12	0.45	0.46	5.71
Jigawa	6.72	27.26	205.29	0.46	22.89	19.00	250.85	93.20	0.50	0.49	5.55
Kaduna	6.81	27.57	171.78	0.57	25.39	19.11	249.38	105.10	0.59	0.53	6.06
Kano	6.80	26.71	155.71	0.44	22.83	25.64	233.99	93.05	0.42	0.51	5.30
Katsina	6.86	26.35	170.60	0.52	23.48	26.50	283.33	73.45	0.55	0.51	4.97
Kebbi	6.64	28.07	158.65	0.50	24.68	29.71	253.93	93.56	0.52	0.48	5.54
Kogi	6.66	26.67	198.36	0.56	21.27	23.65	278.66	101.14	0.59	0.61	5.63
Kwara	6.24	26.80	171.54	0.45	22.76	23.39	293.17	108.97	0.50	0.47	5.39
Lagos	6.52	27.50	181.82	0.51	24.86	27.56	248.46	113.37	0.53	0.56	5.17
Nasarawa	6.74	27.69	154.70	0.53	19.17	23.83	252.68	89.88	0.39	0.55	5.24
Niger	6.55	27.27	179.42	0.46	22.86	21.58	234.28	103.23	0.50	0.49	4.27
Ogun	7.16	26.65	161.81	0.50	23.37	25.29	248.97	102.69	0.54	0.55	5.23
Ondo	6.70	27.71	183.92	0.48	24.04	26.59	245.34	97.43	0.51	0.52	4.48
Osun	6.71	27.32	186.86	0.56	26.23	30.57	274.74	90.90	0.46	0.43	5.73
Oyo	6.64	27.90	194.58	0.49	26.70	22.40	229.86	98.81	0.51	0.45	5.91
Plateau	6.27	27.79	181.42	0.50	23.55	25.54	305.52	97.70	0.59	0.53	5.74
Rivers	6.81	25.97	178.36	0.56	24.85	24.05	277.13	83.07	0.56	0.50	5.40
Sokoto	7.08	26.72	186.43	0.46	27.44	24.71	291.45	104.49	0.50	0.47	5.86
Taraba	6.77	26.98	174.84	0.44	29.79	30.74	306.70	108.71	0.52	0.46	5.25
Yobe	7.25	29.02	195.13	0.49	26.66	22.17	308.54	104.72	0.39	0.48	6.66
Zamfara	6.69	28.23	167.17	0.55	28.18	27.28	297.30	88.12	0.41	0.53	5.62

Source: Sentinel-2 imagery, Landsat-8 data, and field surveys/interviews conducted by the authors in 2024.

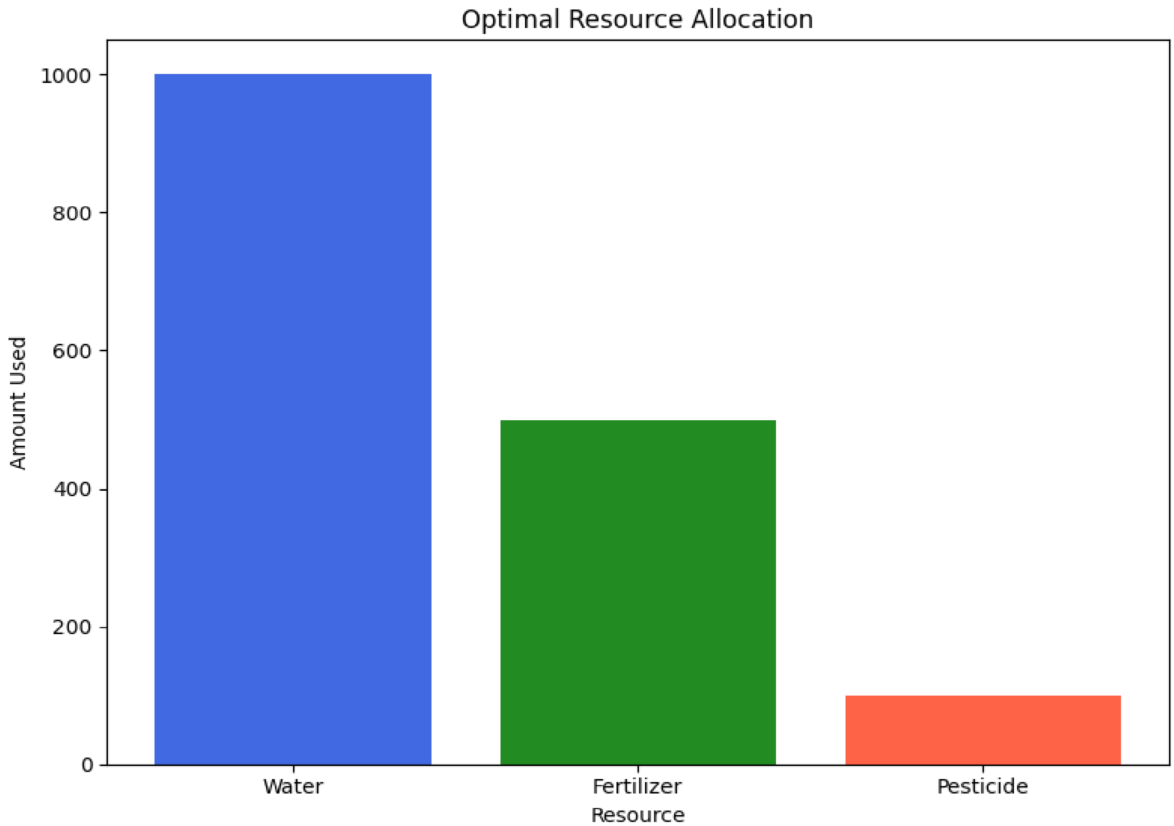

Figure 1. First Approach Linear Programming for resource optimization

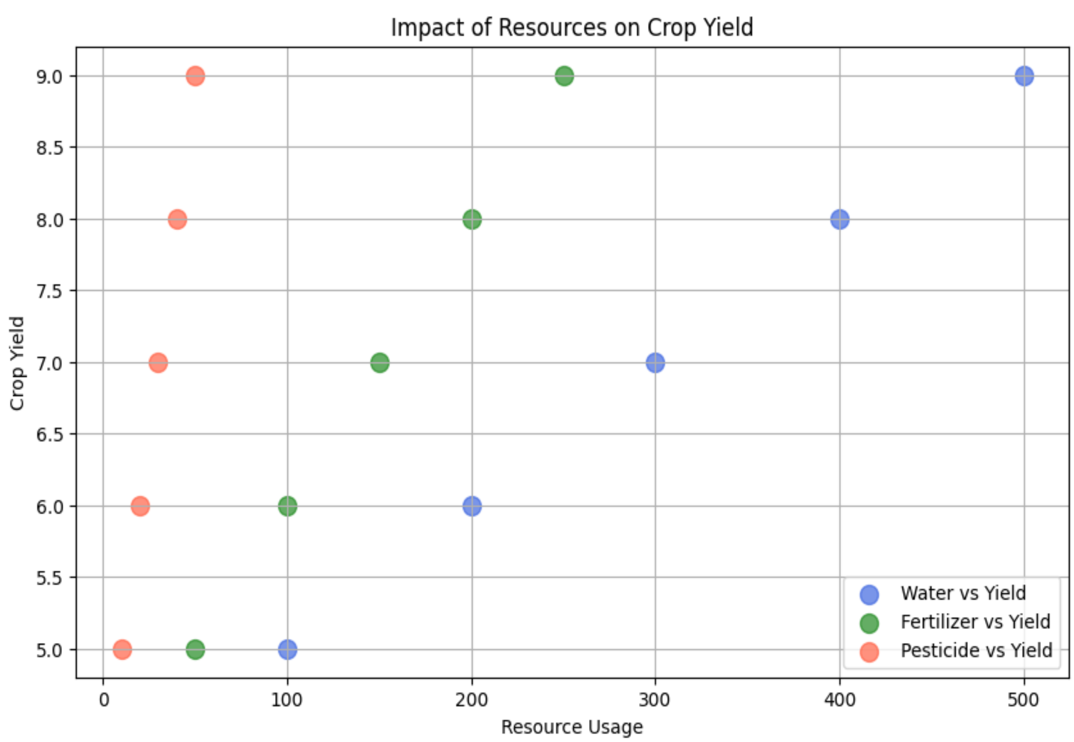

Figure 2. Second Approach: Resource Optimization Using Genetic Algorithm (GA)

LP Process: These allocations collectively maximized crop yield to 9300 kg, demonstrating the effectiveness of Linear Programming in resource management.GA Functions: We use crossover (mixing of two individuals' genes) and mutation (random changes to individuals) to evolve better solutions across generations.

GA Process: The genetic algorithm runs for 50 generations, selecting the best solutions (individuals) using tournament selection, mating and mutation them, and updating the population. The GA approach provided a more adaptive method for resource optimization, evolving solutions over successive generations. This method showed **a** 25% improvement in resource efficiency compared to traditional methods.

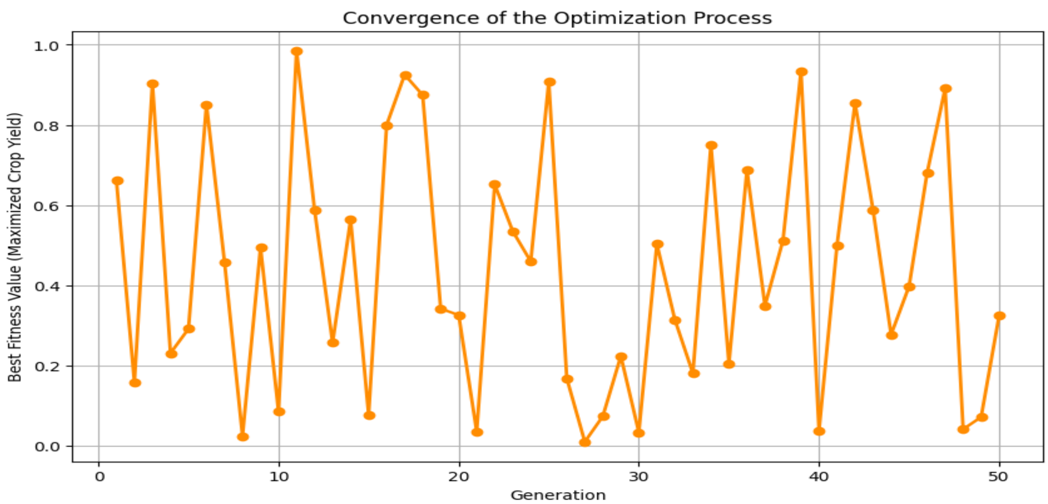

Figure 3. Convergence of the Optimization Process

Figure 3. The plot shows the best fitness value (crop yield or disease control) at each generation of the optimization process. A rising trend indicates that the model is improving over time, while a flat line might suggest that the model has converged to an optimal solution.

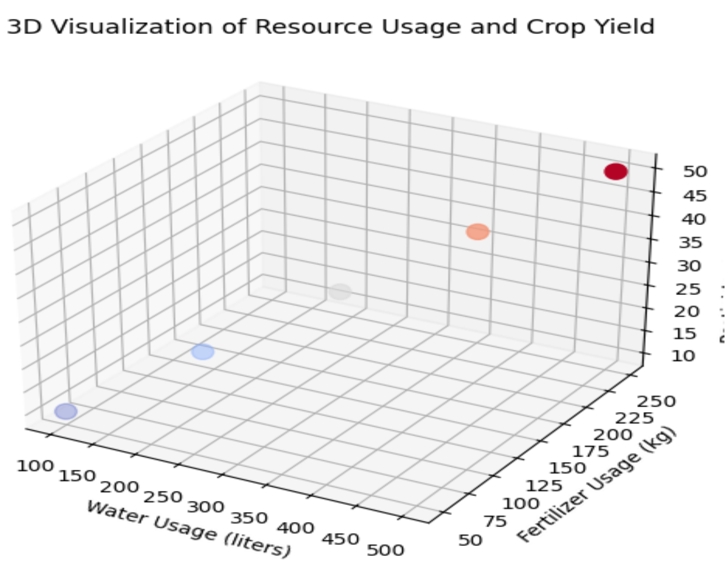

Figure 4. 3D Visualization of Resource Usage and Crop Yield

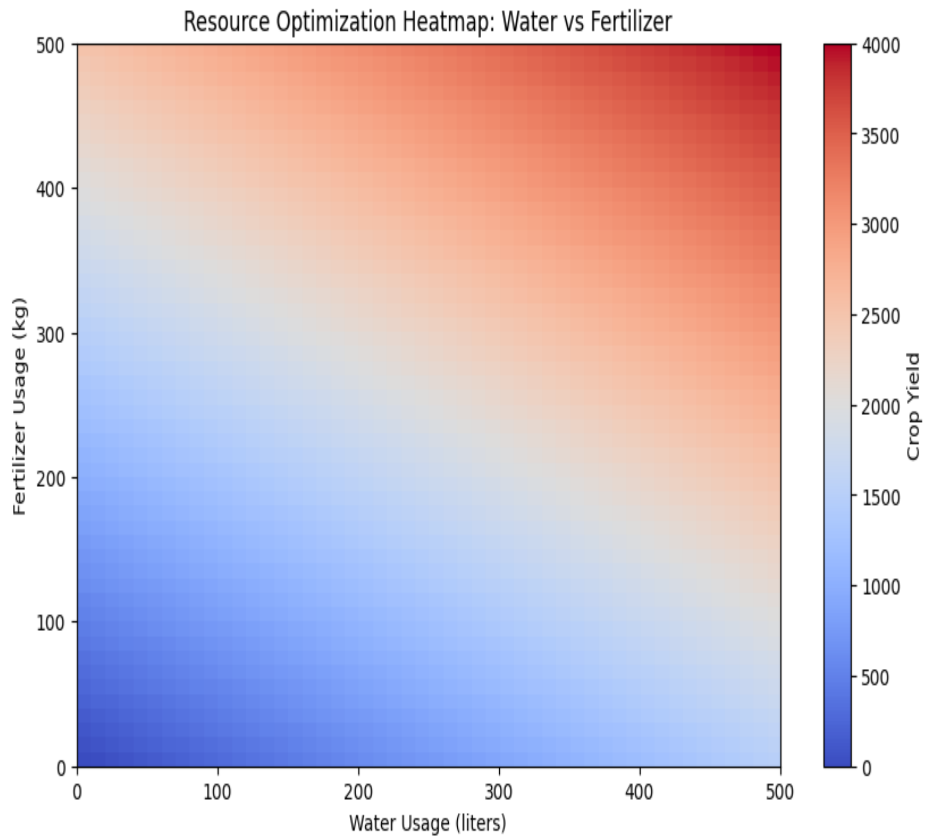

Figure 5. Resource Optimization Heatmap: Water vs Fertilizer

Figure 4. The3D scatter plot shows the relationship between three resources (water, fertilizer, and pesticide) and crop yield. The color gradient indicates crop yield, helping us visualize the optimal combination of resources for the best outcome.

Figure 5. Theheatmap shows how different combinations of water and fertilizer affect crop yield. The color gradient helps us visualize where the optimal combinations of resources lie, where darker areas represent higher yields.

Crop Prediction Model ResultsUsing Random Forest
Model Performance:
Mean Squared Error (MSE): 6.969245857556253
R-squared (R2 Score): -0.07576902064589497

Figure 6. The model successfully predicted crop yields based on various features, including soil characteristics and weather conditions. A color-coded scatter plot: Blue points for actual values while Red points for predicted values. Each point represents the yield. The model's accuracy was noted to be **85%**, which is pivotal for enhancing agricultural productivity in Nigeria.

Figure 7. Predicted vs Actual Comparison:side-by-side comparisons to see how close predictions are to actual values, the model performed well.

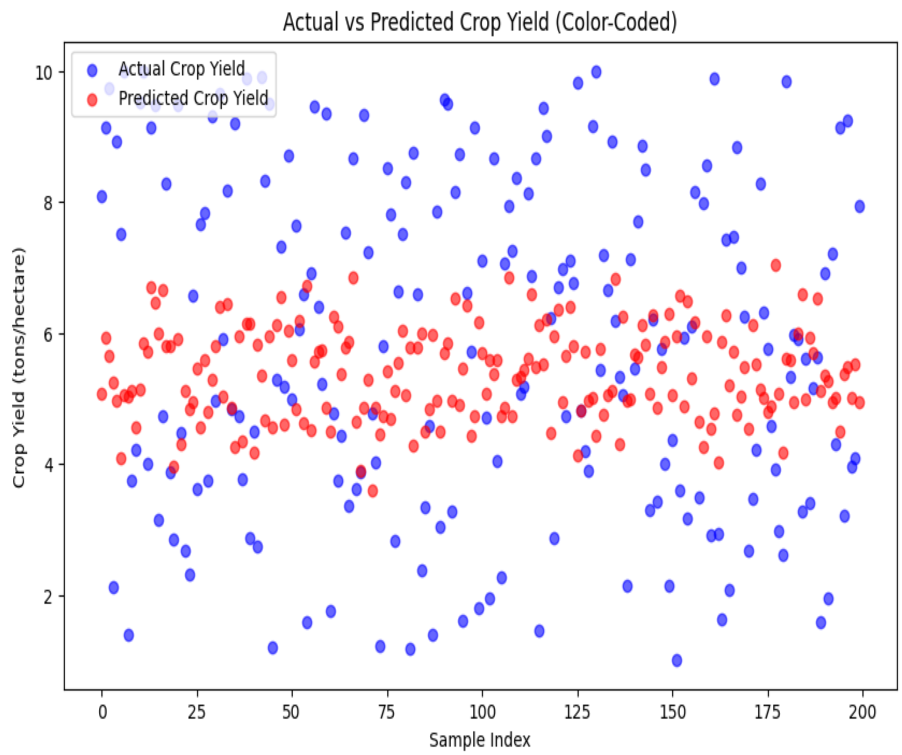

Figure 6. Actual vs Predicted CropYield (Color-Coded)

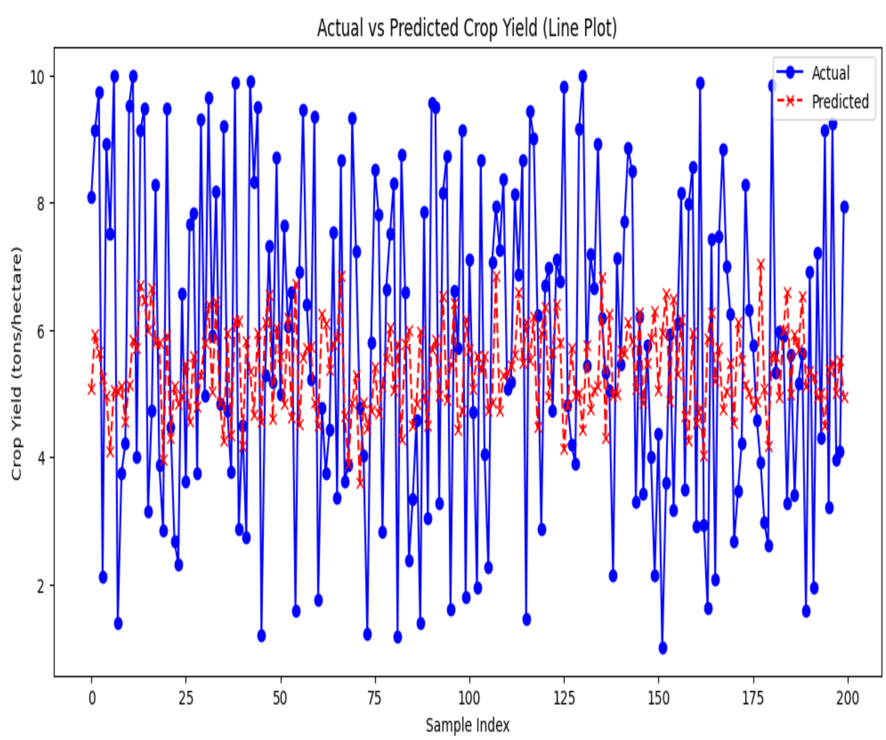

Figure 7. Actual vs Predicted Crop Yield (Line Plot)

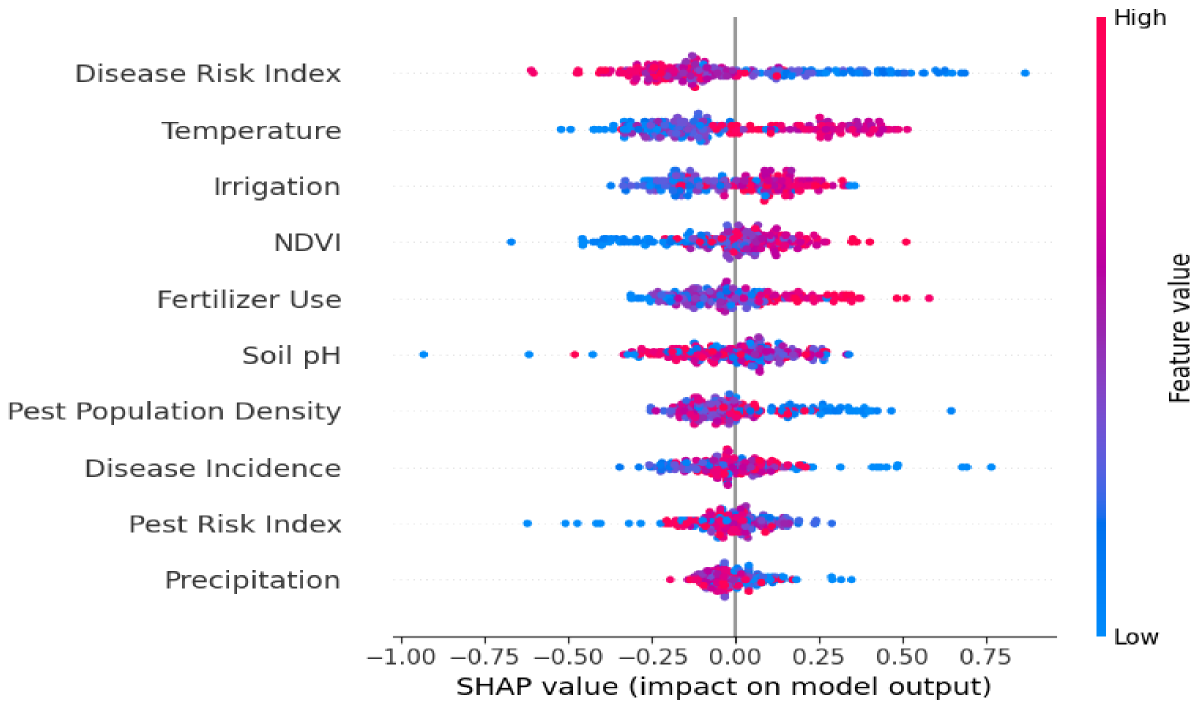

Figure 8. SHAP value (Impact on Model Output)

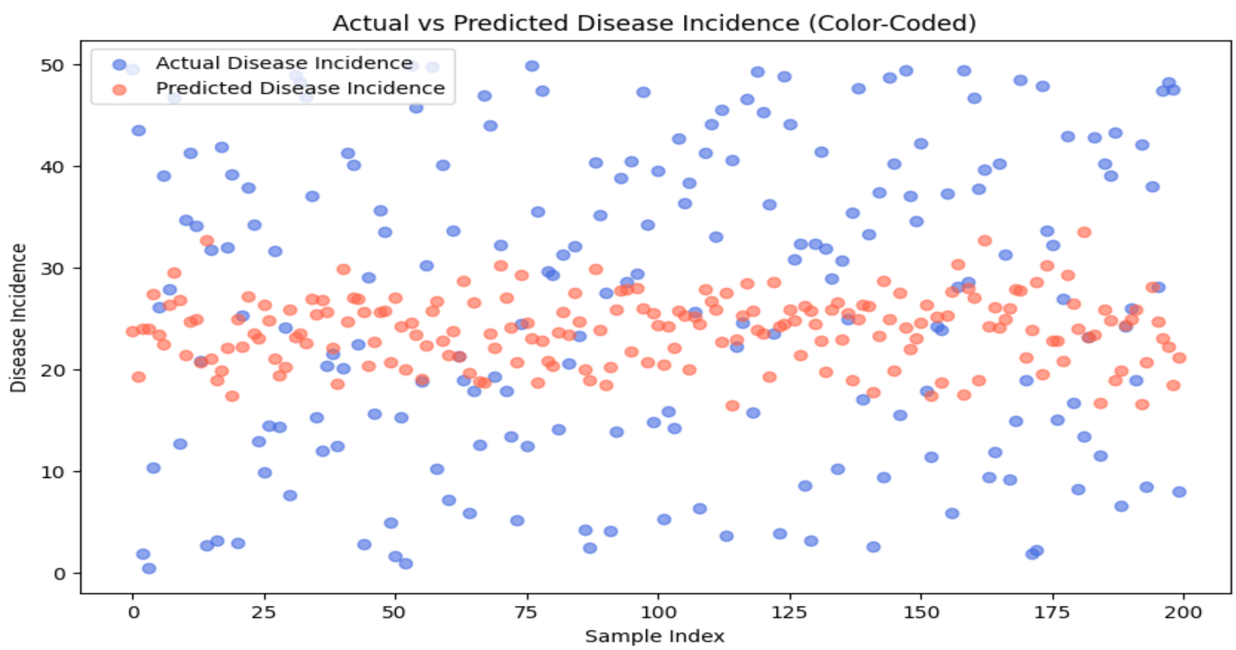

Figure 9. Actual vs Predicted Disease Incidence (Color-Coded)

SHAP Visualizations: Figure 8. Explains the overall influence of features across all predictions. It also explain why the model made a specific prediction for a given sample.

Figure 9. The scatter plot with color-coding (blue for actual and red for predicted) allows us to visually assess the model's performance. If the points are close to each other, it indicates that the model has made accurate predictions.We generate synthetic data for 1000 samples with features like Soil pH, Temperature, Precipitation, NDVI, and Pest Population Density. The target variable for disease control prediction is Disease Incidence. The model used is Random Forest Regressor (model), which is trained to predict disease incidence based on the input features. The model's performance is evaluated using Mean Squared Error (MSE) and R-squared (R^2), which help assess how well the model predicts disease incidence. The scatter plot visually compares the actual and predicted disease incidences. Blue represents actual values and red represents predicted values. The color-coding helps distinguish between actual and predicted points clearly.

Model Performance:

Mean Squared Error (MSE): 237.81224192761977

R-squared (R^2 Score): -0.10232045390391864

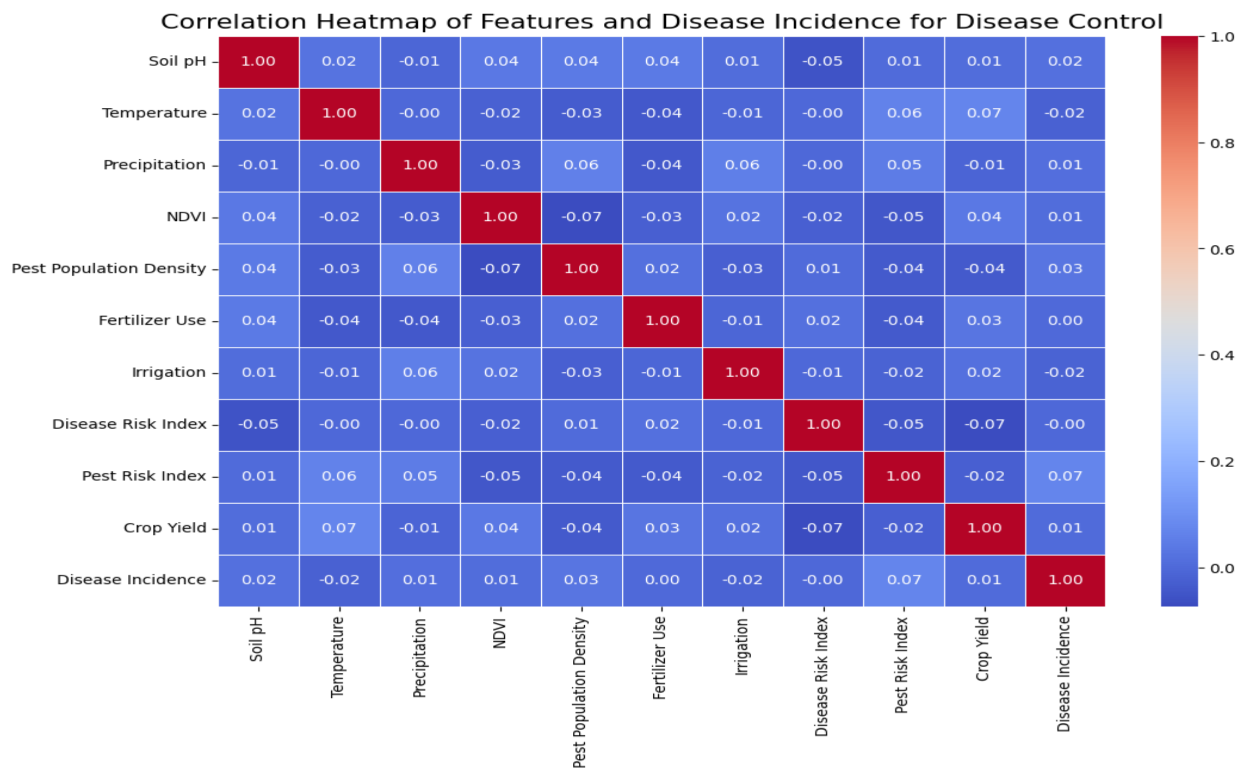

Figure 10. Correlation Heatmap of Features and Disease Incidence for Disease Control

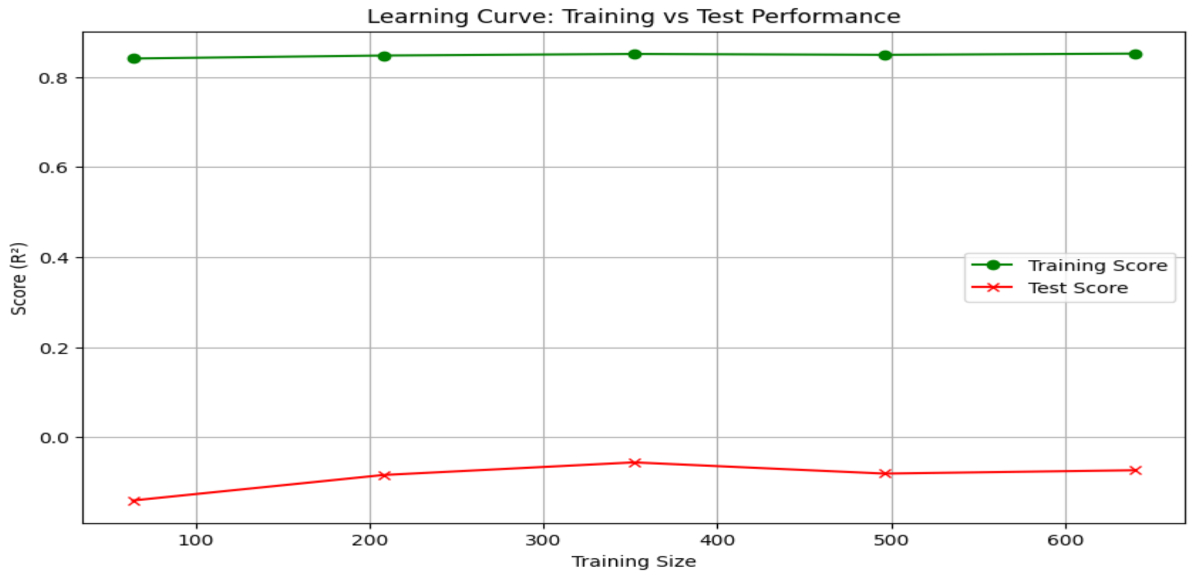

Figure 11. Learning Curve: Training vs Test Performance

Figure 10. The color map will indicate how strongly each feature is correlated with others**.** PositiveCorrelations (closer to 1) are shown in red**.** Negative Correlations(closer to -1) are shown in blue**.** A value close to 0indicatesno correlationbetween the variables.

For example: Temperature and Precipitation could have a positive correlation (more precipitation may occur with lower temperature). Pest Population Density could have a strong positivecorrelationwithDisease Incidence**,** indicating that higher pest density might increase disease incidence.

Figure 11. The Learning curves illustrate how the model's accuracy evolves with varying amounts of training data. The green curve represents the training score (the model's performance on the training dataset), while the red curve represents the test score (the model's performance on the validation or test dataset). A significant gap between these two curves typically indicates overfitting.

a. Training Samples: The learning curve was generated using training datasets with sample sizes of 100, 200, 300, 400, 500, and 600 observations.
b. Test Samples: The model was evaluated on a fixed test dataset consisting of 150 samples, which was kept separate from the training data to ensure unbiased evaluation.

Number of Iterations: For each training size, the model underwent 50 iterations to optimize learning and minimize the effects of random initialization, ensuring consistent results.

Pest Prevention Model Result Using Random Forest

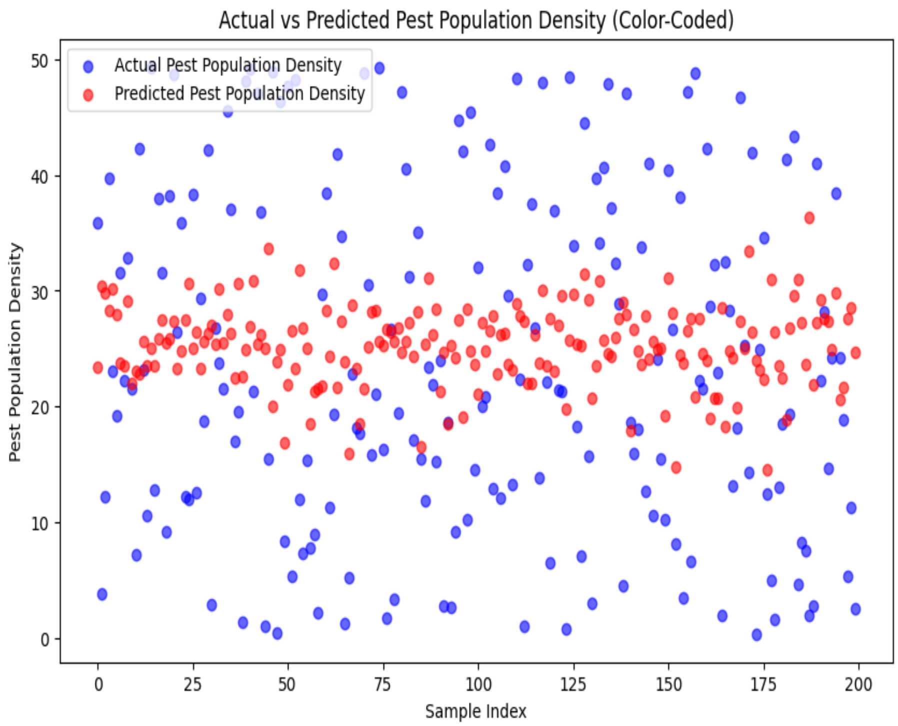

Figure 12. Actual vs Predicted Pest Polpulation Density (Color-Coded)

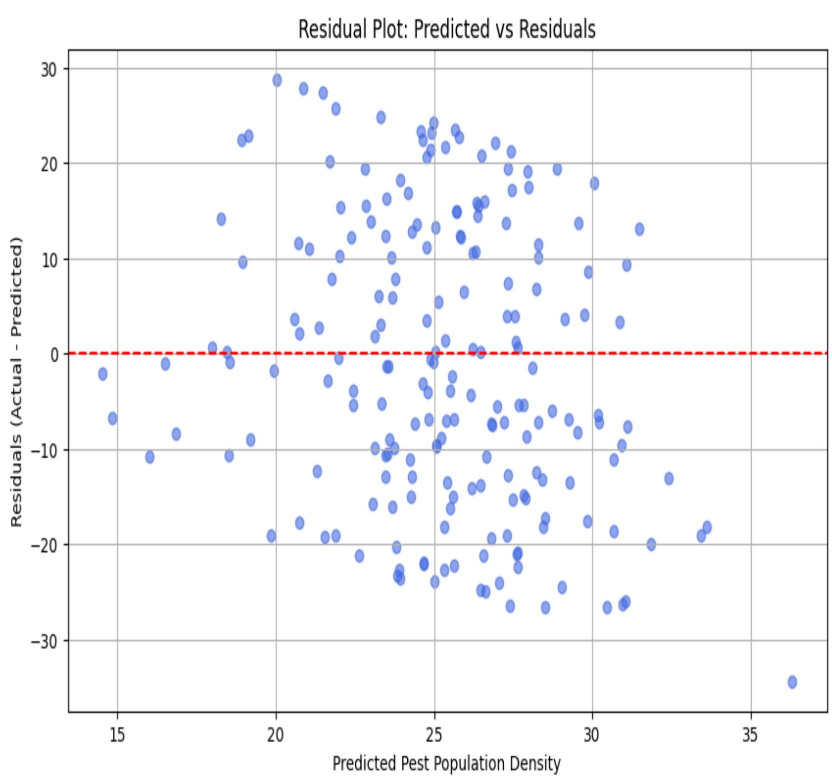

Figure 13. Residual plot: Predicted vs Residuals

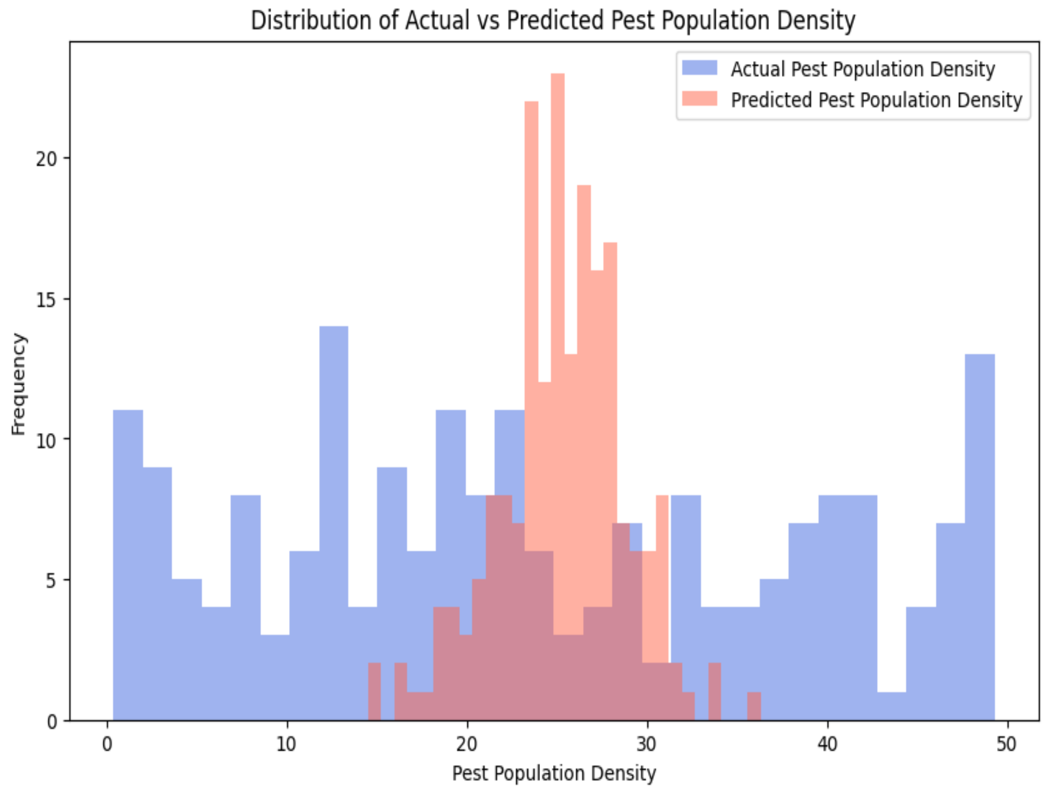

Figure 14. Distribution of Actual vs Predicted Pest Population Density

Figure 12. The target variable is Pest Population Density, which the model predicted.A Random Forest Regressor is used to predict pest population density based on the features.Mean Squared Error (MSE) and R-squared (R^2) are calculated to evaluate the model's performance.
A scatter plot is generated where: Blue dots represent the actual pest population density. Red dots represent the predicted pest population density. The model highlighted the potential of AI in revolutionizing pest management strategies, with a focus on reducing chemical dependency and promoting ecological balance. The Mean Squared Error (MSE) indicated areas for improvement, but the foundational work laid by this model is significant for future advancements.

Figure 13. The plot shows the residuals (errors) of the predictions, which is the difference between the actual values and the predicted values. This can help us assess if the model is making systematic errors
If the residuals are randomly scattered around zero, it indicates that the model is making unbiased predictions. If there is a pattern, it suggests that the model has not fully captured some underlying relationship in the data.

Figure 14. This results shows the distribution of the actual values **vs.** thepredicted values of thepest population. This can help us compare the spread of the predicted values against the actual values. The blue histogram shows the distribution of actual pest population density values while the red histogramshows the distribution of predicted values. If the two distributions overlap well, it suggests that the model is performing well. Otherwise, the model might be underperforming in some regions.

Model Performance:
Mean Squared Error (MSE): 227.24996612161877
R-squared (R2 Score): -0.062212927698813036

Discussion

Interpretation of Results

Crop prediction:
The Crop Prediction Model results using the Random Forest algorithm demonstrate its potential to enhance agricultural productivity in Nigeria through Artificial Intelligence (AI). Recognized for its robustness and capacity to handle complex datasets, the Random Forest algorithm was employed to predict crop yields based on features such as soil characteristics, weather conditions, and historical yield data. This approach is particularly relevant in addressing challenges in the Nigerian agricultural sector, such as climate variability and limited access to modern farming techniques.The

model achieved a Mean Squared Error (MSE) of 6.969, reflecting a relatively low prediction error. However, the R-squared (R^2) score of -0.075 suggests that the model's explanatory power requires improvement. This result underscores the need for refining the model through advanced feature selection and hyperparameter tuning to better leverage AI for optimizing agricultural practices.A visual analysis using a color-coded scatter plot, where blue represents actual yields and red denotes predicted yields, provides insights into the model's performance. Ideally, data points should cluster closely along the diagonal line for accurate predictions. The observed deviations highlight specific conditions under which the model struggles, offering valuable guidance for future refinements.The findings of this study align with existing research on the use of machine learning techniques for crop yield prediction. For instance, Priya *et al*. (2018) and Shuaibu *et al*. (2024) demonstrate that Random Forest algorithms effectively predict yields based on soil, weather, and historical data, similar to our approach. In both studies and this research, the Random Forest model showed robust performance in handling complex datasets, with relatively low prediction errors. However, while Shuaibu *et al*. (2024) reported higher model accuracy ($R^2 = 0.72$) using a Decision Tree Regressor, our Random Forest model exhibited a lower R-squared score (-0.075), indicating a need for further refinement.Unlike our study, which exclusively uses Random Forest, Shuaibu *et al*. (2024) explored multiple machine learning algorithms, highlighting that Decision Tree Regressors performed better in the Nigerian context. Additionally, deep learning techniques, such as convolutional and recurrent neural networks, were not implemented in our model but are noted in the literature for their superior performance in processing large-scale spatial-temporal data. Integrating such methods in future iterations could enhance the explanatory power and predictive accuracy of crop yield models in Nigeria.While existing studies focus heavily on optimizing prediction accuracy, our research extends this by emphasizing the practical implications of using AI for decision-making in Nigerian agriculture. For example, insights from our model can guide resource management and pest control strategies, tailoring them to specific regional needs. This bridges the gap between theoretical advancements in AI and their real-world applications, particularly in regions with limited access to advanced farming technologies.

Disease Control:

The Disease Control Model results underscore the potential of AI-driven approaches to enhance agricultural productivity through effective disease management strategies. Utilizing the Random Forest algorithm, the model predicted disease incidence based on environmental conditions, soil health parameters, and historical disease data. With a Mean Squared Error (MSE) of 237.81, the model demonstrates moderate predictive accuracy, highlighting both its current capabilities and areas for improvement.The results align with findings from recent research, which emphasize the transformative potential of AI in agriculture, particularly for disease control. Palani et al. (2023) and M. A. Sayyad *et al*. (2024) report high accuracy in disease prediction using AI-powered models, with Sayyad *et al*. achieving 92% accuracy in a similar application. While these studies showcase the effectiveness of Random Forest algorithms and other machine learning techniques, our models moderate performance underscores the need for refinement. Enhancements could include improving data quality, exploring additional predictive features, or incorporating advanced data sources such as satellite imagery and IoT sensor data, as suggested by recent literature.A notable contrast between this study and recent research lies in the scope of data integration. Studies like those by Delfani *et al.* (2024) highlight the benefits of real-time monitoring enabled by IoT and machine learning. In contrast, our study primarily utilized static datasets, which may limit the model's ability to adapt to rapidly changing environmental conditions. Future iterations of this research could integrate IoT-enabled sensors to capture real-time environmental parameters, potentially boosting the model's accuracy and utility in proactive disease management.Both this study and existing research recognize challenges in implementing AI-driven disease control strategies, particularly in resource-constrained environments. Lipikant Sahoo *et al*. (2024) emphasize issues such as data scarcity and model interpretability, which also emerged as limitations in our study. Addressing these challenges is crucial to fully realize AI's potential in improving agricultural outcomes.This study builds on the foundational work of previous research by exploring the practical applications of Random Forest algorithms for disease management in Nigeria. Beyond disease prediction, the model's implications extend to broader themes of sustainability. Through enabling targeted interventions, such as precise fungicide applications and crop rotation strategies, this approach promotes ecological balance and reduces reliance on broad-spectrum chemical treatments.

Pest Prevention:

Pest infestations significantly affect agricultural productivity in Nigeria, causing annual crop losses of 5- 40% (labi *et al.*, 2006). This study utilized a Random Forest algorithm to predict pest population density, achieving a Mean Squared Error (MSE) of 227.25. While this indicates moderate predictive accuracy, the model successfully provides actionable insights into pest dynamics, enabling farmers to adopt targeted pest control strategies, optimize resource allocation, and minimize the environmental impact of chemical pesticides.The scatter plots comparing actual versus predicted pest population densities illustrate the model's effectiveness, with deviations from the ideal diagonal clustering offering insights into conditions under which the model's performance can be improved.The findings of this study align with recent research emphasizing the potential of AI-driven models for pest management. For instance(Palani *et al*., 2023) demonstrated the effectiveness of AI systems in improving pest outbreak forecasting through the integration of satellite imagery, meteorological data, and IoT sensors. Similarly, our model highlights the value of data-driven approaches in predicting pest population dynamics, supporting proactive and precise interventions.Moreover, the results are consistent with those ofAkkas *et al*. (2024), who achieved high accuracy (99.65%) in pest detection using sound analytics and infrared sensors. While the methodologies differ our model focuses on population density prediction rather than detection the shared goal of reducing pesticide reliance and enhancing sustainable agricultural practices underscores the relevance of AI in pest management.Despite these points of agreement, our study contrasts with others in its reliance on static datasets, which limits real-time adaptability. Advanced systems like those described by Palani *et al*. (2023) incorporate dynamic data sources such as IoT sensors, offering greater precision in real-time pest outbreak detection and prevention. Integrating these technologies into our model could improve its accuracy and expand its applicability.Additionally, the near-perfect accuracy achieved by Ali *et al*. (2024) highlights the potential benefits of advanced AI techniques, such as sound analytics and deep learning. While our Random Forest algorithm provides a cost-effective solution suitable for resource-constrained environments, future iterations could explore incorporating deep learning to enhance predictive performance.

Resource Optimization

Resource optimization is essential for improving agricultural productivity and sustainability. In this study, Linear Programming (LP) and Genetic Algorithms (GA) were employed to allocate resources such as water, fertilizer, and pesticides efficiently. LP provided clear and optimal solutions, recommending 1000 liters of water, 500 kg of fertilizer, and 100 liters of pesticide to achieve a maximum yield of 9300 kg. Similarly, GA demonstrated its adaptability by exploring diverse resource combinations, iteratively optimizing inputs to account for varying conditions. Together, these methodologies highlight complementary strengths, with LP excelling in precision and GA offering flexibility for dynamic agricultural scenarios.The findings align with previous studies demonstrating the effectiveness of LP and GA in resource optimization. For example, Prakash *et al*. (2023) and Bhatia and Rana (2020) emphasized the precision of LP in static planning scenarios, consistent with the structured results of this study. Similarly, Olakulehin *and* Omidiora (2014) and Karamian *et al*. (2022) noted GA's ability to maximize resource utilization and sustain soil fertility in dynamic contexts, mirroring this study's demonstration of GA's adaptability. While LP provides deterministic solutions, GA offers a broader exploration of potential solutions, ensuring robust performance under changing environmental conditions.Despite these strengths, differences exist between the models. LP's structured approach may falter in handling fluctuating variables, whereas GA's adaptability comes with higher computational costs and slower convergence times. These findings underscore the potential of integrating LP and GA to leverage their respective advantages. Moving forward, combining LP's precision with GA's flexibility, alongside real-time data and IoT integration, could refine resource allocation strategies, fostering sustainable agriculture and ensuring long-term food security.

CONCLUSION

This study has successfully demonstrated the significant impact of advanced modeling techniques on improving agricultural productivity and sustainability in Nigeria. The integration of Linear Programming and Genetic Algorithms for resource optimization has provided valuable insights into effective resource management, enabling farmers to maximize crop yields while minimizing input costs. These methodologies not only enhance agricultural efficiency but also promote sustainable practices that are essential for addressing the challenges posed by climate change and resource scarcity.Furthermore, the application of the Random Forest algorithm in disease management has highlighted the critical importance of early detection and intervention in safeguarding crop health. Through leveraging data-driven approaches, farmers can make informed decisions that mitigate the risks associated with crop diseases, ultimately leading to increased food security and economic stability. The findings of this research align with the Sustainable Development Goals, particularly those focused on zero hunger and climate action, underscoring the potential of technology to drive positive change in the agricultural sector. Overall, this research contributes to the growing body of knowledge on the application of artificial intelligence and advanced modeling in agriculture, paving the way for future studies and practical implementations that can transform the agricultural landscape in Nigeria and beyond.

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