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A Review Of Precision And Innovative Farming For Nigerian Farmers

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Abstract
This study successfully developed a logistic regression model (LRM), a machine learning algorithm to assess farmers' perceptions of precision agriculture (PA) based on key factors such as gender, educational level, farming experience, household size, farm income, access to credit, farm size, and awareness of precision farming. Python programming language was the primary language, utilizing libraries such as numpy, scikit-learn, matplotlib, and seaborn for data processing, model building, and visualization. The dataset comprised 350 samples and was split into training (70%) and testing (30%) sets. The model achieved an accuracy of 81.9%, with a recall of 97.7%, F1 score of 0.899, and precision of 83.3%, demonstrating its effectiveness in identifying positive perceptions of PA. The confusion matrix showed a true positive rate of 84 and a false positive rate of 17, suggesting a need for model improvement in handling false positives. The ROC curve showed an AUC of 0.58 indicating that the model has no discriminatory ability. Overall, the findings suggest that the highlighted factors influence farmers' perceptions of PA. Python proved highly efficient for implementing this machine learning-based study.

Key Word: *Perception, precision agriculture, innovative farming.*

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I. Introduction

Innovation plays a vital role in driving sustainable development, with the United Nations Sustainable Development Goals (SDGs) serving as a holistic framework to tackle various global challenges[1]. Broadly, the trajectory of technological innovation is determined by a set of guidelines that direct the application of available technologies to satisfy societal needs and economic demands[2]. Currently, the adoption of artificial intelligence (AI) and machine learning (ML)-driven solutions is transforming industries and establishing pathways for next-generation research aimed at achieving sustainable development[3]. Khan *et al.*[4] highlight the importance of advanced technologies and innovation in fostering sustainable systems, noting that these technologies are instrumental in addressing critical questions necessary for their effective transition. However, developing nations encounter substantial obstacles in pursuing economic advancement[5], as their systems are often more traditional compared to those in developed countries[6].

The digital era has introduced transformative opportunities for sustainable agriculture, revolutionizing traditional farming methods and approaches[7,8]. This era encompasses a wide array of innovations and technologies, including the digital economy[9], information services[10], and agricultural advancements[11], which collectively offer significant potential for advancing sustainable development. Innovations such as remote sensing, precision farming, blockchain, geospatial analysis, artificial intelligence (AI), machine learning, deep learning, digital twins, and the Internet of Things (IoT) are instrumental in modern agriculture, enabling farmers to monitor crop health, optimize irrigation, enhance yields, and reduce chemical inputs[12,13,14,15].

Globally and locally, agriculture faces numerous challenges[16], including increasing demands for food and ecosystem services provided by the agricultural sector[17,18]. Currently, agriculture is undergoing its "fourth revolution"[19]. Emerging technologies hold the potential to tackle critical challenges within the sector, such as boosting productivity, minimizing environmental impacts, conserving natural resources, and contributing to achieving the SDGs[20,21,22]. The increasing reliance on digital technologies in agriculture presents opportunities to transform production and management decisions while minimizing trade-offs. In this context, digital innovations are anticipated to play a vital role in fostering sustainability in agriculture[19]. However, Walter *et al.*[19] cautioned that positive outcomes from digitalization will not emerge automatically, as the process introduces challenges, costs, and risks across economic, social, and ethical dimensions.

Agricultural productivity in Nigeria is hindered by climate variability and unpredictable weather patterns, poor resource management and soil degradation, and inadequate data for precision farming practices.

Technologies like GIS, remote sensing, and data analytics offer solutions by enabling Nigerian farmers to optimize resources, enhance crop yields, and mitigate environmental impacts. The study will focus on modeling the perceptions of Nigerian farmers regarding precision agriculture adoption.

II. Materials And Methods

Study Area: This study focuses on farmers across three local government areas (Suleja, Tafa, and Lapai) of Niger State, Nigeria, aiming to access their perception of precision agriculture (PA). farmers vary widely in terms of age, education, farming experience, farm size, access to technology, and socio-economic factors, all which can influence their perception of PA.

Data Collection: Data were collected through structured questionnaires that contained demographic, socio-economic, and technological factors that are believed to influence the perception of PA. A total of 350 samples were selected from various farming enterprise to reflect the diversity of the farming population. The obtained dataset is considered representation of the key factors affecting farmers' perception of PA in the study area.

Modelling Approach: An LRM was employed to predict farmers' perception of PA based on the explanatory variables. Logistic regression is appropriate for binary classification tasks where the outcome variable is dichotomous (0 or 1). The logistic regression model uses the following mathematical representations:

$$\text{logit}(P) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \ldots + \beta_nX_n \qquad (1)$$

where:
P is the probability that a farmer has a positive perception of precision agriculture,
$X_1, X_2, \ldots X_n$ are the predictor variable (age, education, income, etc.),
$\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are the regression coefficients for each of the associated variables.

Data Preprocessing:

1. Encoding Categorical Variables: Variables such as gender and educational level where encoded using label encoding. For gender, 0 represented the male while 1 represented the female. Also, educational level of farmers was encoded into numerical categories (0 = Primary, 1 = Secondary, 2 = Tertiary). The awareness to precision farming, access to digital tools, and access to credit, were encoded into numerical categories (0 = No, 1 = Yes).
2. Feature Scaling: Continuous variables such as farm size, farm income, and age were normalized using a standard scaler to normalize the values for logistic regression.

Model Evaluation: The dataset was split into two subsets (training and testing), with 70% of the data used for training and 30% reserved for testing the model. The model evaluation metrics included:

1. Confusion Matrix: The generated matrix was used to compare the actual vs. predicted perception outcomes.
2. ROC Curve and AUC Score: The Receiver Operating Characteristic (ROC) curve was plotted to evaluate the model's ability to discriminate across different threshold values, and the Area Under the Curve (AUC) score was calculated.

Visualization of Results: The coefficients of the model obtained were plotted to show the relative importance of each of the factors influencing farmers' perceptions of PA. Also, confusion matrix heatmaps and ROC curves were generated to visualize the model's performance.

III. Results

Sample Statistics

Table no 1 Shows the distribution of those respondents across communities in the local government areas of the state. The study area as indicated, comprises agricultural communities within Suleja, Tafa, and Lapai local government areas in Niger State, Nigeria. The total number of respondents, N = 350, with 231 from Suleja, 95 from Tafa, and 24 from Lapai local governments area respectively.

Table no 1: Shows population distribution of respondents across the three local government areas

<table>
<tr><td colspan="5">Suleja Local Government Area</td></tr>
<tr><td>Madalla</td><td>Suleja</td><td>Maje</td><td>Kwamba</td><td>Kwankashe</td></tr>
<tr><td>63</td><td>11</td><td>88</td><td>16</td><td>53</td></tr>
<tr><td colspan="5">Tafa Local Government Area</td></tr>
<tr><td>Zuma</td><td colspan="2">Wuse</td><td colspan="2">New Bwari</td></tr>
<tr><td>56</td><td colspan="2">18</td><td colspan="2">21</td></tr>
<tr><td colspan="5">Lapai Local Government Area</td></tr>
<tr><td colspan="5">Lapai</td></tr>
<tr><td colspan="5">24</td></tr>
</table>

Descriptive Statistics
Table no 2 Provides insights into various socio-economic and demographic characteristics of farmers.

Table no 2: Shows the descriptive statistics and correlation between study variable (respondents) from the three local government areas (n = 350)

S/N	Variable	Descriptive Statistics Data	
		Mean	Standard Deviation
1	Age	44.3	14.3
2	Gender	0.7	0.4
3	Education Level	0.9	0.6
4	Farming Experience	26.5	13.9
5	Household Size	7.5	4.2
6	Farm Income	107000	54000
7	Access to Credit	0.3	0.4
8	Farm Size	10.5	5.4
9	Ownership of Machinery	0.4	0.4
10	Awareness of Precision Farming	0.4	0.4
11	Access to Digital Tools	0.4	0.4
12	Internet Availability	0.4	0.4

Regression Equation
The regression equation for the logistic model is:
logit(P) = 1.1440 - 0.2744(Age) + 0.2135(Gender) + 0.0503(Educational_Level) + 0.1350(Farming_Experience) + 0.0411(Household_Size) + 0.0891(Farm_Income) + 0.0288(Access_to_Credit) + 0.0535(Farm_Size) - 0.1921(Ownership_of_Machinery) + 0.2055(Awareness_of_Precision_Farming) - 0.0927(Access_to_Digital_Tools) - 0.0360(Internet_Availability) - 0.1011(Initial_Cost_of_Technology) (2)

Each feature's coefficient β represents the weight of the variable in the model. A positive coefficient increases the log-odds of a positive perception, while a negative coefficient decreases it. From the model above, gender, education, farming experience, household size, farm income, access to credit, farm size, awareness of precision farming, increases the likelihood of perceiving PA positively. However, age, ownership of machinery, access to digital tools, internet availability, and initial cost of technology will lead to less favourable perception of PA.

IV. Discussion

The dataset includes farmers aged between 20 and 70 years, with an average age of 44.3 years. This suggests that the dataset represents a wide range of age groups, reflecting both young and old farmers. The standard deviation is 14.3 years, indicating some variations in the ages, though most farmers likely fall within a middle-aged bracket. Furthermore, the dataset is predominantly male (coded as 0), with an average gender value of 0.7. This implies that around 70% of the respondents are male, highlighting gender imbalance typically of farming communities, particularly in the rural areas. This implies that more effort to promote PA may need to account for gender difference in access to resources and technology.

The educational level is categorized into three tiers. The average educational level is 0.9, which suggests that most farmers in the dataset have attained at least primary education. A higher educational level is typically associated with greater knowledge of and openness to technological advancements. The farming experience of the respondents ranged from 1 year to 49 years, with an average of 26.5 years. It implies that the data set includes both highly experienced and relatively new farmers. The standard deviation of 13.9 years indicates significant diversity in the number of years spent farming and this can influence the farmers' perception of PA.

The household sizes in the dataset range from 1 to 15 members, with an average size of 7.5 members. The variation is reflected in the standard deviation of 4.2, which suggests that while many households are moderately sized, there are a significant number of both smaller and larger households. This has a potential of impacting a farmer's economic status and adoption to PA practices.

The annual farm income of the respondents varies greatly, ranging from ₦10,000 to ₦200,000, with an average income of ₦107,000. The large standard deviation of ₦54,000 indicates that income levels differ widely among farmers and it may affect their ability to invest into modern farming technologies like PA.

Access to credit is binary, and the average value of 0.3 indicates that only about 30% of the farmers have access to credit. This limited access to credit could be a significant barrier to the adoption of PA, since it requires financial investment in technology and infrastructure. The farm sizes recorded in the dataset range from 1 to 20 plots, with an average of 10.5 plots. The relatively high standard deviation of 5.4 plots reflects considerable variability in the size of landholdings. Farmers with larger number plots might likely have more interest in PA technologies due to potential cost savings and efficiency benefits.

With a mean value of 0.4, approximately 40% of the farmers own farming machinery. This could serve as an important factor in the adoption of PA since farmers who already own basic equipment are likely to be more receptive to adopting advanced technologies. However, the lack of machinery ownership could pose a barrier for smaller farmers.

Awareness of precision farming shows a mean of 0.4, meaning that around 40% of the respondents are aware of PA. This indicates that there should be increased awareness campaigns, particularly targeting those who are not yet familiar with the concept. From the dataset, the farmers' access to digital tools, with a mean of 0.4, suggests that around 40% of the farmers have access to digital tools. This is a fairly positive sign, as access to such tools is crucial for the implementation of PA technologies, which often rely on digital data and software systems. Furthermore, 40% of the farmers have access to the internet. Since PA often relies on internet-based platforms and real-time data, this relatively low level of internet availability could hamper the adoption of PA among the farmers.

The LRM performed well in predicting farmers' perception of precision farming, as demonstrated by the ROC curve, which yielded an AUC value, indicating the model's ability to discriminate between positive and negative perceptions. Figure no 1 shows the ROC curve. The AUC score of 0.58 showed that the model has no discriminatory ability.

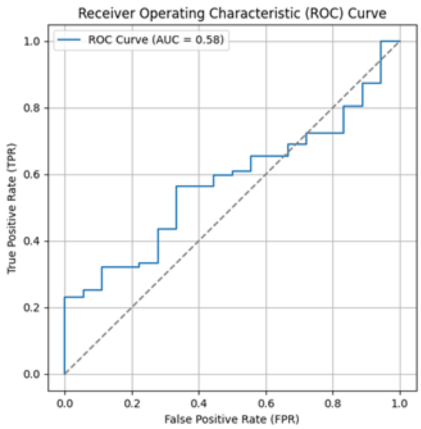

Figure no 1: Shows the receiver operating characteristic (ROC) curve

The LRM assigns coefficients to each feature based on their importance in predicting the outcome (positive or negative perception of PA). The magnitude and direction of these coefficients help us understand which factors have the most influence on the perception outcome. The coefficients were plotted as shown in Figure no 2 to visualize the feature importance, and from the analysis, the most influential features were gender, educational level, farming experience, household size, farm income, access to credit, farm size, and awareness of precision farming.

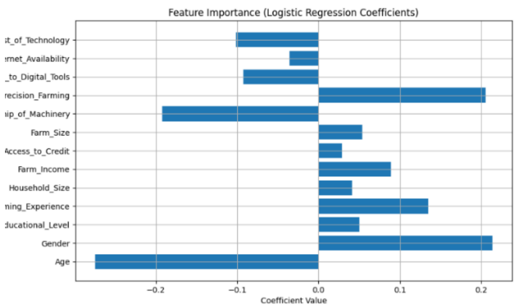

Figure no 2: Shows the feature importance (logistic regression coefficients)

The ROC curve complements the feature importance by demonstrating how well the model performs in differential between farmers with positive and negative perceptions based on these features.

These results suggest that policymakers and agricultural extension services should focus on increasing awareness and educational programs about precision agriculture, especially targeting farmers with smaller farms and lower levels of education.

The confusion matrix helped visualize the classification performance of the logistic regression model. With a relatively balanced dataset and accurate predictions, the confusion matrix revealed a higher number of true positives (TP) and true negatives (TN), showing that the model effectively distinguished between farmers with positive and negative perceptions. Figure no 3 shows the confusion matrix.

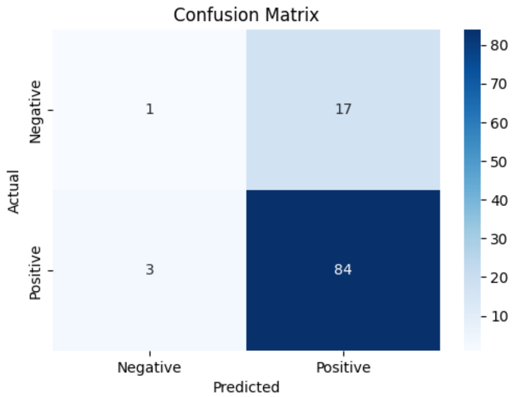

Figure no 3: Shows the confusion matrix

The matrix showed fewer false positives (FP) and false negatives (FN), meaning that while the model was not perfect, it was relatively successful at predicting farmers' perceptions. The few false negatives suggest that some farmers who were predicted to have a negative perception may still have a positive view, which indicates room for further improvement in the model or more detailed feature selection.

The model correctly predicted 1 case where the actual perception was negative (0) and the model also predicted it as negative. Also, there were 17 cases where the model predicted a positive perception (1), but in reality, the perception was negative (incorrect classification). The model predicted 3 cases as negative perceptions (0), but in reality, these farmers had a positive perception (incorrect classification). Finally, the model correctly predicted 84 cases where the actual perception was positive (1), and the model predicted it was positive. Proportion of correct predictions (both positive and negative) out of all predictions can be used to calculate the model's accuracy.

The model has an accuracy of 81.9%, which means it correctly classified 81.9% of the farmers' perceptions. The proportion of true positives out of all predicted positives determines the precision of the model. The precision is 83.3%, meaning that when the model predicts a positive perception, it's correct 83.3% of the time. A recall of 97.7% shows the model is highly effective at identifying farmers with a positive perception. The F1 score is 0.899, indicating a good balance between precision and recall. The FPR is quite high at 94.4%, meaning that the model frequently predicts positive perceptions where the actual perception is negative.

The results of this analysis have practical implications for the promotion and adoption of PA technologies. Since factors like gender, educational level, farming experience, household size, farm income, access to credit, farm size, and awareness of precision farming significantly impact perception, these elements can be strategically targeted by agricultural policymakers and industry stakeholders. Moreover, the results indicate that promoting awareness is key to adoption. Farmers who are more aware of PA and its benefits were shown to be more likely to adopt such technologies, emphasizing the importance of outreach programs to improve knowledge and understanding.

Despite the model's success, several challenges and limitations remain:

1. Data Quality and Availability: The dataset may have limitations in representing the full diversity of farmer types and communities. For instance, unobserved factors such as social influence or environmental conditions might affect farmers' perceptions but are not captured in the model.
2. Binary Perception Outcome: The perception outcome in this model is binary (0 for negative, 1 for positive), which simplifies the analysis. However, farmers' perceptions may be more nuanced, and future studies could benefit from using a multi-class model or a scale-based perception metric to capture a wider range of views.
3. Non-linear Relationships: Logistic regression is a linear model that may not capture more complex relationships between variables. Future work could explore more advanced machine learning models like random forests, support vector machines, or neural networks to improve prediction accuracy.

V. Conclusion

In conclusion, the logistic regression model developed for predicting farmer's perception of PA has an accuracy of 81.9%, with a high recall of 97.7% and a moderate precision of 83.3%. The model also has the ability to effectively identify positive perceptions, though it tends to over-predict positives, resulting in a high false positive rate. Despite this, the developed model has a strong potential for understanding the key factors influencing farmers' adoption of PA, such as gender, educational level, farming experience, household size, farm income, access to credit, farm size, and awareness of precision farming. Future work could focus on reducing the false positive rate to further improve the model's precision.

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