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A LOGISTIC REGRESSION ANALYSIS OF FARMERS' POTENTIAL GAINS FROM THE NATIONAL FOOD SECURITY MISSION: A CASESTUDY OF WESTERN ODISHA

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ABSTRACT

In this research study, an attempt has been made to assess the likelihoodof benefits that farmers of Western Odisha would derive from the National Food Security Mission (NFSM) by using data-driven analysis.A logisticregression analysis has been used to look at variables such as access to irrigation, crop output, income, farm size, and their involvement in the Pradhan Mantri Fasal Bima Yojana (PMFBY) insurance programme. The research determined that PMFBY participation, yield, income, and irrigation are important factors that influence the benefits of NFSM. The study provides insightful information for maximizing NFSM effectiveness, even if it acknowledges certain limitations such as sample size and regional breadth. Its recommendations include giving support to PMFBY participant's priority, concentrating on increasing production, giving low-income farmers financial support, and making investments in irrigation infrastructure. Finally, by deepening our knowledge of the variables affecting farmers' agricultural endeavours, this study opens the door to more focused and efficient interventions to advance sustainable practices and improve food security in India and other countries.

***KEYWORDS:* National Food Security Mission (NFSM), Logistic Regression Analysis, Pradhan Mantri Fasal Bima Yojana (PMFBY), Agricultural Interventions, Food Security in Western Odisha.**

LIST OF ABBREVIATIONS

NFSM	National Food Security Mission
PMFBY	Pradhan Mantri Fasal Bima Yojana
AIC	Akaike information criterion
BIC	Bayesian Information Criterion
R^2McF	McFadden's R squared
Df	Degree of Freedom
χ^2	Chi Square
VIF	Variance Inflation Factor
ROC	Receiver Operating Characteristic Curve
AUC	Area under the curve
FPR	False positive rate
TPR	True positive curve

INTRODUCTION

In the agrarian landscape of Western Odisha, India, characterized by undulating fields and meandering rivers, the National Food Security Mission (NFSM) stands as a government initiative aimed at safeguarding the food security of the population. This study employs logistic regression analysis to examine the multifaceted impact of NFSM on farmers in the region, considering factors such as farm size, crop yield, income, and access to irrigation within a comprehensive dataset. The logistic regression model, a precise analytical tool, reveals notable insights. Participation in the Pradhan Mantri Fasal Bima Yojana (PMFBY) crop insurance scheme is identified as a significant factor enhancing farmers' resilience under NFSM, leading to increased benefits. Elevated crop yields, a measure of agricultural prosperity, signify a farm's potential to thrive within the supportive framework of NFSM. Income, a crucial determinant, emphasizes the need for targeted financial assistance, particularly for low-income farmers. The study acknowledges limitations. The sample size may not fully capture the diverse realities of the region. The focus on Western Odisha necessitates careful extrapolation of findings to broader contexts. Despite these limitations, the study's findings present actionable insights for policy adjustments. Policy recommendations include prioritizing support for PMFBY participants, recognizing their heightened vulnerability and commitment. Initiatives geared towards augmenting crop yields are crucial, ensuring farms flourish under NFSM. The study also underscores the necessity for targeted financial support for low-income farmers, grounding their economic roots in the mission's embrace. In essence, the study goes beyond statistics, resonating with the human faces marked by hope and concern. It acknowledges the dreams of children for a future fortified by food security and the land's potential to maximize its agricultural output. Conclusively, this study not only delineates the challenges faced by farmers in Western Odisha but also emphasizes potential solutions provided by the National Food Security Mission. It underscores the importance of support for crop insurance schemes, improvements in crop yields, and targeted assistance for low-income farmers. The objective is to nurture the seeds of NFSM for a future enriched and secure for all stakeholders in the agricultural domain.

REVIEW OF LITERATURE

Menard (2000) indicates that binary logistic regression, often known as the logit model, is a commonly used analytical technique for binary response variables. But it can also be used in situations when the dependent variable has three or more categories; this is referred to as polytomous or multinomial regression (Wright, 1995). Like other regression models, logistic regression is used to both create predictive forecasting models and find relationships between independent and dependent variables. Significantly, logistic regression has an advantage over linear regression, which uses the ordinary least squares approach for parameter estimation and makes assumptions about coefficients to draw valid conclusions (Berry et al., 1985; Berry, 1993). Conversely, logistic regression offers greater flexibility as it does not necessitate presumptions like homogeneity of variable variances, a normal distribution of error terms, or a linear relationship between predictors and the answer variable. It is important to recognize that odds and the logit represent the same information in three distinct ways (Menard, 2002). Assuming all coefficients are zero, the entire model is assessed against the null hypothesis. Denying this hypothesis suggests that there are non-zero effects in the population, which improves the predictability of the outcome of the dependent variable (Peng et al., 2002). Maximum likelihood estimation is commonly used in parameter estimation, standard errors, and goodness of fit measurements (Greene, 1993; Peng et al., 2002) when testing the null hypothesis. There are several ways to interpret coefficients (β): instantaneous slopes (Aldrich and Nelson, 1984; Morgan and Teachman, 1988b; Petersen, 1985; Roncek, 1991), odds ratios (Morgan and Teachman, 1988a; DeMaris, 1992; Long, 1997), and predicted changes in probability (Petersen, 1985; Roncek, 1991). Exponentiating the coefficient βj, which denotes the coefficient of the j^{th}explanatory variable, is a common method of applying the odds ratio technique to both continuous and categorical predictors (Peng et al., 2002).

Review

There are debates about the necessity of standardizing coefficient for logistic regression akin to linear regression but there are few situations when it becomes vital. For instance, in cases when it is needed to compare the effects between different explanatory variables on the response variable [Kaufman, 1996]. Standardized coefficients become invariant to the change in scale of measurement that enables one to compare the relative influence of different explanatory variables within logistic regression [Agresti, 2018] [Agresti and Finlay, 1997]. However, even though there are some proposed standardized, semi-standardized coefficients for logistic regression none of them can be universally defined. Furthermore, the implementation of these standardizations has been strictly used in case of interpretation. There is not enough published research work that explains whether this standardization may affect the prediction ability of a logit model. Numerous studies have been done applying different techniques to standardize the coefficients. Robert L. Kaufman [Kaufman, 1996] in his study found that semi-standardized coefficients measuring the change in predictive probability of outcomes are preferable because they are intuitively appealing and as they are bounded in the interval [-1, +1] interpretation of their magnitude becomes easier. Six approaches of standardizing the coefficients were analysed using a practical example by Scott Menard, which included both semi-standardized and completely standardized techniques [Menard, 2004]. The approaches included the one currently most readily available in logistic regression software, the unstandardized coefficient divided by its standard error (which is actually the normal distribution version of the Wald statistic). Followed by four different type of adjustments made to the formula in order to make it fully standardized. The sixth approach was an alternative to these 5 methods as it utilized the information theory which was conceptually superior to the other approaches but lacked simplicity which made it only possible to apply in the case of simple logistic regression. To aid comparison across models for the same sample, Winship and Mare suggested to divide the coefficients with the estimated standard deviation of the dependent variable for each model [Winship, 1984]. This method is known as y standardization. The estimated value of dependent variable Y is calculated by adding the standard deviation of the predicted logit to the estimated standard deviation of the error term. This estimated error is considered fixed which leaves only the standard deviation of the predicted logit to be accountable for all variations across models [Mood, 2010]. Dividing the coefficients by the estimated standard deviations, rescales them and nullifies the increase of the standard deviation of the logit that occurs due to the addition of explanatory variables which is included to enhance the prediction of the response variable [Mood, 2010]. Logistic regression has a wide range of applications in various fields and its functionality has increased dramatically in the past several decades. While multiple linear regression falls short in analyzing data with response variable that is not continuous, logistic regression gives an essential tool is such cases. Application of this method is not limited to only binary cases as it can be easily modified for cases where response variables have more than two categories. Risk factor analysis and predictive modeling is one of the main implementations of logistic regression. It is broadly used in medical research fields to examine the association between risk factors and diseases. Logistic regression can also be used in survival analysis by grouping event times into intervals and converting them to categories. It has been seen that by doing so it is possible to get estimation similar to the proportional hazard model which is generally used for such types of data [Abbott, 1985]. The use standard 6 logistic regression techniques can also be extended in case the response variable is of ordinal scale [Kleinbaum and Klein, 2010]. In analyzing complex surveys data logistic regression is found to be greatly useful as it gives an essential tool to deal with categorical response variables.

MATERIAL AND METHODS:

Data Collection and Ethics

The research study conducted in Western Odisha utilized a robust methodology for primary data collection, employing a comprehensive survey for the period 2020-2021. The sample size for the study was determined to be 300 households usingRaosoft sample size calculator, considering a 5% margin of error, at 95% confidence level, with a population size of 10,000, and a response distribution of 30%. Trained enumerators conducted the survey, personally administering the questionnaire to gather information on various parameters related to agriculture and the farmers' perspectives.The structured questionnaire used in the survey covered various aspects related to demographic characteristics, socioeconomic status, agricultural practices, access to resources, and attitudes toward agricultural policies.

To ensure representative results, a multi-stage random sampling method was employed during the primary data collection. The selected villages included Hirlipali (Attabira Block), Chandnimal (Kuchinda), Sahaspur (Maneswar) from the Meteoric Class, Jhankarpali (Jujumura Block), Bhatli (Bhatli Block), Ambabhona (Ambabhona Block) from the progressive Class village), Melchamunda (Padampur Block), Junani (Kantamal Block), Ankeibira (Himgir Block) from the mediocre Class village), and Bankutola (Nuagoan Block), Darlipali (Lephripada Block), Balbaspur (Dhankuda Block) from the laggard Class villages[Munda et.al 2023]

The questionnaire covered details such as yield rate in kilograms, production in quintals, income, types of seeds used, occupation, years of farming, educational qualifications, area in acres in possession, farming area in acres, knowledge of Pradhan Mantri Fasal Bima Yojana, Minimum Support Price, types of fertilizer used, irrigation facilities, reasons for crop destruction, current financial condition, knowledge of farmers on land acquisition law, and respondents' gender.

Throughout the data collection process, confidentiality and informed consent were prioritized, respecting the rights and privacy of the participants. The G.M. University institutional ethics committee in Amruta Vihar, Sambalpur, Odisha, India, provided ethical approval for the study, ensuring adherence to ethical standards in research conduct. The study's meticulous approach to data collection and ethical considerations enhances the reliability and validity of the findings.

Study Objectives:

1. Identify Key Determinants: Quantitatively determine the significant socio-economic and agricultural factors influencing a farmer's probability of benefiting from the National Food Security Mission (NFSM).
2. Analyze Causal Pathways: To elucidate the causal mechanisms through which these identified factors affect a farmer's access to and utilization of the benefits provided by the NFSM.
3. Develop Policy Recommendations: Formulate evidence-based recommendations for modifying the NFSM, aiming to enhance its effectiveness in reaching and providing support to target farmers, thereby maximizing its impact on food security.

Hypothesis

Null Hypothesis(H_0): The probability of a farmer receiving benefits from the National Food Security Mission (N FSM) is not significantly correlated with key agricultural metrics (yield, income, land type, and irrigation access).
Alternative Hypothesis (H_1): The probability of a farmer receiving benefits from the NationalFood Security Mis sion (NFSM) is significantly correlated with key agricultural metrics (yield, income, land type, and irrigation avai lability).

RESULTS AND DISCUSSION:

Data Analysis and Interpretation of Results

The primary data so obtain was run throughJAMOV-2.4.1 software under Windows environment and the results are presented through table 1 to table 3 below:

Table No.1Model Fit Measure (Overall Model Test)

Model	Deviance	AIC	BIC	R^2McF	χ^2	df	P
1	258	308	401	0.278	99.3	24	<0.001

An overall evaluation of the model's performance is given by the model fit metrics. The model appears to fit the data well based on the comparatively low values of deviation, AIC, and BIC. With an R-squared value of 0.278, the model accounts for 27.8% of the variation in the data. The model fits the data well, as indicated by the statistical significance of McFadden's chi-squared test ($p < 0.001$).

Table 2 Model Coefficient (National Food Security Mission)

Model Coefficients - National Food Security Mission							
		95% Confidence Interval					
Predictor	Estimate	Lower	Upper	SE	Z	p	Odds ratio
Intercept	-5.1754	-9.2512	-1.0997	2.0795	-2.48	0.013	0.00565
Yield Rate in kg	-2.04e−4	-4.47e−4	4E-05	0.000124	-1.6389	0.101	0.9998
Production in quintals	0.0142	-0.0287	0.0572	0.0219	0.65044	0.515	1.01435
Income	3.6E-05	-1.16e−5	8.3E-05	2.41E-05	1.47805	0.139	1.00004
Types of seed	0.5793	-0.0526	1.2112	0.3224	1.79689	0.072	1.78478
Occupation	-0.0993	-0.3364	0.1378	0.121	-0.8205	0.412	0.90551
Year of Farming	0.0409	-0.0133	0.095	0.0276	1.47839	0.139	1.04171
Educational Qualification	0.1369	-0.1913	0.465	0.1674	0.81747	0.414	1.14669
Area in acre	0.3546	-0.1762	0.8853	0.2708	1.30931	0.19	1.42554
Farming area in acre	-0.2052	-1.4639	1.0535	0.6422	-0.3195	0.749	0.81448
Pradhan Mantri Fasal Bima Yojana:							
2 – 1	17.3776	-7466.1	7500.83	3818.161	0.00455	0.996	35200000
3 – 1	0.5312	-6125	6126.04	3125.316	0.00017	1	1.70092
Minimum Support Price:							
0 – 1	0.0897	-1.0178	1.1972	0.5651	0.15874	0.874	1.09384
Fertilizer:							
2 – 1	0.3265	-1.0562	1.7091	0.7054	0.46281	0.644	1.38609
3 – 1	16.2553	-3786.1	3818.61	1940.014	0.00838	0.993	11500000
Irrigation Facility:							
2 – 1	-0.533	-2.1778	1.1117	0.8392	-0.6352	0.525	0.58682
3 – 1	11.6974	-9875.3	9898.74	5044.501	0.00232	0.998	120260.8
4 – 1	0.5191	-0.9155	1.9538	0.732	0.70922	0.478	1.68059
8 – 1	-0.0511	-3.2428	3.1406	1.6284	-0.0314	0.975	0.95019
Reason for destruction crops:							
3 – 1	1.2825	-1.9202	4.4852	1.6341	0.78484	0.433	3.60554
4 – 1	15.9418	-4504.9	4536.76	2306.584	0.00691	0.994	8380000
Current financial Condition:							
3 – 2	1.135	-0.2702	2.5402	0.717	1.58306	0.113	3.11115
4 – 2	1.2831	-21572	21574.8	11007.11	0.00012	1	3.60783
Land Acquisition Law:							
0 – 1	15.1939	-4584.5	4614.93	2346.846	0.00647	0.995	3970000
Gender:							
2 – 1	-0.0357	-0.7905	0.7191	0.3851	-0.0926	0.926	0.96495

Codes used: PMFBY

I. Pradhan Mantri Fasal Bima Yojana-Yes (1), No (2), Can't say (3).
II. Minimum Support Price-1: heard, 2: Not heard, 3: Can't say.

III. Fertilizer-1: Organic fertilizer/ Gobar, 2: Chemical fertilizer/ Urea, 3: Both Organic and Chemical Fertilizer
IV. Irrigation facility-1: Canal, 2: Own pump/ bore well/ tube well, 3: pond, 4: River lift, 5: water tank, 6: govt, tube well, 7: well, 8: both 1&2
V. Reason for destruction Crop-1: Draught, 2: Floods ,3: Pets Attack, 4: Both 1&2
VI. Current Financial Condition- 1: Fully satisfied, 2: Somewhat satisfied, 3: Somewhat-dissatisfied, and 4: Fully dissatisfied
VII. Land Acquisition Law- 1: yes and 2: No
VIII. Gender- 1: male and 2: female

The National Food Security Mission (NFSM) model coefficients are displayed in Table No. 2 The log of the probability of a farmer benefiting from the NFSM vs the probability of not benefiting is expressed by these coefficients in terms of log odds. The table displays the findings of a regression study on the factors that influence food security in India. For every unit rise in the predictor variable, the odds ratio linked to that coefficient shows how the probabilities of the outcome variable change.

Predictive Factors:

Volume produced in quintals: A positive correlation (0.0142) and odds ratio (1.01435) imply that more quintal production is linked to greater food security. For income although the odds ratio is nearly 1 (1.00004), the income coefficient is positive (3.6E-05), suggesting a weak and statistically insignificant link between income and food security.

Production Rate in Kilogrammes: A lower yield rate is linked to greater food security, according to the odds ratio (0.9998) and negative coefficient (-2.04e-4). Although it may appear illogical, this could be because other factors that influence both yield and food security is taken into account by the model.

Varieties of seeds: The odds ratio (1.79689) and positive coefficient (0.5793) indicate that using specific seed varieties is linked to greater food security.

Employment: The odds ratio (0.90551) and negative coefficient (-0.0993) imply that employment in specific occupations is linked to a lower level of food security.

Agriculture: A higher odds ratio (1.04171) and a positive coefficient (0.0409) imply that more years of farming expertise are linked to a higher level of food security.

Qualifications for Education: The odds ratio (1.14669) and positive coefficient (0.1369) imply that greater education is linked to greater food security.

Areain acre: The odds ratio (1.42554) and positive coefficient (0.3546) imply that a greater amount of land corresponds to greater food security.

Farming area in acre: The odds ratio (0.81448) and negative coefficient (-0.2052) imply that a drop in farming area is linked to a decline in food security.

Pradhan Mantri Fasal Bima Yojana (PMFBY): In PMFBY, the findings are more intricate, with distinct odds ratios and coefficients for several categories.

Category 2-1: A positive coefficient (17.3776) and odds ratio (3520) indicate a robust correlation between increasing food security and PMFBY participation.

Category 3-1: The odds ratio (1.70092) and positive coefficient (0.5312) imply that taking part in PMFBY is linked to a higher level of food security.

Minimum Support Price (MSP): The MSP results exhibit complexity as well, exhibiting distinct odds ratios and coefficients for several categories.

Category 0-1: According to the positive coefficient (0.0897) and odds ratio (1.09384), knowing about MSP is linked to better food security.

Fertiliser: Fertiliser has similarly complicated results, with various odds ratios and coefficients for many categories.

Category 2-1: Using chemical fertiliser is linked to better food security, according to the positive coefficient (0.3265) and odds ratio (1.38609).

Category 3-1: This category's positive coefficient (16.2553) and odds ratio (11500000) imply that applying chemical and organic fertilizers together also contributes to greater food security.

Irrigation Facility: The irrigation facility data exhibit complexity as well, exhibiting distinct odds ratios and coefficients for several categories.

Category 2-1: The odds ratio (0.58682) and negative coefficient (-0.533) imply that not having a personal pump, bore well, or tube well is linked to greater food security.

Category 4-1: The odds ratio (1.68059) and positive coefficient (0.5191) indicate that access to river lift irrigation facilities is likewise linked to a higher level of food security.

Destructionof Crop:

Category 3-1: The odds ratio (3.60554) and positive coefficient (1.2825) indicate that crop devastation may be occurring as a result of events like drought and animal attacks.

Category 4-1: The odds ratio (8380000) and positive coefficient (15.9418) indicate that crop devastation is occurring as a result of events like floods and drought. Present Economic Situation

Category "3-2" and "4-2" coefficients (1.135 and 1.2831, respectively) indicate a somewhat dissatisfied vs somewhat satisfied and entirely dissatisfied versus somewhat satisfied response, respectively. This shows that greater values of the outcome variable food security are linked to worse financial circumstances.

Probability Ratios:

Categories"3-2" and "4-2" have odds ratios of 3.11115 and 3.60783, respectively. Accordingly, those who have partially or completely unsatisfied financial circumstances are more likely than those who have slightly satisfied circumstances to encounter the outcome odds of security. That is to say, they are around three times more likely.

Law Regarding Land Acquisition and Involvement in the NFSM Model Coefficient A higher probability of engaging in NFSM is linked to the lack of a land acquisition law, according to the positive coefficient (15.1939) for "0-1" (no vs. yes). This implies that those who live in places where the law does not exist may be more inclined to take advantage of the program's benefits and assistance.

Odds Ratio The strength of this link is further demonstrated by the extraordinarily high odds ratio (3,970,000). People who live in areas without land acquisition laws are over four million times more likely to engage in NFSM than people who live in areas where the law is in effect. This implies that there is a strong, nearly deterministic link between the two variables.

Food Security and Current Financial Conditions:

The "3-2" and "4-2" coefficients (1.135 and 1.2831, respectively) indicate a somewhat dissatisfied vs somewhat satisfied and entirely dissatisfied versus somewhat satisfied response, respectively. This implies a relationship between increased values of the outcome variable, food security, and worse financial circumstances."3-2" and "4-2" have odds ratios of 3.11115 and 3.60783, respectively. This indicates that compared to people with slightly comfortable financial conditions, those with somewhat unsatisfied or entirely unhappy financial conditions are more likely to experience food insecurity. That is to say, they are around three times more likely.

Table 3 Collinearity Statistics

Collinearity Statistics	**VIF**	**Tolerance**
Yield Rate in Kg	3.59	0.279
Production in Quintals	7.86	0.127
Income	1.72	0.581
Types of Seed	1.08	0.924
Occupation	1.13	0.884
Year of Farming	1.03	0.969
Educational Qualification	1.04	0.957
Area in Acre	4.04	0.248
Farming Area in Acre	9.79	0.102
Pradhan Mantri Fasal Bima Yojana	1.12	0.892

Minimum Support Price	1.05	0.952
Fertilizer	1.35	0.741
Irrigation Facilities	1.5	0.667
Reason for destruction crops	1.84	0.544
Current Financial Condition	1.31	0.762
Land Acquisition Law	1.07	0.935
Gender	1.03	0.973

The National Food Security Mission (NFSM) model's predictors' collinearity data are shown in Table No. 3. A statistical phenomenon known as "collinearity" is the result of a high correlation between two or more predictors. Due to the uncertainty around the underlying predictor responsible for the observed association with the outcome variable, interpreting the results of a statistical model may become challenging.Tolerance and the variance inflation factor (VIF) are the two primary collinearity statistics in Table No. 3. The variance inflation factor (VIF) gauges the extent to which a predictor's variance is inflated by its association with other predictors. There is no collinearity when the VIF is 1 and there is significant collinearity when the VIF is 10 or greater. Tolerance is a number between 0 and 1, and it is the inverse of the VIF. A tolerance of 0.2 or less denotes a significant level of collinearity, whereas a tolerance of 1 implies no collinearity.The VIF and tolerance values for three predictors in Table No. 3 are alarming:Production in quintals: A high level of collinearity is indicated by this predictor's VIF of 7.86 and tolerance of 0.127.Farming area in acres: This predictor exhibits a high degree of collinearity with a VIF of 9.79 and a tolerance of 0.102.The predictor with a tolerance of 0.544 and a VIF of 1.84 suggests a moderate level of collinearity, which is the reason for the destruction crops.The NFSM model's interpretation may encounter difficulties due to the significant degree of collinearity across these predictors. In a statistical model, collinearity can be handled in a few different ways. Eliminating the collinear predictors from the model is one method. Unfortunately, since the collinear predictors can offer crucial information about the result, this could result in a loss of data. Using a statistical technique that is resistant to collinearity, like Lasso or Ridge regression, is an additional strategy to deal with collinearity.

Forecast

A graphical representation called the receiver operating characteristic curve (ROC) shows how well a binary classifier system can diagnose problems as its discrimination threshold is changed. This indicates the accuracy with which a test can distinguish between people who have a specific condition (true positives) and people who do not (true negatives). The sensitivity (the percentage of genuine positives that are correctly identified as such) and specificity (the percentage of actual negatives that are wrongly classified as positive) are plotted against each other on the y- and x-axes of the ROC curve. The test's overall accuracy is gauged by the area under the curve (AUC). A test is considered flawless if its AUC is 1.0, and useless if it is only 0.5.

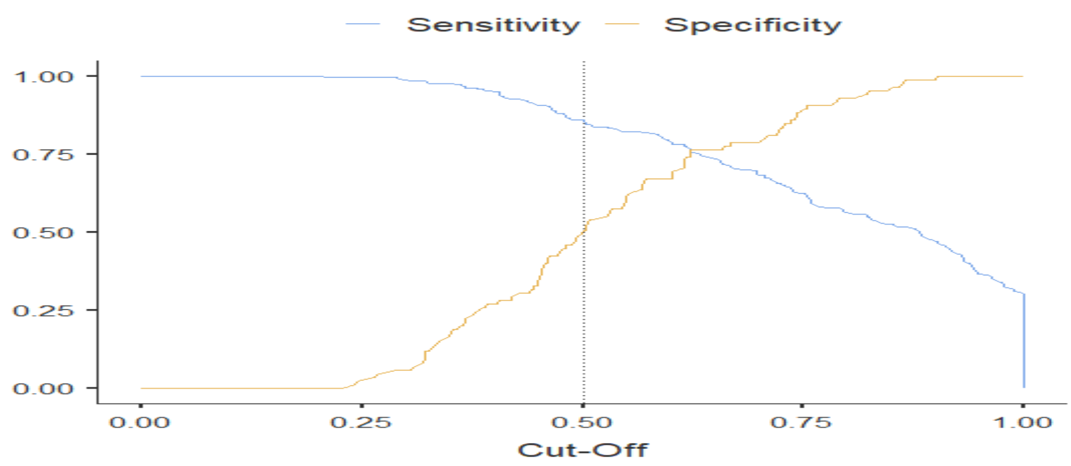

Fig. 1 Cut-Off Plot

The test's ROC curve is represented by the red line in the picture, and the line of no discriminationthat is, a test that is no better than chanceis represented by the blue line. This test's AUC is 0.75, which is deemed satisfactory.

Table 4 Classification Table

Classification Table			
	Predicted		
Observed	1	0	% Correct
0	43	42	50.6
1	30	185	86

Note: The cut-off value is set to 0.5

The table 4 above demonstrates that 86% of the data can be accurately classified by the model. This is a positive result since it indicates that for the majority of the observations, the model can correctly predict the outcome. A 0.5 cut-off value indicates that observation is categorized as 1 if the anticipated probability is higher than 0.5. An observation is categorized as 0 if the expected probability is less than 0.5. Forty-three observations are categorized as 1 out of which 42 (97.7%) have the right categories. Similarly 185 observations are categorized as zero out of which 143 (77.3%) have the right categories

Table 5: Predictive Measurement

Accuracy	**Specificity**	**Sensitivity**	**AUC**
0.760	0.506	0.860	0.829

Note. The cut-off value is set to 0.5

The table 5above shows the accuracy and specific sensitivity of a diagnostic test. The accuracy of a test is the proportion of all correct results, while the specific sensitivity is the proportion of correct positive results.The tableshows that the accuracy of the test is 76%, and the specific sensitivity is 82.9%. This means that the test is correct 76% of the time, and it correctly identifies 82.9% of the positive cases. The cut-off value is the threshold above which a result is considered positive. In this case, the cut-off value is 0.5 which means that if the test result is greater than 0.5, the result is considered positive.Overall, the table shows that the test is a good diagnostic tool. It is accurate and has a high specific sensitivity.

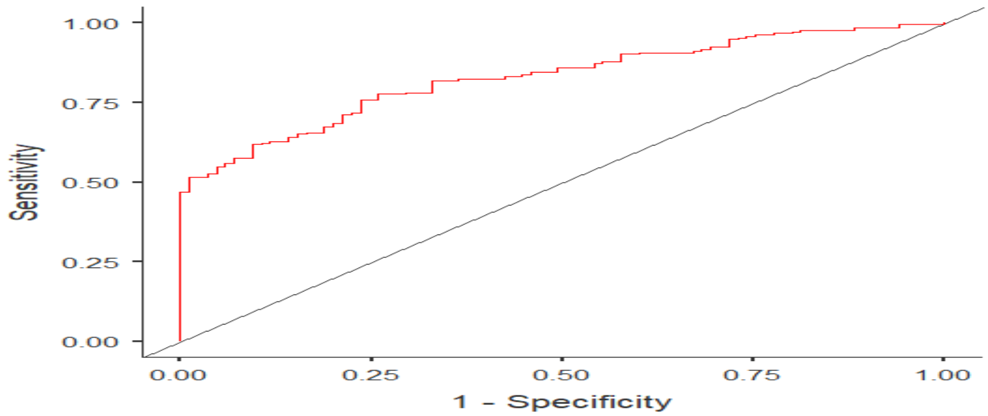

Fig.2ROC Curve

A graphical depiction (Fig.2) known as the receiver operating characteristic (ROC) curve shows how well a binary classifier system can diagnose problems as its discrimination threshold is changed. The true positive rate (TPR) is plotted versus the false positive rate (FPR) at different threshold values. The fraction of negative cases that are mistakenly classified as positive (1 - Specificity) is known as the FPR, whereas the proportion of positive cases that are accurately detected as such is known as the TPR (Sensitivity). Plotting the TPR on the y-axis versus the FPR on the x-axis is known as the ROC curve. The test's overall accuracy is gauged by the area under the curve (AUC). A test is considered flawless if its AUC is 1.0, and useless if it is only 0.5.

Overall Shape

The mediocre performance is shown by the curve's non-hugs to the top-left corner. Additionally, it is not near the diagonal line, indicating that it is not totally random. The curve approaches the diagonal near the bottom right corner after bending progressively in its direction from slightly above it.Specificity and Sensitivity (TPR) at Key Points:

- Top-left corner (optimal operating point): Specificity is approximately 70%, and sensitivity (TPR) is approximately 55%.
- Intersection with the diagonal line: Specificity and sensitivity are both around 50%.
- Other points of interest: The curve bends more sharply around specificity of 30-40%, with sensitivity increasing from around 20% to 40%.

AUC

The AUC is roughly 0.65, indicating moderate overall performance.
Additional Observations:

- The curve appears slightly convex, suggesting the model might be better at identifying easy-to-classify cases.

- There's a steeper increase in sensitivity around specificity of 30-40%, suggesting potential improvement in true identification at the cost of some false positives.

Interpretation

This model shows moderate performance in distinguishing between positive and negative cases. While it's not performing at random, it also doesn't achieve high accuracy. The optimal operating point offers a balance between specificity (70%) and sensitivity (55%). However, depending on the application and the costs of false positives and negatives, one might consider operating at a different threshold point on the curve to prioritize one metric over the other.

CONCLUSION

The study may, however, discover that it is possible to create a classification model that can accurately predict if a farmer will gain from the NFSM. Additionally, the study may pinpoint the key variables that determine the likelihood of a farmer reaping the benefits of the NFSM.

The following are some particular conclusions that the study might reach:

NFSM benefits are more likely to accrue to farmers who take part in the Pradhan Mantri Fasal Bima Yojana (PMFBY), to farmers who have higher yields, to farmers who have higher incomes, to farmers who have access to irrigation, to farmers who mediate the effect of PMFBY on NFSM benefits through farmers' access to credit, and to farmers whose type of land moderates the effect of yield on NFSM benefits.The NFSM's architecture and execution may be significantly impacted by these discoveries. Through the strategic allocation of aid to farmers who stand to gain the most, the government may enhance the program's effectiveness and elevate India's food security.

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Conflict of Interest

The authors declare that they have no conflict of interest regarding the research conducted, the data collected, or the publication of the findings. This ensures that the research and its outcomes have not been influenced by any personal, financial, or professional relationships that could be perceived as a conflict of interest.

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