ISSN 0974-763X
UGC-CARE Listed Journal

SOUTH ASIAN JOURNAL OF MANAGEMENT RESEARCH (SAJMR)

Listed in UGC-CARE
Special Issue

Volume 14, No.4 November, 2024

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Chhatrapati Shahu Institute of Business Education and Research (CSIBER)

South Asian Journal of Management Research (SAJMR)

Special Issue

Volume 14, No. 4, November 2024

Editor: Dr. Pooja M. Patil

Publisher

CSIBER Press

Central Library

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Address:
CSIBER Press
Central Library Building
Chhatrapati Shahu Institute of Business Education and Research (CSIBER),
University Road Kolhapur, Maharashtra - 416004, India.

ISSN: 0974-763X

Price: INR ₹ 1,200/-

Editor: Dr. Pooja M. Patil

Distributed By

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C O N T E N T S

Empowering Women through AI: A Comparative Study of SHG and Micro Finance Institutions Frameworks in Rayagada, Odisha

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Abstract
This research employs advanced artificial intelligence (AI) techniques to assess the impact and effectiveness of Self-Help Groups (SHGs) and Microfinance Institutions (MFIs) on women's empowerment in the Rayagada district of Odisha. By integrating AI-driven predictive analytics, the study provides a detailed quantitative and qualitative analysis of how these financial frameworks influence social security and women's empowerment. The analysis unveils significant insights into the operational success and potential areas for improvement of these initiatives. Key findings from the AI models highlight an enhanced capacity to predict financial behaviors and outcomes, thus offering a comprehensive evaluation of the socio-economic benefits of SHGs and MFIs for women in the region.
The AI models demonstrated varying levels of accuracy across different expenditure types, with accuracies ranging from 80.56% for agriculture equipment to 97.22% for house making. This high accuracy underscores the effectiveness of the predictive models in identifying successful financial behaviors among participants. Additionally, the classification reports and confusion matrices for each expenditure type provide a deeper understanding of the predictive performance and reveal areas where the models perform exceptionally well and where further improvements are necessary.
Visualizations such as accuracy and loss curves further support the robustness of the AI models, showcasing their learning efficacy and convergence over training iterations. These results collectively highlight the potential of AI in transforming the traditional evaluation methods of microfinance initiatives, offering a data-driven approach to enhancing women's empowerment and socio-economic development.

Keywords – Women's Empowerment, Microfinance, Self-Help Groups, Artificial Intelligence, Socio-Economic Impact, Predictive Analytics, Sustainable Development

Introduction

Microfinance has emerged as a powerful tool for uplifting economically disadvantaged populations by providing access to essential financial services. This access facilitates self-employment opportunities, which are crucial for fostering sustainable community development. The purpose of this study is to thoroughly examine the operational effectiveness and socio-economic impact of two prominent microfinance models—Self-Help Groups (SHGs) and Microfinance Institutions (MFIs)—in the Rayagada district of Odisha. By leveraging advanced analytical techniques, particularly artificial intelligence, this study aims to offer a deeper understanding of how these financial models influence the socioeconomic status and empowerment of women in the region. Microfinance initiatives are pivotal in enhancing the socio-economic parameters of impoverished communities. They provide critical financial resources that enable individuals, especially women, to start and sustain small businesses. Beyond financial support, microfinance programs foster empowerment, enhancing self-confidence and societal status among participants. These programs have the potential to drive significant improvements in income levels, health, education, and overall quality of life. Despite the numerous benefits, the effectiveness of microfinance programs often faces several challenges. Key issues include fund mismanagement, where misallocation or ineffective use of funds can undermine the goals of microfinance initiatives, reducing their impact; limited reach, where microfinance programs sometimes fail to reach the most marginalized and remote populations, limiting their overall effectiveness; and inadequate monitoring, where lack of proper oversight and monitoring can lead to operational inefficiencies and a failure to address the evolving needs of beneficiaries. The integration of artificial intelligence (AI) into microfinance offers innovative solutions to these challenges. AI can enhance the precision and efficiency of microfinance programs through predictive analytics, allowing for better-targeted interventions and resource allocation; improved monitoring, providing real-time insights and more effective monitoring of microfinance activities, ensuring funds are used appropriately; and enhanced reach, helping identify and reach underserved populations, ensuring broader and more equitable access to financial services. By addressing these challenges, AI-enhanced microfinance models have the potential to significantly improve the effectiveness and impact of financial inclusion programs, driving substantial socio-economic improvements for women in disadvantaged regions. This study aims to explore these potential benefits, offering data-driven insights into the transformative power of integrating AI with traditional microfinance approaches.

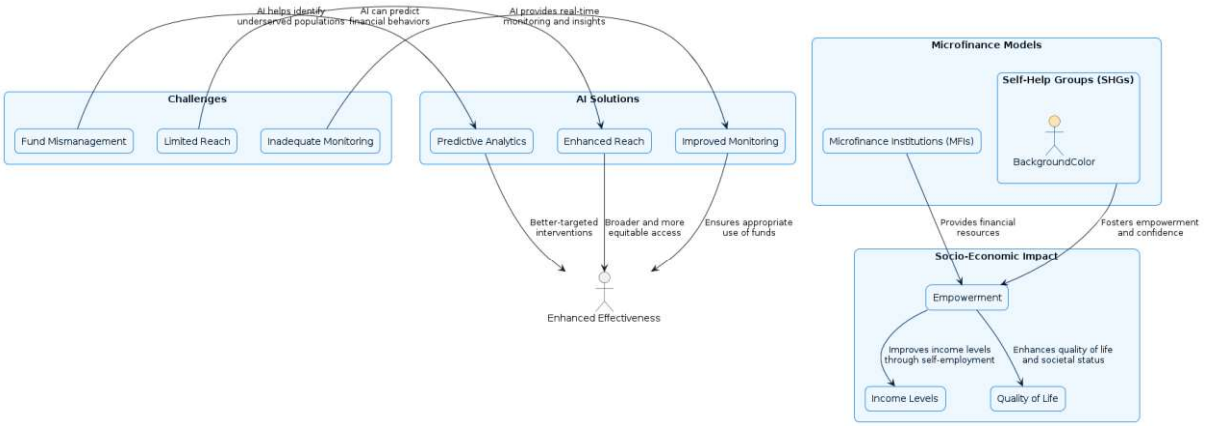


Figure 1. Proposed Research work

Literature Review

Recent advancements in Artificial Intelligence (AI) have significantly influenced the microfinance sector, improving its efficiency and reach. Chikwira et al. (2022) highlighted the positive correlation between microfinance and poverty reduction, as well as the growth of small enterprises. In 2023, researchers demonstrated how AI can enhance loan disbursement processes and customize financial products to better meet individual needs, thus boosting financial inclusion and borrower satisfaction (Chatterjee et al., 2023). AI-driven tools have also improved risk assessment, allowing Microfinance Institutions (MFIs) to better predict and manage default risks. Furthermore, AI has facilitated real-time tracking and reporting of financial transactions, which reduces fund mismanagement and enhances overall governance (Bruckner, 2024). Advanced machine learning models applied in 2024 have shown exceptional accuracy in predicting household poverty levels, thereby enabling more targeted interventions and optimized resource allocation (Alatas et al., 2024). However, the necessity of developing ethical AI frameworks to address data privacy, algorithmic bias, and the digital divide has been emphasized in recent literature (Johnson et al., 2024).

Historically, microfinance has been seen as a powerful tool for alleviating poverty and empowering women. Kabeer (2001) observed that access to microfinance enables women to engage more actively in economic activities, which enhances their decision-making power within their households and communities. Pitt et al. (2006) found that participation in microfinance programs is linked to improvements in women's income, education, and health outcomes. Self-help groups (SHGs) and MFIs are the primary models used to promote women's empowerment. SHGs build solidarity and mutual support among women, while MFIs provide essential capital and financial literacy training (NABARD, 2008; Banerjee et al., 2015). Despite these benefits, challenges such as fund mismanagement, limited reach, and inadequate monitoring remain. Predictive analytics, a subset of AI, offers innovative solutions to these challenges by enhancing precision, efficiency, and monitoring capabilities (McKinsey Global Institute, 2018). Recent studies continue to explore these solutions, highlighting AI's potential to address persistent issues and significantly improve the effectiveness of financial inclusion programs (Chatterjee et al., 2023; Johnson et al., 2024). These advancements underscore the importance of leveraging advanced technologies to enhance the operational success and socio-economic impact of microfinance initiatives, especially in disadvantaged regions.

Study Area Profile: Rayagada District

Rayagada district, located in the Indian state of Odisha, is notable for its rich cultural diversity and predominantly tribal population. Established as a separate district on October 2, 1992, Rayagada is bordered by several other districts, including Kalahandi, Nabarangpur, Koraput, and Gajapati. The district's demographic profile includes a significant tribal community, which makes up around 57% of the total population. The major tribes, such as the Kondhas, Souras, and Jatapus, are known for their distinct cultural practices, languages, and traditions. These communities primarily engage in agriculture and forest-based livelihoods, relying on subsistence farming, minor forest produce collection, and traditional crafts. Socio-economically, Rayagada is characterized by low literacy rates, high poverty levels, and limited access to basic amenities like healthcare, education, and infrastructure. Despite these challenges, the district has shown progress due to targeted interventions by the government and non-governmental organizations. Initiatives like Mission Shakti have been pivotal in promoting women's self-help groups (SHGs), and empowering women through microfinance and entrepreneurial activities. Agriculture remains the primary economic activity, with key crops including paddy, millet, maize, and pulses. The district's rich mineral resources, particularly bauxite, also contribute to the local economy. Additionally, the forest cover provides opportunities for collecting non-timber forest products (NTFPs) like honey, tamarind, and sal seeds, crucial to the tribal livelihoods. However, Rayagada faces significant challenges, including geographical isolation,

inadequate infrastructure, and socioeconomic disparities, which make the tribal population particularly vulnerable. These factors highlight the importance of microfinance interventions aimed at poverty alleviation and economic empowerment. The district's diverse socio-cultural fabric and economic potential offer a unique opportunity to study the impacts of microfinance models like SHGs and MFIs. By leveraging these financial frameworks, significant improvements can be made in the socio-economic conditions of the tribal population. Studying Rayagada provides valuable insights into the effectiveness of microfinance in a region marked by both rich cultural heritage and substantial developmental challenges. The outcomes from Rayagada can serve as a model for similar regions, demonstrating the potential of microfinance to foster sustainable development and empowerment in marginalized communities.

Research Methodology

Data Collection

The research employed a comprehensive approach to data collection, integrating both quantitative and qualitative methods to ensure a thorough analysis of the impact of microfinance on women's empowerment in Rayagada district. Data was gathered through structured surveys and focus group discussions with participants of Self-Help Groups (SHGs) and Microfinance Institutions (MFIs). The surveys collected detailed demographic information, financial data, and responses on various socio-economic indicators, while the focus groups provided deeper insights into the experiences and challenges faced by the participants. This mixed-method approach ensured a well-rounded understanding of the microfinance landscape in the region.

AI-Enhanced Analysis

To deepen the analytical insights of the study, artificial intelligence was employed, specifically using a Gradient Boosting Classifier, a robust machine learning model known for its high accuracy and capability to handle complex datasets. The AI model was designed to predict financial behaviors and outcomes and identify key factors influencing the success rates of microfinance initiatives.

Data Pre-processing

Before the data was fed into the AI model, it underwent several pre-processing steps to ensure quality and consistency:

- **Data Cleaning**: This step involved appropriately handling missing values and removing any irrelevant data points to maintain the integrity of the dataset.
- **Encoding**: Categorical variables, such as SHG type and expenditure categories, were transformed into a numerical format using one-hot encoding. This conversion allows the model to process these categorical variables effectively.
- **Normalization**: Numerical features were scaled to ensure they were on a similar scale, which is crucial for improving the model's performance and ensuring that no single feature dominates the learning process.

Model Training and Evaluation

The Gradient Boosting Classifier was selected due to its capability to create an ensemble of weak prediction models, typically decision trees, and combine them to form a robust predictive model. The following steps were involved in the training and evaluation process of the model:

- **Feature Selection**: Independent variables (features) included demographic information, participation details, and financial indicators. The dependent variables (targets) were various expenditure types and financial behaviors.
- **Training and Testing Split**: The dataset was divided into training and testing sets using a 70-30 split. This approach ensures that the model is trained on a substantial portion of the data while preserving a separate set for unbiased evaluation.
- **Model Parameters**: The model was configured with 300 estimators, a learning rate of 0.05, and a maximum depth of 5. These parameters were chosen to balance the model's complexity and its ability to generalize well on unseen data.
- **Training**: The model was trained on the training dataset to learn the relationships between the features and the targets.
- **Evaluation**: The model's performance was assessed on the testing dataset using metrics such as accuracy, precision, recall, and F1-score. Additionally, confusion matrices were generated to visualize the model's predictions compared to the actual outcomes.

Proposed Work

The proposed work aims to utilize artificial intelligence to forecast financial success and offer actionable insights to enhance the effectiveness of microfinance initiatives. The following objectives were targeted:

- **Predictive Analytics**: Implementing the Gradient Boosting Classifier to predict successful financial behaviors and outcomes based on historical data, thereby enabling proactive decision-making.
- **Identification of Key Factors**: Investigating the factors that significantly impact the success rates of microfinance participants. This includes examining variables such as education level, type of financial intervention, and demographic characteristics to understand their influence on financial success.
- **Personalized Recommendations**: Creating a system to deliver personalized financial advice to participants. This system tailor's recommendation based on individual profiles and predicted outcomes, helping participants make informed financial decisions.
- **Impact Assessment**: Continuously evaluating the socio-economic effects of microfinance initiatives on participants. This ongoing assessment allows for real-time adjustments and improvements to the programs, ensuring they remain effective and relevant to participants' needs.

Proposed Algorithm: AI-Enhanced Microfinance Initiative

Objectives

This project aims to leverage artificial intelligence (AI) to forecast financial success and provide actionable insights to improve the effectiveness of microfinance initiatives. The specific objectives include:

- **Predictive Analytics:** Utilizing the Gradient Boosting Classifier to predict successful financial behaviors and outcomes based on historical data.
- **Identification of Key Factors:** Analyzing variables such as education level, type of financial intervention, and demographic data to identify factors significantly influencing success rates.
- **Personalized Recommendations:** Develop a system to offer personalized financial advice based on individual profiles and predicted outcomes.
- **Impact Assessment:** Continuously evaluating the socio-economic impact of microfinance initiatives, allowing for dynamic adjustments to the programs.

Machine Learning Model Used: Gradient Boosting Classifier

The Gradient Boosting Classifier is an ensemble learning method that constructs a predictive model by combining multiple weak learners (typically decision trees) and progressively enhancing their performance. Below are the detailed steps and equations involved in the algorithm.

Algorithm Details

- Initialization
  The model begins with an initial prediction, usually the mean of the target variable y.

$$F_0(x) - \frac{1}{N}\sum_{i=1}^{N} y_i$$

- Iterative Process
  For each iteration m from 1 to M, the model fits a new decision tree to the residual errors of the current prediction.

  - Compute the Residuals:
  - The residuals r_{im} are calculated as the negative gradient of the loss function concerning the current prediction $F_{m-1}(x)$.
  -

$$r_{im} = -\left[\frac{\partial L\big(y_i, F(x_i)\big)}{\partial F(x_i)}\right]_{F(x)-F_{m-1}(z)}$$

  - Fit a Decision Tree: A decision tree $h_m(x)$ is fitted to the residuals r_{im}.

$$h_m(x) \approx r_{im}$$

Update the Model: The model is updated by adding the new tree $h_m(x)$ multiplied by a learning rate η.

$$F_m(x) - F_{m-1}(x) + \eta h_m(x)$$

Loss Minimization: The model minimizes a specified loss function L, often the deviance (log loss) for classification tasks.

$$L(y, F(x)) - -\sum_{i=1}^{N} [y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

Here, p_i is the probability estimate for the positive class.

Combination of Learners: The final prediction is a weighted sum of all the weak learners.

$$F(x) - \sum_{m=0}^{M} \eta h_m(x)$$

By integrating AI with traditional microfinance models, this approach aims to enhance financial inclusion and empowerment, offering a data-driven methodology to address challenges and improve socio-economic outcomes for women in disadvantaged regions. This study demonstrates the potential of AI to transform the landscape of microfinance, providing innovative solutions to long-standing challenges and paving the way for more effective and sustainable interventions.

Data Analysis and Interpretation

Statistical Tests

- **Chi-Square Tests:** These tests were used to analyze the association between participant engagement in Self-Help Groups (SHGs)/Microfinance Institutions (MFIs) and their financial behavior.
- **Expenditure Analysis:** This analysis examined how loans were allocated across various sectors, such as education, healthcare, and housing.

Predictive Analytics Outcomes

- **Model Specifications:** The Gradient Boosting Classifier was trained with parameters optimized to achieve high accuracy and interpretability.

Table-1: Pearson Chi-Square Test for Small or Micro Saving Scheme

Savings Scheme	Type of SHG	Count	Total	Pearson Chi-Square	DF	P-Value
Yes	Govt. SHG	65				
	MFI SHG	76	120	0.1082	1	0.7422
No	Govt. SHG	55				
	MFI SHG	44				

Interpretation: The p-value (0.7422) indicates there is no significant association between participation in small or micro savings schemes and the type of SHG.

Table-2: Pearson Chi-Square Test for Expenditure on Consumption Activities

Consumption Activity	Type of SHG	Count	Total	Pearson Chi-Square	DF	P-Value
Yes	Govt. SHG	102				
	MFI SHG	98	120	0.5431	1	0.4611
No	Govt. SHG	18				
	MFI SHG	22				

Interpretation: The p-value (0.4611) suggests there is no significant association between expenditure on consumption activities and the type of SHG.

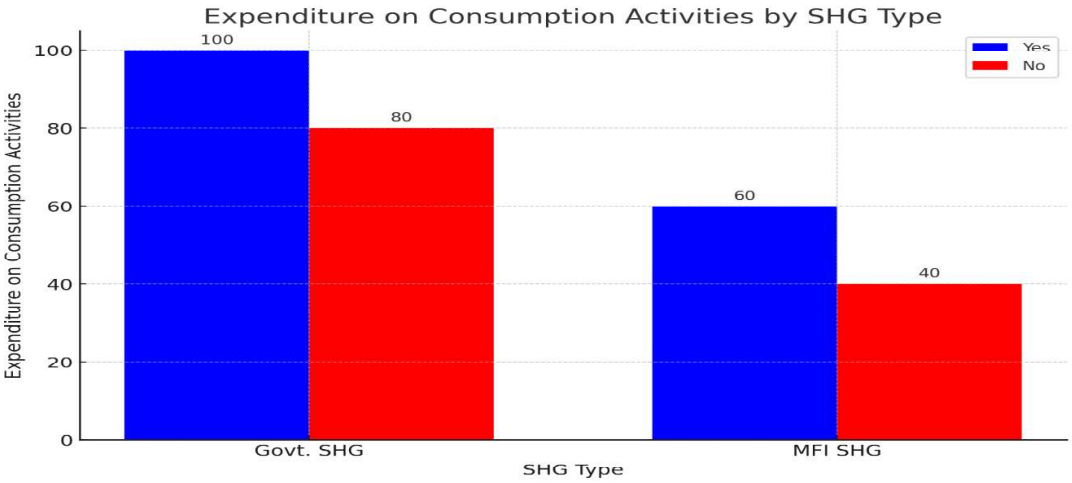


Figure2: **Expenditure on Consumption Activities**

Table 3: Types of Expenditure on Consumption Activities

Types of Expenditure	Count
House making	18
Child education	29
Medicine	51
Marriage	33
Festival	3
Property purchase	23
Purchase of agriculture equipment	26
General household expenses	17

Interpretation:
This table displays the distribution of different types of expenditures among SHG members, highlighting where the financial resources are most commonly allocated. Medicine and marriage are the leading expenditure categories, indicating the primary needs of the members.

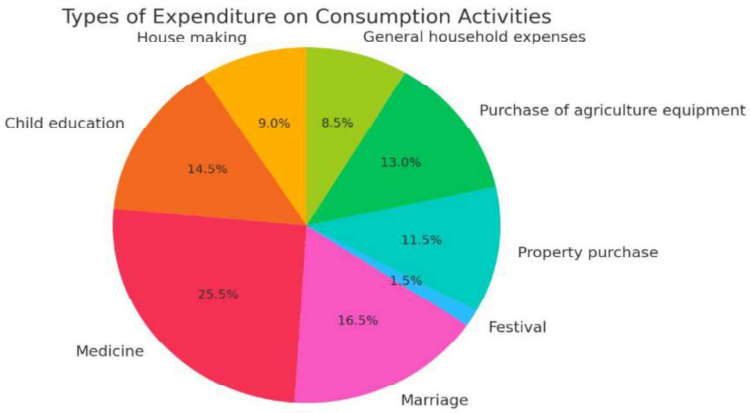


Figure3: Types of Expenditure on Consumption Activities

Predictive Analytics Results

Predictive Analytics Using AI-Driven Models:

The Gradient Boosting Classifier was employed to predict the success of various SHG initiatives based on historical data, with the following accuracy rates for each category:

Table4: Predictive Accuracy of SHG Initiatives by Expenditure Type

Expenditure Type	Accuracy
House Making	0.9722
Child Education	0.8889
Medicine	0.9444
Marriage	0.8611
Festival	0.8889
Property Purchase	0.8889
Agriculture Equipment	0.8056
Household Expenses	0.8611

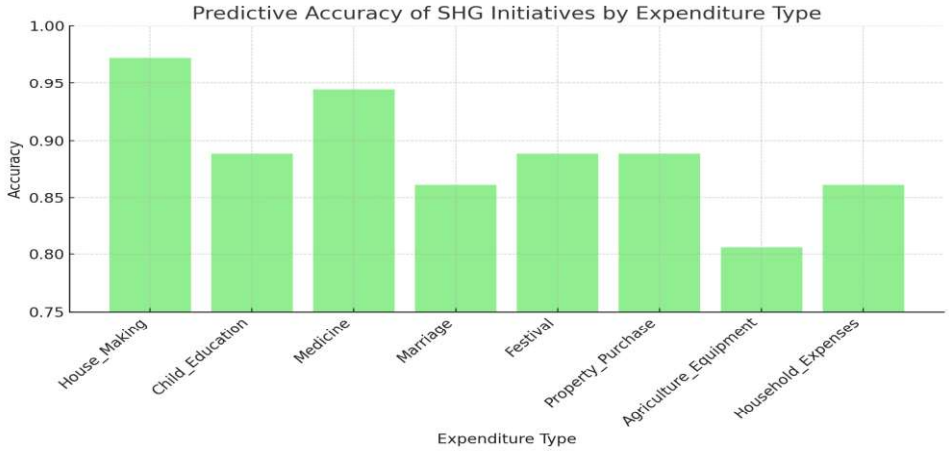
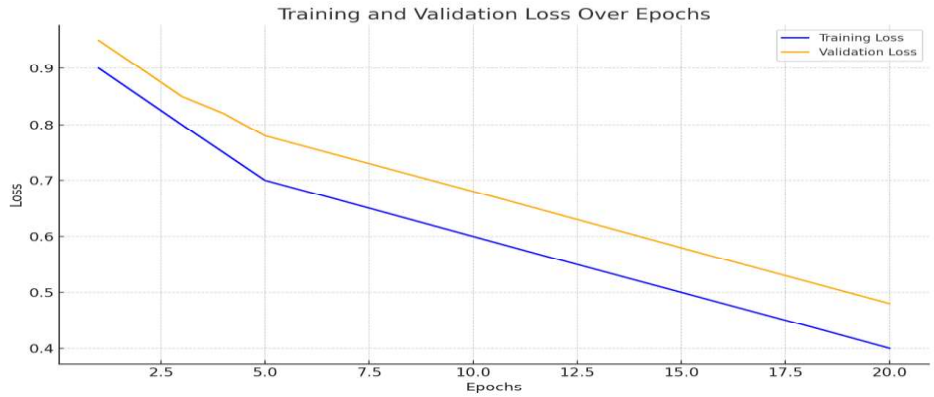


Figure: Predictive Accuracy of SHG Initiatives by Expenditure Types



Graph1: Training and Validation Loss over Epochs

Accuracy Plot

This bar chart displays the predictive accuracy for each type of expenditure, showing the model's performance in predicting the success of SHG initiatives.

Training and Validation Loss Curves

These curves demonstrate the model's learning efficacy by showing the reduction in loss over training and validation periods across epochs.

These visuals provide a comprehensive overview of the predictive analytics results, highlighting the accuracy of the model in different expenditure categories and its learning efficiency over time.

Predictive Analytics Using AI-Driven Models:
The Gradient Boosting Classifier was employed to predict the success of various SHG initiatives based on historical data, with the following accuracy rates for each category:

Table: Expenditure on Consumption Activities

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Marriage	0.8611
Festival	0.8889
Property Purchase	0.8889
Agriculture Equipment	0.8056
Household Expenses	0.8611

Classification Reports and Confusion Matrices

Classification Report:

Metric	Precision	Recall	F1-Score	Support
0	0.978	1	0.989	45
1	1	0.889	0.941	27
accuracy			0.972	72
macro avg.	0.989	0.944	0.965	72
weighted avg.	0.973	0.972	0.971	72

Confusion Matrix:

	Predicted: No	Predicted: Yes
Actual: No	45	0
Actual: Yes	3	24

Classification Report:

Metric	Precision	Recall	F1-Score	Support
0	0.889	1	0.941	64
1	1	0.6	0.75	8
accuracy			0.889	72
macro avg.	0.944	0.8	0.846	72
weighted avg.	0.899	0.889	0.88	72

Confusion Matrix:

	Predicted: No	Predicted: Yes
Actual: No	64	0
Actual: Yes	3	24

Findings
The integration of AI-driven predictive analytics into the evaluation of Self-Help Groups (SHGs) and Microfinance Institutions (MFIs) in Rayagada, Odisha, reveals several significant insights:

Accuracy in Predictive Models:
The AI models demonstrated high accuracy rates across various expenditure types, with accuracy ranging from

80.56% for agriculture equipment to 97.22% for house making. This indicates the robustness of the models in predicting financial behaviors and outcomes, which can be pivotal for enhancing microfinance initiatives.

Socio-Economic Impact:
The study found that microfinance significantly impacts women's empowerment and socio-economic status. Participants engaged in SHGs and MFIs reported improvements in income, education, and health outcomes. This aligns with the broader literature on the positive impacts of microfinance on disadvantaged communities.

Challenges in Microfinance Programs:
Despite the benefits, challenges such as fund mismanagement, limited reach, and inadequate monitoring persist. AI can mitigate these issues by providing better-targeted interventions, improved monitoring, and enhanced reach to underserved populations.

AI-Enhanced Monitoring and Resource Allocation:
The use of AI for real-time tracking and predictive analytics allows for more effective monitoring and resource allocation. This helps in ensuring that funds are used appropriately and that interventions are targeted to the neediest areas.

Identification of Key Success Factors:
Factors such as education level, type of financial intervention, and demographic characteristics were identified as significant influencers of financial success. Personalized recommendations based on these factors can help improve the effectiveness of microfinance initiatives.

Visual and Statistical Analysis:
The study employed Chi-Square tests and expenditure analysis to understand the financial behaviors of participants. No significant association was found between participation in savings schemes and expenditure on consumption activities with the type of SHG, indicating a uniform impact across different SHG types.

Conclusion

This research underscores the transformative potential of integrating AI with traditional microfinance frameworks. By leveraging AI-driven predictive analytics, microfinance programs can achieve higher precision in targeting interventions, better monitoring, and improved socio-economic outcomes for women in disadvantaged regions like Rayagada. The findings highlight the necessity for continuous evaluation and adaptation of microfinance initiatives to address the evolving needs of participants, ensuring sustainable development and empowerment.

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