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ARTIFICIAL INTELLIGENCE IN MICRO-FINANCE IN INDIA: THE KEY FOR SUSTAINABLE DEVELOPMENT

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ABSTRACT

The development of mobile and internet technologies has revolutionised every sector of the economy worldwide. Artificial intelligence has brought about the next wave of micro-finance revolution. Micro-finance has played a significant role in transforming lives of millions of households across the globe. The Micro-finance institutions (MFIs) are undergoing a digital transformation to save costs, determine credit worthiness of potential borrowers and risk. This conceptual paper focus on understanding how artificial intelligence is shaping the micro-finance sector in the 21st century. We review the literature to draw from different experiences of the micro-finance industry around the world and provides evidence from a Micro-finance Institution in Haryana, India. Both logistic regression and neural network (NN) methods was applied to the data of the MFI and results were compared. This article demonstrates how a credit scoring model can be applied for an India-based micro-finance company to estimate the relative importance of each factor involved in the probability of default. To identify the main causes of default by the micro-finance clients, a logistic regression model and Neural networks model was used and the latter was found to have better prediction power.

Keywords: *Artificial Intelligence, Micro-Finance, Machine Learning, Micro-Finance Institutions, Logistic Regression, Neural Network, Probability of Default.*

Introduction

The use of Artificial intelligence has become extremely popular in business worldwide, especially in the financial sector. Due to the gains in efficiency and productivity that it brings, it contributes to enhancing economic growth (Mokyr, 2018). As businesses operate in an increasingly challenging world with growing volatility, uncertainty, complexity, and ambiguity or more commonly referred to as the VUCA world, technological innovations including artificial intelligence are altering the way of running businesses (Millar et al., 2018). Artificial intelligence has revolutionised the financial sector which comprises of both the financial markets as well as financial institutions. AI “seeks to make computers do the sorts of things that minds can do” (Boden, 2018).

The penetration of credit in the rural credit is attracting attention due to the development of the rural market, which is very crucial for the growth of the developing economy like India. Inadequate access to formal channels of credit by banks, in particular for the poorest of poor, small farmers and women is a serious concern which needs to be resolved. Few groups of people are still underserved by financial institutions. Hence, there exist huge potential for digital techniques to determine the creditworthiness of borrowers in the rural setup. The credit scoring techniques used by most financial institutions are based on customer’s data, such as past borrowing habits, repayments etc. But owing to lack of documented credit histories, it becomes difficult for the customer to get credit. In such a situation, technologies based on artificial intelligence and machine learning can be of great assistance in determining the credit score,

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as it provides complete information about the borrower's income, employment and their ability to repay the loans in time. For the agricultural sector, the data required for credit reporting including characteristics of agricultural land, historical data and cash inflow forecasts is difficult to be found. Hence, credit scoring using artificial intelligence can aid lenders in assessment of the credit risk. The digital datasets related to agriculture include demographic data, agricultural surveys, weather forecasts, records of transactions, satellite images for productivity forecasting, calendars etc. With sufficient mobile and internet penetration and coverage, other data sources such as data from mobile operators, data gathered from mobile devices, transmission data, data from social media, etc., can also be made use of. Digital credit scoring can also provide competitive advantage to startups in the Fintech sector in identification and classifying rural farmers into various categories with speed and accuracy. The micro-finance sector has been updating itself using the latest technology to provide institutional credit to millions of poor people. Initially, starting with providing loans to financially excluded population, micro-finance services also includes micro-savings, insurance, fund transfer etc. There has been significant growth in the Fintech sector around the world since 2015 but in India limited growth of fintech industries can be attributed to lack of funds and ideas (Kandpal and Mehrotra 2019). In India, micro-finance is provided through General Commercial Banks (SCBs) which lend both directly and indirectly. The indirect credit is provided through corporate agents (BC) and self-help groups (SHG); cooperative Bank; non-banking financial companies (NBFCs) and NBFC-MFI (micro-finance institutions) and others. This paper is an attempt to explore the existing literature on how micro-financial institutions are embracing the different ML technologies. This study summarises the findings of different researchers in relation to supremacy of ML algorithm over traditional methods corresponding to credit scoring as well as choice within the existing ML techniques. The findings and recommendations of existing research work can help in identifying appropriate ML algorithms for credit assessment specifically for rural borrowers. This study can also help fintech startups, banking and non-banking financial institutions in India to develop more financially inclusive products.

Review of Literature and Motivation of the Study

Table 1: Key Findings Drawn from the Empirical Studies of the Reviewed Works of Literature in this Study

Author	Year	Country	Technique	Dataset/Variable Used	Key Findings/ Recommendations
Ampountolas et al	2021	Africa	Decision tree classifier Extra tree classifier k-NN classifier Random forest classifier Multilayer perceptron model XGBoost classifier Neural Network Adaboost classifier	Data on micro-loans from Innovative Microfinance Limited from January 2012 to July 2018	Tree-based ML algorithms perform better in credit scoring with the Random Forest classifier producing the most accurate prediction. They are also more affordable.
Petropoulos et al.	2018	Greece	Machine learning algorithm, called Boruta XG Boosting Deep neural networks logistic regression discriminant analysis methods	Dataset of loans for a 10 year period	XG Boost and Deep Neural networks provide better performance as compared to traditional methods for classificatory accuracy and credit rating.
Henry Ivan Condori-Alejo and et al.	2020	Peru	Logistic Regression k-Nearest Neighbour Random Forest Artificial Neural Network Decision Tree Support Vector Machine	Data collected from microfinance institutions in Peru	Artificial Neural Networks showed best performance over traditional techniques
J. Wu, S. Vadera, K. Dayson, D. Burridge and I. Clough	2010	Germany	Five data mining methods were examined including J48, K Means, EM, Naive Bayes and FReBE	ELM loan dataset and German credit dataset of subprime lenders	Decision tree emerges as the best performing technique for create risk assessment of subprime loans
Ozpinar and Birol	2016	-	Artificial Neural Networks	Custom dataset	ANN is continuously improving
Ghita Bennouna et al.	2018	Morocco	Fuzzy Logic	Micro-finance institutions in Morocco	Used for classification of borrowers into low risk, medium risk and high risk
Sofie De Cnudde et al.	2019	Phillipines	Social Network Analysis Support Vector Model	Meta data including the socio-demographic data, Interests data and Social Networks data	Model using interest data did not perform significantly worse than model using all data from facebook

Awoin et al.	2020	Ghana	Decision tree algorithms	Dataset of Rural Banks of Ghana	One of the algorithms C5.0 had 100 % accuracy , others has accuracy of around 84%
Ifft et al.	2018	USA	Gaussian Naive Bayes and traditional techniques	Agricultural resource management survey	Many machine learning models have higher predictive power organ standard econometrics techniques

One of the biggest issue with the micro-finance sector in India is the non-performing assets. Therefore, micro-finance institutions need efficient credit scoring techniques so that they can achieve higher repayment rates and volume of credit for greater financial inclusion. Many MFIs are leveraging artificial intelligence to achieve speedy credit disbursements. The traditional financial institutions use traditional methods for credit scoring mainly the 5 Cs of “character, capacity, collateral, capital, and conditions” (Kumar et al, 2021). However, this method fails for those borrowers who do not have documented credit histories or involve in limited transactions. Also, these techniques do not predict the probability of default. As a result, banks and MFIs resort to digital techniques of credit scoring by either establishing their own credit scoring methods or by taking help of third party services. In digital credit scoring methods, there are two distinct lines that branch between models like the standard econometric models and those based on ML.

It can be concluded from the few selected studies of reviewed literature covering micro-finance institutions worldwide and their credit scoring techniques that machine learning techniques are being increasingly used in the Micro-finance sector for classification of loans as well as determining the credit worthiness of the borrowers (Table 1). The literature review suggests that machine learning algorithms achieve better accuracy and precision than traditional methods, however, it is always not the case. Machine learning techniques have an edge over traditional methods because they can make use of “big data” to make predictions. However, the best model (whether traditional or machine learning) for a given situation depends on factors like data availability and adequacy, computing power, and objectives of the research (Kumar et al). As far as machine learning techniques is concerned, ANNs have become a significant tool in predictive analytics and is primarily used in data science classification.

Artificial Intelligence, Machine Learning and Deep Learning in Micro-Finance

Socially responsible investment in micro-finance must be balanced with risk. Advanced technologies in the field of micro-finance include MIS (management information systems), mobile banking and online lending. Later, there has been work on information systems to achieve operational excellence. There has also been use of crowd-lending in giving credit to the poor.

- **Uses Data to Determine Credit Worthiness and Risk:** Micro-finance targets population which has limited access to banks, due to which previous data is not available. Technology can help in assessment of credit-worthiness and riskiness of potential borrowers even without credit histories. For example, a NBFC-MFI launched a “Swadhaar Saathi Money Management and Financial Education App”. This app aids in financial education of women from their homes and help them learn to record their income and expenses on their devices, which helps lenders make transactions and decide whether to lend. The problem of information asymmetry can be resolved by using credit scoring models to assess risk in extending loans to the poor through micro-finance institutions whose objective has been financial inclusion and upliftment of the poor (Bumacov et al., 2014). To make an assessment of credit-worthiness of the new borrowers various online credit scoring platforms are being developed which use social data to determine whether a potential borrower is risky or safe. This includes analysis of their location, market conditions, purchase behaviour etc. The use of mobile banking replaces the cash with the digital transactions , the latter becoming huge source of data. These data helps the micro-finance institutions to make a better assessment of the riskiness of the potential borrowers and therefore, help in management of risk. The micro-finance institutions are also using face recognition and biometrics technology to detect multiple loans/accounts by the same person. What we really need is a different interface for the micro-finance borrowers other than PayTM or M-Pesa which can intelligently communicate orally.
- **Cost Saving:** The problem of high transaction costs can be dealt with mobile banking by reducing the transactions costs of lending to the poor. There is no paperwork involved, reducing the cost considerably. Due to the repetitive nature of the task, AI in micro-finance helps in

lowering operational costs. It also helps in business expansion enabling higher efficiency and accuracy in its operations.

- **Prediction of Future:** Using historical data, artificial intelligence helps in predicting the future which can thereby improve the decision making ability of the companies better regarding lending, insurance payments and remittances. For instance, by predicting the monsoons, the micro-finance firms can determine the credit-worthiness of the agricultural borrowers as their incomes are strongly correlated with agricultural incomes.

Credit Scoring

Credit scoring refers to "the process of evaluating an individual's creditworthiness that reflects the level of credit risk and determines whether an application of the individual should be approved or declined" (Thomas et al. 2017). The use of technology in credit scoring and other operations/processes is limited for micro-finance institutions. For unbanked population, due to the absence of credit history, early studies employed logistic or linear regression in determining micro-lending scoring rates (Provenzano et al. 2020). However, studies establish that machine learning techniques can provide better credit score assessment (Provenzano et al., 2020; Petropoulos et al. ,2019).

There are many machine -learning algorithms for dealing with credit risk in micro lending. Adaptive Boosting (AdaBoost) is an ensemble algorithm used by Freund and Schapire (1997) which involves training and deploying trees in time series. Chen and Guestrin (2016) proposed the XGBoost (extreme gradient boosting method) boosting tree algorithm which is one of the most extensively and effectively used machine learning method. It is superior method as it reduces variance and bias both. Variance is reduced due to use of multiple models while bias is reduced because each subsequent model is trained using the residuals from the previous models. Decision tree classifiers involves making a tree flow (like a progress graph), with a tree- like structure made up of nodes. Based on the data set used, the decision tree classifier makes a detailed decision-making. The random forest classifier (Breiman, 2001) is a frequently used ensemble learning technique used in different academic disciplines. It is called Forest classifier because it is based on random generation of a number of classification trees. The process is based on decision trees iteratively performed so that in each iteration, by way of bootstrap a random sub-sample from the selected features gets selected from the dataset. The prediction from each tree is obtained by entering the input and thereafter all the predictions are aggregated. The extremely randomized trees classifier (or extra trees classifier) establishes a set of decision trees using a top-down approach (Geurts et al., 2006). Artificial Neural Networks (ANNs) are very popular and have many layers inspired by the human mind.

Micro-finance institutions can use the 5 Cs model of credit scoring but there could be serious faults in assessment of the probability of default if any of the Cs is not properly analysed. The discriminant analyses was subsequently used in 1966 followed by logistic regression as it fulfilled the Basel II requirements. In 1970s, K nearest method for credit scoring was introduced followed by use of Artificial Neural Networks (ANN) since 1990s. The hybrid model is at the present the most popular method of credit scoring.

Objective of the Study

There is a dearth of empirical studies on artificial intelligence in micro-finance in India. Using primary data collected from an MFI in Haryana, we attempt to bridge this gap by evaluating the relative efficiency of the logistic regression and Neural Network model to estimate default by the micro-finance clients.

Additionally, some of the important questions answered are:

- Which key variables are highly predictive of loan defaults in micro-finance?
- How effectively can logistic regression methods be used for this purpose?
- Can we use a Neural Network Model to check its predictive accuracy?
- Apart from identifying the most important variables in predicting default, can we rank these factors in terms of their relative importance?

Data and Methodology

Primary data was collected of an MFI in Haryana whose mission is to provide microcredit to people who cannot obtain loans through traditional banking channels. An alternative funding source in this case is a private moneylender, whose interest rates range from about 30% to 100%. The MFI's mission is to transparently provide financing to these customers at a reasonable cost while seeking an acceptable return on investment to ensure commercial viability.

Logistic regression (or logit model), oft used for predictive analytics is used to model a causal relation between a binary dependent variable and independent variables which can be continuous, categorical, or both. The binary variable is categorical taking a value of 0 or 1 which represents the occurrence or non-occurrence of an event. Logistic regression is widely used for credit scoring models in the financial services industry (Agbemava, 2016, Frolov, 2023). Logit regression is considered better than an ordinary linear regression since the dependent variable is a categorical which is default or no default on the micro-finance loan. The model was used, therefore, depending on the data and purpose of study.

Neural networks are universal approximations and very powerful predictive analytics tools. If the main objective of research is hypothesis testing, then traditional and well-established statistical modelling should be used. However, if prediction is the main goal then neural networks is a preferred statistical modelling technique whose results are more accurate than the statistical regression modelling. The NN model, however, has a shortcoming since it cannot aid in finding an equation representing the relationship between the dependent and independent variables, due to presence of multiple layers. The key objective of this article is to identify the main independent variables which determines whether the micro-finance clients defaults or not as well as to find the relative advantages of using NN and logistic regression techniques in credit risk modelling.

Most micro-finance institutions (MFIs) have a way of making decisions about lending to individuals which is typically mostly speculative and mostly evidence-based (for instance, information is taken from credit bureau) based on experience with previous decisions other than objective analysis. There has been debate over the years about which method is the most effective. The purpose of this study is therefore to identify the risk factors that influence the credit default of customers in the micro-finance sector and to develop a model that links these factors to the credit default of each customer in the sector. We identify 10 variables relevant to prediction of the credit risk based on extensive discussions with organisation. These are age, monthly expenditure , duration of stay in the house , total number of family members, requested loan amount, total household income , toilet in own house, house type, religion and caste. The MFI does not use any modelling techniques such as the logistic regression or neural network to predict credit risk.

A sample size of 600 customers, including 520 good (non-default) and 80 bad (default) accounts, was selected from the company's database to model default behaviour. Logistic regression and multi-layer perceptron (MLP)-based neural networks model was used for credit defaults to classify in terms of prediction and reality, and to find out the relative importance of independent variables in influencing default by the clients. SPSS software was used to obtain the results of logistic regression and NN (MLP).

Findings

- **Discussion of Results from Logistic Regression Model**

Our results show an overall good predictive accuracy of 89 percent for the logistic regression model for correct classification (Table 1). Of the 520 true cases that belonged to "not overdue” category, the model incorrectly predicted only 5% of the total sample size as “overdue” which amounts to 30. This is called a Type I error i.e percentage of total “not overdue” cases which are incorrectly predicted to be “overdue”. Of the 80 cases in the "overdue" category observed in the real data, the model incorrectly predicted 27 as "not overdue” which corresponds to 33.7 percent of the total sample. The error committed in incorrectly predicting the cases to belong to the “ not overdue” category when actually they belong to the “overdue” category is called a type II error. We can see that the overall prediction accuracy is satisfactory (89 percent) as the error for type II is large, but the model was unable to find a good balance between type I and type II.

Table 1: Logistic Regression Results

	Predicted			
		Overdue		Percentage Correct
Observed		No	Yes	
Overdue	No	490	30	95
	Yes	27	53	66.3
Overall percentage				89

Source: SPSS Output

Our analysis shows that duration of stay in the house, total household income, amount of credit required, and monthly expenditure are by far the most important predictors of credit default based on the 5% level . The following points are worth noting:

- The variables of type of house and age are significant at 5%, suggesting they are are important in assessing default behaviour of the borrower.
- Caste is found to be a very important predictor of default at the 5% level of significance.
- The number of family members is moderately significant as a predictor of default.
- The duration of stay in the household (indicator of employment), Household income, Number of family members, Monthly expenditure, Type of house, and Caste are found to be good predictors of loan delinquency.
- The loan amount demanded by the client is also an important risk predictor.

- **Discussion of results from Neural Network Model**

NN model was found to have performed better than the logistic regression in predicting the credit default with the prediction accuracy of about 93 percent on the training sample and 94 percent on the test sample. The type I error is smaller than the logistic regression on both the training data (2 percent) and test data (4 percent). The type II error is significantly lower than logistic regression on both training data (22 percent) and test data (15 percent). Figure 1 shows the relative importance of independent variables in influencing default and we find that household income (24.53%), monthly expenditure (13.26%), duration of stay (10.31%) are the most important predictors. Together, these variable carry a normalised importance of 48 percent as these strongly linked to the financial status of the client. The variables age (9.73%), type of house (9.14%), loan amount (8.1%), caste (7.03%), size of family (6.9%), type of toilet (6.1%), And religion (4.9%) are the other predictors. It is not possible to fully address the deficiencies of NNs in terms of the exact form of the explanatory variables and equations, so we are limited to logistic regression models for predicting loan defaults.

Table 2: Neural Networks Model Results

Sample	Observed	Predicted		
		No	Yes	Percentage Correct
Training	No	339	7	98
	Yes	12	44	78
	Overall Percent			92.8
Testing	No	167	7	96
	Yes	4	20	85
	Overall Percent			93.6

Source: SPSS Output

We combine the results of both logistic regression and NN to list the main predictors of credit risk namely duration of stay, Household income, amount of credit demanded, monthly expenditure, age of the client, type of house, Family size, caste, and access to toilet.

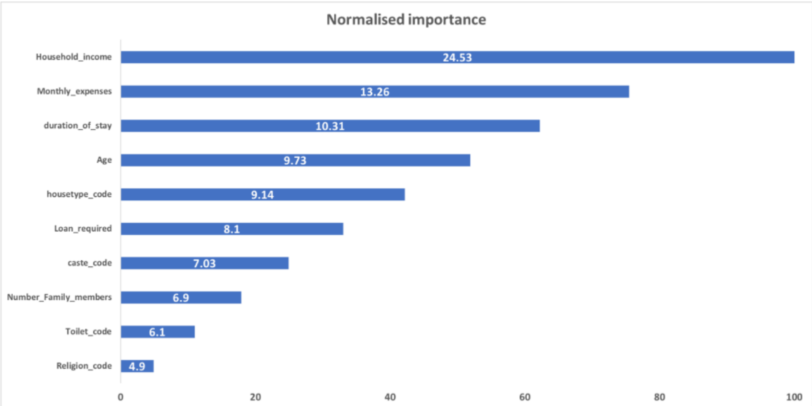

Figure 1: Relative Importance of Variables

Source: Based on Author's own calculations

Conclusions and Recommendations

Financial inclusion plays a crucial role in the economic development of any nation. The advent of Micro-finance in the 1990s was revolutionary as it provided access to institutional sources of credit to the unbanked population in the rural sector. But this sector is plagued by high non-performing assets due to which they have to resort to credit score assessment of the borrowers, especially the who do not have documented credit histories. With small and marginal famers having the highest proportion in the agricultural sector leading to vast fragmented farm data, AI-ML based credit scoring is the future. Micro-finance institutions can achieve greater credit penetration by integrating machine learning algorithms for credit scoring. This survey provides an overview of existing research on the benefits of different machine learning algorithms in different micro-finance contexts. Several studies have shown that tree-based algorithms such as decision tree algorithms and adaboost prove powerful in contexts where data sets tend to have many categorical variables. It also turns out that the existing microfinance space deals with information asymmetries and a lot of human contact (as decisions are made by lenders, who have strong opinions as they have primary knowledge of rural environments), these elements can be incorporated into machine learning systems by implementing fuzzy logic which is more intuitive in nature. Additionally, studies have shown that social media data analysis can also help create predictive models for rural environments where mobile and mobile apps penetration is already present. Finally, several research methods have also explored deep learning models such as artificial neural networks (ANNs) to predict microcredit scores.

In this research article, we have successfully demonstrated the power of an India-based micro-finance company's credit scoring model in terms of predicting the probability of default. Additionally, we were able to determine the relative importance of individual factors. The study clearly demonstrates the advantages and limitations of logistic regression and Neural Network in relation to the predictive power of modelling the credit risk in loaning micro finance. NN performs significantly better than logistic regression in predicting the credit default behaviour. However, it is not possible to fully address the deficiencies of NNs in terms of the exact form of the explanatory variables and equations, so we restrict ourselves to logistic regression models for predicting loan defaults. The main factors for loan delinquency by integrating logistic regression and NN are duration of stay, Household income, amount of credit demanded, monthly expenditure, age of the client, type of house, Family size, caste, and access to toilet. While each of these analytical models is not a substitute for existing credit scoring models based on ratings in the micro-finance sector, they can serve as a critical decision-support tool to help you assess the lowest credit risk increase.

There is a need to develop mechanisms for better credit scoring and quick decision making in the micro-finance sector and also enable the adoption of these techniques by the MFIs. Moreover, Intelligent and automated customer support can be leveraged to improve efficiency in micro-finance initiatives. Oral intelligent technologies can be used to overcome the barrier of illiteracy in the application of AI in the micro-finance sector. For instance, mobile phones can combine the photographs of currency along with the voice communication to enable illiterate user to comprehend it. The focus should be “Learning how to learn” if AI is to have a future in the financial sector. There are also ethical and emotional concerns in production and use of AI products and therefore we recommend educational institutions to prepare students to be agile and adaptable as well as diverse set of researchers to work on AI. The real challenge for MFIs is to integrate the recent AI-ML based with traditional methods and implement them at the ground level.

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