Review

Machine Learning (ML) Technologies for Digital Credit Scoring in Rural Finance: A Literature Review

Anil Kumar [1,*] , **Suneel Sharma** [2] and **Mehregan Mahdavi** [3]

1   Doctor of Business Administration (DBA), SP Jain School of Global Management, Mumbai 400070, Maharashtra, India
2   SkyzHotech Solutions Pvt. Ltd., Bengaluru 560102, India; suneel@skyzhot.com
3   Sydney International School of Technology and Commerce (SISTC), Sydney, NSW 2000, Australia; mehregan.m@sistc.nsw.edu.au
*   Correspondence: anil.dm20dba016@spjain.org; Tel.: +91-9109370270

Abstract: Rural credit is one of the most critical inputs for farm production across the globe. Despite so many advances in digitalization in emerging and developing economies, still a large part of society like small farm holders, rural youth, and women farmers are untouched by the mainstream of banking transactions. Machine learning-based technology is giving a new hope to these individuals. However, it is the banking or non-banking institutions that decide how they will adopt this advanced technology, to have reduced human biases in loan decision making. Therefore, the scope of this study is to highlight the various AI-ML- based methods for credit scoring and their gaps currently in practice by banking or non-banking institutions. For this study, systematic literature review methods have been applied; existing research articles have been empirically reviewed with an attempt to identify and compare the best fit AI-ML-based model adopted by various financial institutions worldwide. The main purpose of this study is to present the various ML algorithms highlighted by earlier researchers that could be fit for a credit assessment of rural borrowers, particularly those who have no or inadequate loan history. However, it would be interesting to recognize further how the financial institutions could be able to blend the traditional and digital methods successfully without any ethical challenges.

Keywords: machine learning (ML); artificial intelligence (AI); digital credit scoring; rural finance; credit score; micro lending

1. Introduction

Credit penetration among the farming community is gaining attention because of the development of rural markets, recognizing it as a growth engine for an emerging economy like India. Banking accessibility particularly for the poorer households, smallholder farmers, and individual women farmers is still by far a concern and needs to be addressed. These are a few defined groups of people who are probably still unserved or underserved by the existing banking or financial institutions. Therefore, the requirement of digital channels for credit scoring to know the creditworthiness of the rural borrowers is extremely crucial. Most of the financial institutions developed their credit scoring approach based on the customer's historical data, previous borrowing habits, and so forth. In the absence of any historical data for bank finance, these kinds of customers in particular or any new banking customers have to face all the difficulties to get credit from any of the formal banking institutions. Therefore, for them artificial intelligence (AI) and machine learning (ML)-based technologies may provide a big help to assess their credit score as it provides a comprehensive profile of the borrower's current level of income, his or her employment opportunities, and their potential ability to repay their intended loan.

For the farming community, most of the data required for credit assessment like farm characteristics, historic transaction records, and cash flow projections are already in

practice, hence digital credit scoring can give lenders a promising starting point. Some of the farm-related digital datasets are: demographics, agronomic surveys, transaction records, satellite imagery for yield forecast, weather forecasts and records, credit history, and alternate data. It has been a prime assumption that small and marginal holders possess higher credit risks, but those who have structured farm cash flow can have better credit scoring. With adequate mobile coverage and mobile penetration, alternate data sources like mobile network operator data, data stored on mobile phones, e-commerce data, social media data, etc., would be used further for their feasibility and eligibility check. Digital credit scoring can also provide excellent unique selling propositions (USPs) for the fintech startups to give an edge to the age-old banking institutions by identifying and differentiating the eligible rural peasants with higher speed and more accuracy in loan disbursements (SAFIRA and Grow Asia 2019). Currently, efficiency is the most challenging aspect for most lending institutions and after the adoption of ML technologies for credit scoring, now they are finding difficulties integrating ML technology into their traditional way of credit scoring. In addition, in both aspects, fintech startup firms are emerging as a clear solution provider for rural consumers.

As per the World Bank Report in 2017, it was mentioned that approximately one-third of the world's adult population is devoid of any banking and hence they rely mostly on other informal channels, semi-formal channels, or micro-lending institutions. For micro-lending institutions, databases for the customers are not adequate to assess their creditworthiness, and sometimes it becomes very difficult to decide to whom a loan should be given or to whom it is to be denied because of limited banking transactions. Hence, ML algorithms are capable of assessing creditworthiness for these customers who need short-term loans or loans required for any specific purpose (Ampountolas et al. 2021). Nowadays, we have wider availability of internet services with the lower internet cost; this leads to the increasing penetration of smartphones particularly in the rural areas enabling farmers to go digital. It is estimated that approximately 85% of financial and other fintech firms are using AI techniques in their routine activities (O'Neill and Biallas 2020). Fintech has been gaining importance since 2015, and though India is trying to match the fintech developments with the other countries across the world, the issues of funds and lack of new ideas are some of the obstacles which fintech startups are facing (Kandpal and Mehrotra 2019). Government initiatives like Digital India, Make in India, and Jan Dhan Yojana will give a boost to the sustainable development of fintech startups. Fraud detection and other various anomalies like KYC compliance, money laundering, and financing terrorism are the most common reasons for most financial institutions to adopt AI techniques. The International Committee on Credit Reporting (ICCR) highlighted various risks associated with assessing credit scoring such as inaccurate data, usage of data without customer's consent, fault in design, and algorithm decisions. These kinds of risks can be overcome by way of adopting AI-ML techniques in the credit assessment process.

For a farmer, both agricultural as well as non-agricultural credit facilities are extremely important for their well-being and sustainable development. What kind of data is required, related to the farms for their better credit score assessment, and how the digital platforms of the various banking institutions can be helpful for the farmers to increase their accessibility to the credit, are some of the questions which need to be addressed. Therefore, the main aim of this research paper is to explore various available literature studies highlighting the adoption of different ML technologies by financial institutions and how these institutions are utilizing ML-based techniques and other digital channels for obtaining accurate credit scores to reduce their non-performing loans. This study is an attempt to present the ideas of different authors who identified the appropriate ML algorithm that fits the credit assessment specifically for rural borrowers. The findings and recommendations of this research paper may be beneficial to policymakers, fintech startup firms, and all other banking or non-banking institutions to draw their attention to come up with their most appropriate ML model for the credit score assessment so that they can serve unserved and underserved rural farmers, particularly small farmers, in more efficient ways.

The remainder of this paper is structured as follows, the next section (Section 2) is about the relevant literature and motivation of study, Section 3 depicts the material and methods adopted, Section 4 represents findings and discussion, and finally, the conclusion with the recommendation is provided in Section 5.

2. Relevant Literature and Motivation of Study

Competition among the lending institutions is increasing day by day and hence so is the number of loan defaulters. Banking institutions are currently at bigger risk because their non-performing loans are mounting up. They require more efficient credit scoring methods with high accuracy and speedy disbursal of loans so that they can withstand the ongoing challenges of the digital ecosystem created by the fintech startups. Banks are now leveraging the AI-ML technology for credit score assessment for their faster loan disbursal. Hence, the main objective of the literature review is to understand the ongoing research on digital credit scoring employed by AI-ML techniques and to make the readers aware of how the banking industry is evolving to mitigate all kinds of risks associated with credit. The entire literature review is categorized into three broad aspects provided below.

2.1. Traditional Method vs. Digital Method for Credit Assessment

Traditional financial institutions are evaluating the creditworthiness of the borrowers based on subjective methods focusing mainly on the 5Cs: character, capacity, collateral, capital, and conditions. This method largely is unable to assess the borrowers who have no loan history and have limited banking transactions, particularly the customers residing in rural areas. In addition, this method fails to provide a comprehensive profile of a potential borrower as there may be a chance of missing the vital and relevant information required for the credit assessment. Hence, banking institutions gradually started following the digital method of credit assessment to fulfill the requirement of potential borrowers with their exact loan eligibility and also to minimize their non-performing loans. Banks can establish their credit assessment methods or can take the help of third-party services in the form of Fair Isaac Corporation's credit scoring system (FICO), popularly known as the FICO score. Most of the lenders are now applying the FICO score method for their credit assessment requirements. The FICO score is nothing but a person's credit score in the range of 300 (poor) to 850 (excellent). The biggest lacuna for the traditional methods is that they just inform the borrower's credit assessment and they fail to predict their probability of default. Therefore, baking institutions are adopting more advanced methods now for credit assessment by employing ML technologies which are mainly helpful in the prediction of a borrower's repayment behavior.

We are generating huge data on a daily basis; therefore, to manage the ever-increasing large datasets and to warehouse and interpret them properly, AI-ML-based models have a higher importance. Under the digital methods for credit assessment, two distinct lines are bifurcating between the standard econometric model-like models based on logistic regression and ML-based models. ML-based models are mainly categorized into the five broad areas: generalized line models (most basic including ordinary least square method and logistic regression), Bayesian models, ensemble models, support vector machines (SVM), and nearest-neighbor models (Jennifer Ifft et al. 2018). The authors used 2014 Agricultural Resource Management Survey (ARMS) data to predict new credit demand with the help of demonstrating and evaluating various ML-based models. It has been found that ML-based models have a higher prediction power than that of standard econometric approaches when they have used the expanded features set. ML-based models have achieved higher average accuracy, recall, and precision scores than the standard econometric approaches for the expanded features set. Many earlier researchers also have highlighted the importance of ML-based models over standard econometric models to solve classification problems among different debtors. However, the best model for a given situation depends on data availability and the prediction outcome that must be relevant to the person or organization as a whole. It is also not necessary that an ML-based model will always improve

prediction power and, in many cases, it is observed that standard econometric approaches perform very well. However, currently most businesses, government institutions, and academic researchers are applying big data to solve agricultural and food sector issues. Models based on standard econometrics do not support large data sets and as a result ML-based models have all the advantages in dealing with this. Factors like computing power, data adequacy, and availability, and objectives of the research largely drive which methods to adopt (whether it is ML-based or standard econometric-based) to assess the borrower's creditworthiness. It is observed that under a cost-based valuation approach, if the acquisition cost of a customer is high compared to their potential value, then the logistic regression model performs well, and vice versa, if the customer's acquisition cost is low over their potential value, then the Gaussian Bayes model performs well. Therefore, to avoid using ML models blindly while assessing credit scoring, it must be dependent upon organizational cost involvement, model-specific features, and business objectives.

There are many examples shown in the earlier research where logistic regression was used to determine the classification problems like credit scoring, debt recovery, and bad debt management (Wijewardhana et al. 2018). However, artificial neural networks (ANN) have emerged as a powerful tool in prediction analysis and are mainly used in the classification of data science. However, ANN works well only with the numerical variables. ANN is a standard ML method consisting of interconnected neurons, and these connections are not equal and have different weights. It is analyzed that ANN alone has a high prediction power over the affinity analysis model. However, more accuracy in prediction can be obtained by mixing ANN and affinity analysis models or hybrid methods (Wijewardhana et al. 2018).

2.2. Fintech and Big Tech Companies Are Using Digital Channels for Providing Specific and Speedy Banking Solutions

Traditional banking has its challenges in expanding financial inclusion. Financial inclusion is successful only when our large unbanked population may have indulged in banking transactions. For this, fintech has done tremendous work to educate the rural population in particular regarding the usage of their digital services. They are also guiding them to invest wisely from their hard-earned savings. They are working with the motto of "making rural life easier". The demonetization in the year 2016, which led to cashless transactions in a bigger way, ultimately helped fintech startups and big tech companies to position themselves among the unserved and underserved rural population (Kandpal and Mehrotra 2019). During 2005–06, it was an NGO-driven microfinance model aimed to expand financial inclusion, under which we have the popular examples of Grameen Bank in Bangladesh and Bancosol in Bolivia. However, just after one year in 2007, Safaricom launched M-Pesa in Kenya which was a huge success, between 2006 and 2019 the share of the banked population in Kenya more than tripled from 26.7% to 82.9% (Beck 2020). This financial innovation categorically known as the payment-led inclusion approach was converted from the microfinance-led approach. Another financial innovation introduced by the People's Republic of China (PRC) was in the form of a QR code where customers make the payment through their mobile app. Most fintech companies are smaller and often use digital technology to offer specific financial services targeted to a particular customer, whereas big tech companies utilize their existing digital technology to offer financial services. It has been observed that both fintech and big tech companies, by using their developed digital platform, outperform the bank's (relying on credit-bureau data) prediction model for loan default assessment.

2.3. Empirical Analysis of Existing Research on ML Methods Adopted by Various Financial Institutions Worldwide for Credit Scoring

This section in particular describes how the financial institutions in developed and developing economies are evolving and adopting advanced technologies based on the AI-ML techniques, to address their various risks associated with the credit. Today, most financial institutions are confronting different kinds of risks every day. Some of these risks

are credit risk, market risk, operational risk, and liquidity risk (Leo et al. 2019). Earlier research studies mainly focused on the demographic and other statistical parameters of a customer in assessing their credit score and very few authors have touched upon the socio-economic impact for assessing the creditworthiness of the borrowers (Rafiei and Moradi 2019). The authors stressed that economic factors are not independent of political fluctuations. Thus, they considered politico-economic factors also for credit risk assessment. They first trained an adaptive network-based fuzzy inference system to predict whether an individual loan is a performing or a non-performing one. The socio-economic impact is becoming the most crucial factor (because of COVID-19) for most of the lending agencies now. One of the authors used the data sets of an Iranian bank to assess their customer's credit score particularly during special political and economic conditions. He used the fuzzy inference system (by taking behavioral features of customers of Iranian banks) for the assessment of credit scoring and recommended that this model can outperform the other traditional models particularly when there is a situation of economic crisis. Another research study (Linh et al. 2019) highlighted the socio-economic aspects existing in rural credit markets of Vietnam, where farmer access to the credit mainly depends upon their output level, household income, etc. Farmers have access to the credit mainly from the three channels: formal, semi-formal, and informal channels. However, the author has not included here the determinants of semi-formal lenders. It is also restricted to the rural credit markets of Vietnam only and does not compare to the markets of other developing countries.

Credit scoring started gaining popularity at the beginning of 1990. However, it does not approve or reject a loan application, rather it predicts the performance of creditors defined as defaulters or non-defaulters by the lenders. Fuzzy logic is an ML-based credit scoring technique that uses human behavior or response rather than any mathematical calculations (Bennouna and Tkiouat 2018). Researchers have emphasized that the drivers of bank lending have non-linear and non-parametric relationships with outstanding bank loans (Ozgur et al. 2021). They have shown the impact of 19 bank-specific, macroeconomic, and global variables on bank loans for the period between 2002Q4 and 2019Q2 in Turkey. They compared the regression model with the ML-based methods to assess the impact of these factors. Authors further observed that the standard linear regression methods could not handle the large dimensional datasets as compared to ML-based algorithms, and ML-based models have the flexibility to accommodate the complex nature of variables. Banking institutions are mainly dependent on third-party sources for their debt recovery management which incur higher costs and market risks. Hence it is always recommended to have a strong debt repayment prediction method in place before disbursing any credit to the borrowers. Few authors (Wijewardhana et al. 2018) have attempted to predict the debt repayment behavior of the customers by using the historical data of a US-based collection agency. They used mathematical, data mining, and statistical models to assess the debt repayment behavior of a customer with considerable accuracy. However, sample selection bias is the commonest issue for most of the research authors in consumer credit literature. It is extremely important to note that the accuracy of the prediction is directly related to the data sets taken for the research study, hence proper relevant and adequate data is the central point for most of the prediction studies while assessing the credit score. In addition, because of the limited sources of data, it is highly difficult for banking institutions to come up with an excellent ML-based algorithm to improve some of the key banking operations like fraud detection, the credit assessment, customer churn prediction, etc. Data mining techniques even offer little help. Therefore, few researchers (Ranjbarfard and Ahmadi 2020) have identified the data based on the content analysis of previous research and developed their entity-relationship model. This model would be projected to be a supporting tool for improving the bank's intelligence system. However, these were highly selective in choosing the existing academic paper for their study and analysis. Some researchers (Sánchez and Lechuga 2016) have attempted to evaluate credit scoring in terms of cost efficiency by reducing operating costs, decreasing response time, and avoiding grants of

bad loans. They also recommended their model to streamline the lending process at a minimal cost. Researchers here referenced the working of Cooperative Savings and Loan Societies (S and L), and the finance companies' community (SOFIPO). SOFIPO is the part of the Mexican financial system responsible for the microfinance market. This research study is mainly focused on SOFIPO; however, this study is limited to the cost-benefit analysis of savings institutions and is required to explore further in the analysis for any bottlenecks existing in adopting these new initiatives. Most of the research studies have attempted to identify different ML techniques specifically to classify the borrowers, and some have used the attributes of 5432 clients of a Brazilian financial institution to classify each client as non-defaulters, temporarily defaulters, and defaulters. They found that the artificial neural networks radial basis functions (ANN RBF) algorithm was superior for providing the best accuracy in the credit assessment process (Assef and Steiner 2020). Some authors used ML techniques like random forest (RF) and AdaBoost to classify borrower's adequacy (Aniceto et al. 2020). Researchers analyzed the adequacy of the borrowers by using Brazilian Bank's loan database and explored various ML methods. Data sets are mainly comprised of low-income borrowers from large financial institutions in Brazil. The default rate of the portfolio was almost 48%. Based on real data, they developed an ML-based model and shown that RF and AdaBoost performed better in comparison to other models. Few authors recommended a decision tree model to classify the lender as a performing or non-performing loan risk. This researcher used the C5.0 algorithm (decision tree model) and recommended that if rural banks (Bank Perkreditan Rakyat) of Indonesia could have adopted this method then they can reduce their non-performing loan risk to a considerable extent (Mandala et al. 2012). Researchers have attempted to identify various factors to be considered by the rural bank for assessing the credit application. They used a decision tree model by using a data mining methodology for credit assessment so that non-performing loans can be minimized. They identified five discrete or non-continuous variables, gender, type of collateral, type of business activities, source of funding, credit status, and use of the loan, and eight continuous variables, age, monthly income, credit amount, expenses per month, current payment per month, savings, collateral values, and loan period for the modelling phase of the data mining process. It has been found that collateral value is one of the most important factors to be considered by the rural banks for credit assessment for the rural borrowers specifically to minimize the non-performing loans. Most of the researchers stressed that credit scoring is a classification problem (Boughaci and Alkhawaldeh 2018). They evaluated German and Australian credit data sets and compared this with well-known classifier benchmarks. They used the local search method (LS), the stochastic local search method (SLS), and the variable neighborhood search (VNS) method combined with the support vector machine (SVM) model for the credit score assessment.

Table 1 summarizes the key findings drawn from the empirical studies of reviewed literature of the last 10 years (2012 to 2021) covering the financial institutions worldwide and their credit scoring techniques.

Table 1. Key findings drawn from the empirical studies of the reviewed works of literature in this study.

Author (from Reference List)	Year	Country or Financial Institution	Credit Scoring Techniques Followed	Datasets/Variable Used	Key Findings or Recommendations
Fernanda M. Assef, Maria Teresinha A. Steiner	2020	Brazilian financial institution	Artificial Neural Networks Multilayer Perceptron (ANN-MLP), Logistic Regression (LR) and Support Vector Machines (SVM)	5432 companies (2600 clients—non-defaulters, 1551—defaulters, and 1281—temporarily defaulters)	Hybrid techniques for credit risk assessments may be followed for better results
Somayeh Moradi and Farimah Mokhatab Rafiei	2019	Iranian banks	Fuzzy Logic	Behavioral features of banking customers during special political and economic conditions	A few qualitative predictors like accountability, commitment, honesty, reputation, and ethics should also be added for the risk analysis
José Francisco Martínez Sánchez, Gilberto Pérez Lechuga	2016	Mexican financial system/SOFIPO	NPV, IRR, and payback period	Banking infrastructure and human capital for credit risk assessment	Evaluation of credit scoring system in terms of cost-efficiency, for the finance companies' community SOFIPOs
Ghita Bennouna, Mohamed Tkiouat	2019	Morocco (microfinance institutions)	Fuzzy Logic	History of client behavior (descriptive variable, a behavioral variable, and variable characterizing loans contracted) of microfinance institutions	Evaluation of customer behavior by using the fuzzy logic approach, to reduce loan default
Maisa Cardoso Aniceto, Flavio Barboza and Herbert Kimura	2020	Brazilian bank	AdaBoost and Random Forest models, and compare with a benchmark based on a Logistic Regression model	Database (large Brazilian financial institution) of 124,624 consumers' loans and their repayment schedule	Random Forest and AdaBoost perform better when compared to other ML models for borrower's adequacy classification
I Gusti Ngurah Narindra Mandalaa, Catharina Badra Nawangpalupia, Fransiscus Rian Praktikto	2012	Rural bank (Bank Perkreditan Rakyat), Indonesia	Decision Tree model (data mining methodology)	Variables like gender, collateral type, source of fund, business activity, etc., taken for credit risk assessment	Critical factors identification for a rural bank (Bank Perkreditan Rakyat) to assess the credit application
Dalila Boughaci, Abdullah Ash-shuayree Alkhawaldeh	2018	Vietnam	LS, SLS, and VNS for feature selection, combine these methods with SVM classifier	German and Australian credit datasets	Future research is recommended to know the impact of the feature selection-based method with the other machine-learning techniques for credit scoring

Table 1. *Cont.*

Author (from Reference List)	Year	Country or Financial Institution	Credit Scoring Techniques Followed	Datasets/Variable Used	Key Findings or Recommendations
Ronald Aliija, Bernard Wakabi Muhangi	2017	Uganda/microfinance institutions	Linear Regression	38 loan officers and six credit managers in six microfinance institutions in Fort Portal municipality, Western Uganda	To examine the challenges faced by credit officers at the loan appraisal stage
Onder Ozgur, Erdal Tanas Karagol and Fatih Cemil Ozbugday	2021	Turkey	Comparing the performance of six ML techniques (Tree Regression, Bagging, Boosting, Random Forest, Extra-Trees, and Xgboost) with the standard Linear Regression	19 deposit banks in Turkey, the data set contains nine bank-specific variables, seven macroeconomic indicators, and three global factors to determine the lending behavior of the bank, for the period 2002Q4–2019Q2	This study analyzes that the Random Forest model has the lowest predicting error
Paweł Pławiaka, Moloud Abdar, Joanna Pławiak, Vladimir Makarenkovc, U Rajendra Acharya	2020	-	Genetic Algorithm	Statlog German credit approval data (1000 instances—accepted/good applicants—700 and rejected/bad applicants—300)	Proposed Deep Genetic Hierarchical Network of Learners (DGHNL) model with a 29-layer structure helps in getting the prediction accuracy of 94.60%
Rui Ying Goh, Lai Soon Lee, Hsin-Vonn Seow and Kathiresan Gopal	2020	-	Hybrid Model (HS-SVM and HS-RF)	German and Australian data sets which are publicly available at the UCI repository (https://archive.ics.uci.edu/)	A Modified Harmony Search (MHS) model is proposed to achieve comparable results for credit scoring

Lending, however, should not be solely dependent on one's past loan record or several banking transactions. This is thanks to fintech and other innovative banking institutions who are truly revolutionizing credit scoring methods based on advanced ML-based technology, to assess an individual's creditworthiness. It has opened a new path for all the rural customers in terms of credit accessibility whether they have had adequate past banking relationships or not. Their data related to farms and farming could be sufficient to avail short-term or long-term credit. However, there may inevitably be the occurrence of digital discrimination if personal data like age, gender, race, income, culture, religion, location, etc., have not been properly trained (Criado and Such 2019). Most of the personal data have been automatically processed by an algorithm and may yield biased outcomes. Therefore, the first line of defense is to detect the discrimination in the data itself and subsequently in the model development process.

3. Materials and Methods

This research study followed the systematic literature review method to address the below-mentioned research questions (RQ) which are highlighted after reviewing the analysis of various eminent research papers:

RQ1: What can be the 'best fit' ML model for banking or non-banking institutions for credit score assessment?

RQ2: How would this best fit model be appropriate for mitigating the issues of increasing non-performing asset (NPA) loans?

RQ3: What role will the regulators play to integrate the digital method with traditional methods for credit score assessment in banking or non-banking institutions without having any ethical challenges?

Therefore, we have attempted a thorough analysis of the various existing literature to find out probably the best solutions for the above problem statements. Thus, initially for these activities, 110 articles were identified, thereafter based on title, abstract, and relevance of the study and by following the methods of inclusion and exclusion theory it was shortlisted further to 45 articles for the review. After that, based on the scope of the study, 25 articles were critically reviewed (Table 2 referred below). The reason for conducting a systematic literature review (SLR) is because it allows transparency in paper selection and reduces the researcher's bias, if any (Zeng et al. 2017). The main steps of SLR are to search the article through various databases like Scopus, Web of Science, Google Scholar, and other valid academic peer-reviewed online resources, to further screen the relevant material based on their abstract part, the scope of the study, and the full analysis of that particular article or research/conference paper. The keywords (artificial intelligence, machine learning, credit scoring, rural finance, micro loan) have been used to obtain the relevant information and to collate the analysis performed by the previous researchers. We applied inclusion and exclusion criteria to screen relevant and appropriate studies for the empirical analysis of the shortlisted literature (Afonso Fontes 2021). We were highly specific in shortlisting only the literature which had five prominent sections such as the introduction, literature review or motivation of study, methods or ML algorithm adopted, results or findings, and finally the discussion and analysis. These five sections are critical and produced many insights and analyses.

It is assumed that with the initiation of credit cards during the 1960s, probably the necessity of credit scoring was felt. According to Hand and Henly, credit scoring is a term used to describe a statistical method to classify good and bad risk borrowers and they recommended that future trends would be more complex for credit score assessment (Goh and Lee 2019).

Table 2. Different credit scoring methods referred from reviewed works of literature in this study.

Credit Scoring Method	Type	No. of Articles Referred
ANN	AI method	3
SVM	AI method	3
Decision Tree	AI method	2
Logistic Regression	Econometric	4
GA	AI method	1
Fuzzy Logic	AI method	2
Random Forest	AI method	3
XGBoost	AI method	1
Descriptive analytical approach	Econometric	1
Hybrid model	Hybrid system	2
Linear Regression	Mathematical/Statistical	1
Theoretical/Subjective judgement/Other	Expert system	2

Referring Table 3. and after obtaining the empirical studies of past research, we grouped various methods of the credit scoring model into (Spicka et al. 2019) the following: the theoretical model of the expert system on the basis of the 5Cs (character, capacity, capital, collateral, and condition) (Yu et al. 2015) or market risk model (Pollak), statistical data analysis (Altman and Hotchkiss), probability theory (Wilcox) or logistic regression model (Zmijewski), AI or data mining techniques like SVM, neural networks (Haung et al.), decision trees (Klepac and Hampel), and currently the much prevalent hybrid model (AI with other statistical/mathematical model or AI with AI techniques).

Table 3. Credit scoring technique (widely adopted for credit scoring—decade wise).

Credit Scoring Technique							
Expert System (based on 5Cs)							
Linear Programming							
Logistic Regression							
AI-ML-Based							
Genetic Algorithm (GA)							
Hybrid Model (AI + AI) OR (AI + other)							
Year	1970	1980	1990	2000	2010	2020–2021	

The authors emphasized that credit scoring models have not been used extensively in agriculture which could probably be because of subsidy bias. The authors highlighted Gurcik's and Chratinova's index to predict the financial viability and sustainability of various farms. It has been observed that earlier credit processing officers mainly believed in the technique of the 5Cs more than the credit scoring technique or credit bureau reference check while processing for loans (Aliija and Muhangi 2017). Micro-financial and some of the other lending institutions mainly consider the 5Cs model of credit scoring; however, if any of the Cs are poorly analyzed then the rate of default probably could be higher resulting in increasing the non-performing loans. Therefore, it is very essential to mitigate these risks, and lending institutions must develop their policies and procedures while analyzing the 5Cs before extending the loans. One of the most basic methods for credit scoring is the discriminant analysis; it has been employed for score assessment since 1966. However, later some researchers compared logistic regression with discriminant analysis and cluster analysis and concluded that logistic regression was superior to the

other methods in evaluating credit risk (Yu et al. 2015). During the last few decades, it has been observed that among the traditional methods logistics regression was considered as the standard credit scoring model as it fulfilled all requirements of the Basel II accord (released in the year 2004) (Goh and Lee 2019). Earlier, there was a trend of usage of linear programming for credit score assessment, firstly introduced by Mangasarian in 1965 for classification prediction, then in the year 1970 Chatterjee and Barcun introduced the K-nearest neighbor (KNN) method for credit scoring, and since then (refer Table 4.) it has been used extensively in individual credit scoring (Yu et al. 2015). Since the 1990s, artificial neural networks (ANN), an artificial intelligence method, have been used widely for bankruptcy prediction. Traditional statistical methods like discriminant analysis and logistic regression often violate real-world banking practices, but neural networks are consistent in their approach because of their ability to classify correctly and predicting the loan defaults (Eletter et al. 2010). It has been concluded that ANNs were more robust and accurate in banking risks assessments. However, a few researchers claimed that the classification and regression tree (CART) and multivariate adaptive regression splines (MARS) for individual credit scoring (MARS) outperformed ANNs in individual credit scoring (Yu et al. 2015). It is also recommended that random forest (an extension of the decision tree method, introduced by Breiman in 2001, which consists of a large number of decision trees) outperforms logistic regression in providing accuracy (Antunes 2021).

Table 4. Credit scoring techniques introduced or employed by eminent author/researcher.

Popular Author/Researcher	Credit Scoring Technique Studied/Employed	Year	Studied on
Chatterjee and Barcun	KNN	1970	Individual credit risk estimation
Henley and Hand	KNN	1997	Individual credit risk estimation
Rivoli and Brewer	Logistic Regression	1998	Credit risk estimation
Mangasarian	Linear Programming	1965	Prediction classification
Altman et al.	Logistic Regression	1980	Credit risk estimation for SMEs
Goovaerts and Steenackers	Logistic Regression	1989	Personal credit scoring
Tam and Kiang	ANN	1992	Bankruptcy prediction
Desai et al.	ANN	1996	Individual credit risk estimation
Lee et al.	CART and MARS	2006	Individual credit risk estimation
Desai et al.	GA	1997	Individual credit risk estimation
Huang et al.	2 stage genetic programming	2006	Individual credit risk estimation
Chen et al.	Hybrid SVM and three strategies	2009	Individual credit risk estimation
Jacky	Machine Learning	2018	Credit fraud detection
Keqin Chen et al.	Hybrid (Logistic Regression and Evidence Weight)	2020	Individual credit risk estimation
Rui Ying Goh et al.	Hybrid model—HS-SVM and HS-RF	2020	Individual credit risk estimation

Support vector machines, another effective AI technique for credit scoring, were firstly introduced by Vapnik in the year 1998 (Goh and Lee 2019). Past research studies suggested that SVM can be used as the basis of the feature selection method to draw features to obtain credit defaulters. Further, it has been observed that some advanced techniques like the metaheuristic algorithm (MA), one of the AI-based data mining approaches, gained popularity in recent years to assess credit scoring (Goh and Lee 2019). In addition, it has been observed from the past research studies that some aspects of the evolutionary algorithm (EA) which is a part of MA, like the genetic algorithm (GA) and genetic programming (GP) were found superior to some of the benchmarks such as ANN, decision tree, logistic regression, etc., in individual credit scoring. MA has been further categorized into three broad heads which are largely used in the credit scoring domain: the first is EA (its GA and GP are very common now in credit scoring); the second is swarm intelligence (SI) (its common examples are ant colony organization (ACO), scatter search (SS), harmony search (HS), etc., used in credit scoring domain); and the third is iterate based (IB) such as simulated annealing (SA) and tabu search.

The hybrid model is currently extremely popular as it takes care of the limitations of existing individual models and nowadays it is effectively exploited to address the problems, if any, while using any individual model for credit scoring. Past research studies recommend that the hybrid model has all the potential to provide better prediction accuracy. It is also proposed that the application of EA helps in improving the performance of classical ML methods (Paweł Pławiaka et al. 2020). A powerful forecast hybrid model can also be developed by mixing evidence weight and logistic regression for the detection of personal credit fraud (Chen et al. 2020). Reserve Bank of India (RBI) emphasized that 25% of non-performing asset loans cannot be recovered. This is a huge number and would alter the balance sheets of most of the commercial banks with higher NPAs if they had not developed their robust model for credit score assessment (Kumar and Gunjan 2020). It is also found that 100 million Americans are out of accessing credit because of their low credit score in the range of 300 to 670. Therefore, now most of the emerging fintech startups are employing custom-built ML algorithms to tap these individuals who have a sub-prime score but are eligible for getting credit (Kumar and Gunjan 2020).

4. Findings and Analysis

Most of the earlier studies on risk assessment for biological assets or farm assets were based on an analytical hierarchy process combined with fuzzy logic which is mainly a subjective kind of study. However, risk evaluation for farm assets would be categorized under binary classification and for this the ML method is most appropriate (Zhu et al. 2020). It has been observed that farmers have insufficient effective collaterals and as a result they face difficulties in obtaining actual credit. Thus, to study them and to assess their credit risk assessment, researchers used 1249 production and operation data samples of new agricultural entities in three provinces of China. They constructed an XGBoost model and compared it with logical regression, SVM, and RF algorithms to obtain the appropriate model. It is recommended that XGBoost, being an integrated ML method based on the gradient boosting decision tree (GBDT), is highly useful for the study on having a dichotomy problem (whether the customer will repay or will default). It was proposed by Dr. Chen Tianqui in the year 2016 and since then is gaining popularity for the credit risk assessment. It has been found that the asset–liability ratio and the educational level of the new agricultural entities are important credit risk indicators. Usually, the following four risks are associated while extending credit to the rural people: individual risk, operational risk, risk of farm assets, and policy and market risk of farm produce. Therefore, to mitigate such risks and to have higher accuracy on loan default prediction, AI and Big data are going to play a crucial role in making loan decisions (Abuhusain 2020).

During the last decades we have seen tremendous changes in the methods employed by banking and non-banking institutions for credit scoring, which are getting transformed from human-led interventions to machine-led methods (Fairooz and Wickramasinghe 2019). Most of these institutions are applying diffusion of innovation theory, technology-organization-environment frameworks, and actor-network theory to integrate their traditional method into the digital method of credit scoring. These institutions are applying the ML method to reduce the human bias factor for making loan decisions, and it is also estimated that the ML method outperforms the age-old Fair Issac corporations' credit scoring system (FICO) method for providing better credit score and risk assessment (Munkhdalai et al. 2019). Artificial intelligence or ML-based models for credit scoring have greater applications because other's feasibility and accuracy are highly accustomed when the question of big data handling comes (Goh et al. 2020). Credit scoring is a classification problem between the identification of defaulters and non-defaulters. Both SVM and RF are black-box models and are sensitive to hyperparameters; therefore, researchers proposed a modified harmony search random factor that is more robust in terms of performance, explainability, and computational time.

However, it is not completely known that AI-ML algorithms will not cause bias especially against minorities like small and marginal holdings, women communities, etc.,

and with the other specific class (Stephens and Schmidt 2019). Therefore, ensuring fair and transparent AI-ML applications have the utmost challenges. Sometimes even an applicant using working e-mail for the loan application may face rejections. AI-ML-based models which are derived from historical decisions by the loan officers may also result in bias while extending loans. Hence, to reduce the impact of human biasness it is necessary to train the data appropriately so that more robust AI-ML algorithms can be formed.

Referring to the below table (Table 5) of the comparative analysis of credit scoring techniques, it can be stated that the hybrid model (whether it is AI-ML with AI-ML-based or AI with any other method of credit scoring) could be the best fit for credit score assessment, whereas logistic regression yields a lesser impact on credit scoring. To study this, we have identified four parameters that ultimately define the strength of the ML-based model for credit scoring. This analysis has been performed by assigning the weightage (sum of weightage is one) to the below given four parameters: accuracy (0.3), performance (0.3), robustness (0.2), and volume of data (0.2). This weightage has been assigned on the basis of the importance of these parameters highlighted in the existing literature for credit scoring assessment. Accuracy and performance are the two main features of any ML-based model, then comes the almost equal weightage of robustness and the size of the data handling. The rating has been assigned from 1 (very low performance) to 5 (very high performance), depending on how these models performed and what the results have been interpreted as after having the empirical studies of the existing literature.

Table 5. Comparative analysis of credit scoring techniques.

Parameters	Weights	Comparative Analysis—Credit Scoring Techniques											
		ANN		SVM		RF/XG Boost		Logistic Regression		GA		Hybrid Model	
		Rating	Score	Rating	Score	Rating	Score	Rating	Score	Rating	Score	Rating	Score
Accuracy	0.30	4	1.2	4	1.2	5	1.5	3	0.9	4	1.2	4	1.2
Performance	0.30	4	1.2	3	0.9	5	1.5	3	0.9	4	1.2	4	1.2
Robustness	0.20	3	0.6	3	0.6	3	0.6	3	0.6	4	0.8	5	1
Volume of Data	0.20	3	0.6	3	0.6	3	0.6	2	0.4	3	0.6	5	1
Total	1.00		3.6		3.3		4.2		2.8		3.8		4.4

5. Conclusions

Higher credit penetration in rural areas is one of the main agendas for most of the developing and under-developing economies of the world. As stated earlier, large sections of small farmers, youth, and other vulnerable groups are untouched by the banking transactions and as a result, they cannot exploit the benefits from the various government schemes whether it is subsidy-related or anything else for their sustainable development. Therefore, financial institutions, whether banking or non-banking, have a herculean task to come up with a robust credit scoring model so that all these untouched sections will become part of their credit facilities. This study probably gives an insight into how these ML algorithms (highlighted by the earlier research) apply to fulfill the different objectives required by the financial institutions for the rural borrowers. In India, small and marginal farmers have the highest proportions among the farming community and being the most heterogeneous group, they have varied, vast, and fragmented farm data. Therefore, AI-ML-based algorithms for credit scoring show the way for guiding their credit eligibility check in the shortest computational time with perhaps higher accuracy.

Speed and accuracy in the loan decision-making process are the two critical aspects for the success of any banking institution. During recent years, fintech startups have played a pivotal role in this direction and they are also helping some of the traditional banking institutions to make a loan decision faster with the utmost accuracy. Existing works of the literature recommend hybrid or AI-ML-based methods for credit scoring, though the real challenge for the financial institutions is to implement this at the ground level with the adequate blending of traditional plus digital methods. Future research must be in the

direction of the end-to-end implementation of ML-based technology for credit scoring. Borderless data sharing and mishandling of the data may result in unethical practices; therefore, an adequate regulatory framework is to be adopted worldwide. Further, it is observed that the earlier studies used the existing data sets of Germany, Australia, Japan, and some other countries for the analysis and comparison of various credit scoring techniques, hence it is advisable to use real live data sets for the assessment of an AI-ML-based model or hybrid model for credit scoring with these existing data sets as a benchmark.

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