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A Review of Machine Learning Approaches for Loan Approval in Banking

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***Abstract*— Banker loans were slow, did not accept applications from the general public, were utilized through a limited banker's circle of confidants, and were largely a wasteful and biased waste of time. As happens with almost every natural language processing subject, the judgment done by the machine learning (ML) in the last few years has come a long way and making the loan process a lot more automated. This study examines the use of the loans approval system and the application of the machine learning techniques used for solving the case on the other hand of benefits, drawbacks and impact on the financial industry. The clustering algorithms as well as logistic regression, decision trees, support vector machines and other supervised and unsupervised learning techniques are discussed in the study. It also presents newer methods, including deep learning and reinforcement learning. It provides mention of fairness, ethical issues, and important issues such as data quality, model interpretation, etc., and transparent, unbiased systems. Additionally, the paper also shows some cases that banks have used machine learning for practical uses of loan approval system and real-world examples of how machine learning is applied. This is a well-known problem in the sector where loan acceptance forecast is a long-standing problem. Historically, the subjective criteria and manual methods have been the only means of measuring loan applications such that lenders had always had to rely always use subjective criteria and manual techniques to come to a default decision on a loan and are more likely to wind up at opposite ends. Nowadays, newer, more accurate prediction models of machine learning techniques have emerged, which may be used by financial institutions to make their lending decisions as fast as possible.**

Keywords—Deep learning, supervised learning, unsupervised learning, reinforcement learning, fairness, data quality, model interpretability, explainable AI, automated systems, financial inclusion, machine learning, loan approval, banking, and ethical artificial intelligence.

I. INTRODUCTION

One piece of software that can foretell a customer's loan eligibility is the Loan Prediction System. The customer's income, spending habits, marital status, and other variables are taken into account by this strategy. This is used for clients with a big number of trained data sets [1]. A financial institution's process of lending to customers is an important factor behind the final approval given to any loan due to the fact that they are the ones responsible for approving loans to their customers. A loan approval process deserves being well designed such that a lender profits from lending to customers unlikely to default. By providing an indicative loss ratio the system further helps the lender to manage risk and, using the system, to protect income from lending to customers deemed to be high risk [2]. Moreover, if the loan approval process is effective, customer satisfaction will improve, customer loyalty will also be improved, and the customer base will expand as well. All of which leads to larger number of loans and bigger lender's profit. In addition, a proper and well performed loan approval affects directly the financial stability of the applicants. [3] This increased demand has led to the further difficulty of the manual process in the loan approval process. Eventually, the processes become so manual that the loans are not assessed in a timely fashion and so there is an increase in the risk of error[4]. Also, questions of efficiency are a good example illustrating the fact that as loan applications start coming in more and more for the increase in the number of lenders receiving applications, manual loan approval processes are progressively facing a disadvantage. During peak application periods, manual processes are inefficient and may hinder the rapid processing of loan applications. This leads to long periods of waiting for answers and dissatisfaction on the part of applicants [5] Furthermore, the time-consuming nature of manual processes can incur additional costs for organizations [6].

The bank will run into financial problems and lose money if it doesn't pick the right one. Investing their assets in secure hands is the goal of banks. Considerations such as the borrower's intended use of the funds, their ability to repay the loan, the legitimacy of their supporting documents, etc. should precede a bank's decision to extend credit. Because of this, we need machine learning algorithms that can choose the candidate instantly [7][8] are examples. These machine learning algorithms can help both job applicants and workers. This model's main goal is to speed up the choice process and find the best option. There are many ways to make predictions, but data mining is one of the best because it uses records of clients to teach a system to guess when acceptance will happen. Here are some ways to guess what will happen: Random Forest, Naïve Bayes, Logistic Regression, Support Vector Machine, and Classification. Based on how well these algorithms work, we can safely expect the loan to be approved [6].

The primary function of almost all banks is to grant loans. The primary function of almost all banks is to grant loans. Banks typically get their capital from the profits they make on lending. Money storage security is the main focus of the financial system. Although it is not yet known which applicant was selected from all the applicants, many financial institutions and banks do validate and verify borrowers before approving loans. In order for this system to be able to predict whether a certain candidate is safe, machine learning technology will automate the entire feature verification procedure. Credit forecasting has many uses, including helping bank employees and applicants. We seek to choose eligible individuals in a clear, rapid, and straightforward manner. Banks can have special benefits using it [9]. Automatic generation of new test data for each feature involved in credit processing is possible with the credit forecasting system, and the same characteristics will be processed with the supplied weights. The model can pinpoint a due date in order to ascertain the borrower's loan eligibility.[10].

II. Overview Of Loan Approval In Banking

Due to financial constraints, lending from banks has grown in importance as a means for people and corporations to access external finance. The bank makes the greatest money from loans, but there are dangers involved with lending more money out, such as the possibility that borrowers won't be able to repay the loan by the due date or under the specified circumstances (also known as "credit risk"). Due to resource constraints, banks place a premium on selecting borrowers who can reliably return their loans on schedule. The primary duty of the financial institution is to choose the most suitable applicant. When done manually, selecting the appropriate approver can be a real pain. If the bank doesn't pick the right one, it will run into money problems and lose money[11]. Investing their assets in secure hands is the goal of banks. Considerations such as the borrower's intended use of the funds, their ability to repay the loan, the legitimacy of their supporting documents, etc. should precede a bank's decision to extend credit.

A. Importance of efficient loan approval processes

1) Streamlining Operations for Enhanced Efficiency

Effective loan management is critical to the efficiency that is the bedrock of every thriving company. Organisations can improve their loan management procedures by utilising technology and creating efficient processes. Some important strategies to think about are:

- Automation: When processing loans, automating as much of the manual work as possible can save a lot of time and cut down on mistakes. An organisation can improve its data input, document management, and workflow automation processes by using cutting-edge software solutions that connect well with current systems.
- Centralized Data Management: Information pertaining to loans can be more easily accessed and monitored in real-time if it is centralised in a database. Lenders are able to make quick, well-informed judgements with complete visibility into borrower profiles, repayment history, and collateral details.
- Workflow Optimization: In order to maintain consistency across the loan lifecycle, it is important to design workflows with clear parameters. An organization's operational efficiency, turnaround time, and bottlenecks can all be improved with well-defined duties at each step[12].

- Traditional approaches to loan approval.
- When small business owners take out loans from banks and pay them back over time, this kind of loan is known as a traditional loan. Bank term loans are an example of a traditional loan.

1. Bank Loans

Personal loans are available from most banks; borrowers can use the money for anything from paying bills to launching a company [13]. Most of the time, these loans do not require collateral. Lenders and banks often want proof of income, property, and other specifics before approving a personal loan amount. The applicant's ability to repay the loan depends on their salary or assets. A personal loan application may be as short as one or two pages. The decision on the loan is communicated to the borrower within a few days.

2. Government Loans

A non-bank financial company (NBFC) that supports the expansion of small businesses across the country is MUDRA. With MUDRA's refinancing support, banks and microfinance institutions can lend to small enterprises. Micro-businesses can take use of MUDRA's finance options through the Pradhan Mantri MUDRA Yojana Scheme. The supplementary products are meant to bolster the industry's development efforts.

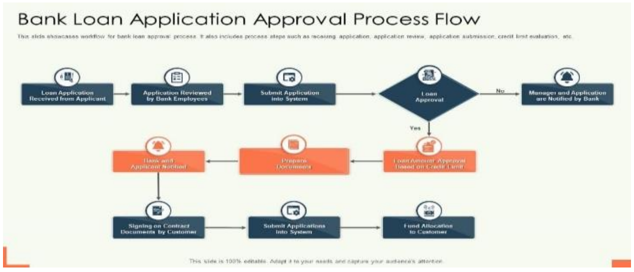

Fig. 1. Bank Loan Application Approval Process Flow

Trying to get a loan? The loan approval procedure is fraught with mystery and uncertainty mentioned in Figure 1. Nevertheless, the procedures for obtaining a loan, be it for operating capital, property, equipment, or a house, are quite simple. You can relax and enjoy the transaction better if you know what to expect.

STEP 1: GATHERING AND SUBMITTING APPLICATION & REQUIRED DOCUMENTATIONS

Filling out an application and sending in the essential documents is the initial step in getting a loan. The paperwork that is needed depends on the kind of loan, the size, and the intricacy of the business that is asking for the loan [5]. A smaller loan usually necessitates fewer paperwork. An applicant's personal financial statements, a release of credit authorisation, tax returns or financial statements from the previous two to three years, and copies of paperwork pertaining to a legal organisation are the most frequently requested documents. The lending procedure continues with loan underwriting when the lender accepts the application and essential paperwork.

STEP 2: LOAN UNDERWRITING

At this point in the loan application process, underwriting analysts examine the applicant's character, capital, collateral, capacity, and conditions, which is a variation of the Five C's of Credit. Several things will be considered throughout this assessment, including credit ratings, repayment records (within the lender and with other lenders), accessible funds, individual down payment amount, overall economic conditions, industry conditions, collateral, and available industry data. The time required to finish the underwriting process for a loan is directly proportional to its complexity. Information gathering for a conclusion takes more time when there are more entities or parties involved.

STEP 3: DECISION & PRE-CLOSING

Once the loan request is approved, the applicants will receive a quick answer. If the loan has been approved, the applicant will also be advised of the conditions and terms at this point. Following mutual agreement between the borrower and lender about the conditions and terms, the next step is to place an order for the required products, It could comprise a variety of documents such as a survey, an appraisal, financing paperwork, title insurance, and more. As soon as we receive these, we verify if they meet the requirements for the loan approval. The closure schedule is established[14] once everything is ready.

STEP 4: CLOSING

The tension and worry that come with waiting and assembling the necessary supplies are virtually eliminated once you reach this stage. Usually, a loan closing takes place at the office of the lender, title , lawyer, or insurance provider. The necessary loan documentation, along with any transaction-specific documents, are signed at closing, and the funds are released in compliance with the approval [15] It is standard practice to provide the applicant and lender with copies of all signed documents.

STEP 5: POST CLOSING

Usually, the loan transaction is completed at this point, and you will receive welcoming information. Information about the organization, how to access your account, and the time and location of payment will all be included in this message. Additionally, you will receive post-closing materials that provide information about the advantages of patronage, the benefits of being a cooperative member, and how it affects your rate [16]

B. *Role of Machine Learning in Loan Approval*

Loan applications are reviewed in accordance with the standing of the applicant under the lending policies established by banks seen in Figure 2. Loans are frequently only approved by banks after a thorough evaluation of the applicant's condition, either through methodically examining submitted documents or through direct asset verification. The person chosen from among all the applicants may not be the greatest choice, nevertheless. There are many components that describe in loan eligibility. Machine learning can be utilized as an automation function to identify loan eligibility by processing large quantities of information and identifying consumer patterns and trends to reduce human error. A pivotal strength of ML is the ability to draw conclusions about future behavior based on previously available information. Loan eligibility can be precisely predicted by banks using models that take into account many applicant criteria, such as gender, employment position, qualifications, etc., by subjecting ML algorithms to past loan data and decision outcomes[17]. Additionally, ML models can positively impact the loan application process by increasing the efficiency of identifying high-risk applications and determining which applications require human errors based on important risk factors.

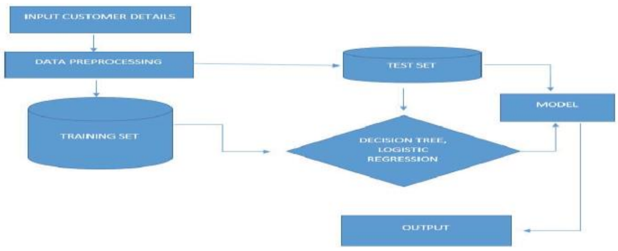

Fig. 2. Role of Machine Learning in Loan Approval [18]

III. MACHINE LEARNING ALGORITHMS FOR LOAN APPROVAL

Previously, the process of approving a loan would be evaluated with a manual inspection of certain parameters such as loan types, credit history, employment status and likewise financial metrics. A credit history outlines a person's past loans and debts repayments and amount of payment history supports decision making on the applicant's eligibility for a loan [7]. Income level determines whether a person has the financial capability to fulfill loan repayments, while employment level reflects a person's potential for a steady source of income [8]. Numerous other financial metrics can be assessed include, but are not limited to, debt-to-income ratio as a financial parameter in loan processing. All of these metrics assist a lender in deciding a loan applicants limits of loan eligibility, and requirements around loan repayment terms. Since this loan approval process is completed through manual inspection of each of these parameters, it is also a time consuming process whenever human errors can occur and correction can lead to increased time delays.

A. *Types of Machine Learning Algorithms*

1. Supervised Learning

Labelled data that is, input data that has been marked with the appropriate output is used to train supervised learning algorithms. In order to anticipate the output for fresh data, Input-output mapping learning is the goal of these algorithms.

- Logistic regression is used to put things into two groups, like guessing whether an answer will be yes or no. To get a rough idea of the odds, a logistic formula is used.
- Linear regression is one way to guess results that will keep happening. It turns data that has already been collected into a linear equation that shows how one or more independent factors are connected to a dependent variable.
- Support Vector Machines (SVM): Although SVM is mostly used for classification, it can also be used for regression and does very well in high-dimensional spaces.
- Decision Trees To predict the value of a goal variable, these models use simple decision rules that are made from the data's features.
- Random Forests are a group of decision trees used for regression and classification. They try to cut down on overfitting and improve model accuracy.
- Neural networks are strong models that can pick up on complex, non-linear relationships. They are used a lot in deep learning apps.

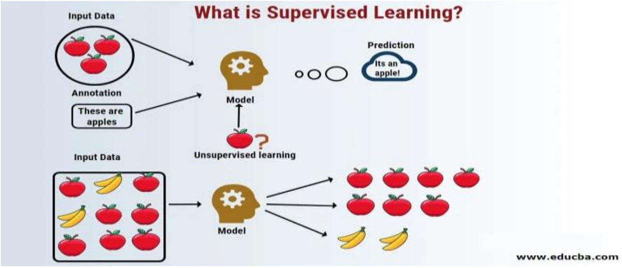

Fig. 3. Unsupervised Learning

Algorithms for unsupervised learning are used on data sets that don't have labelled answers. The objective is to obtain the basic structure of a set of data points seen in Figure 3. For independent learning, common methods include:

- K-means, hierarchical clustering, and DBSCAN are some of the algorithms used for clustering, which is the process of dividing a set of objects into subsets defined by their degree of similarity to one another.
- Association These algorithms, similar to market basket analysis, find trends in large datasets.
- A statistical technique called principal component analysis (PCA) can be used to transform a set of data for potentially linked variables into a set of values for variables that are not linearly related. An orthogonal modification can also be used to accomplish this.
- Autoencoders A unique kind of neural network that can efficiently learn unlabelled data coding's.

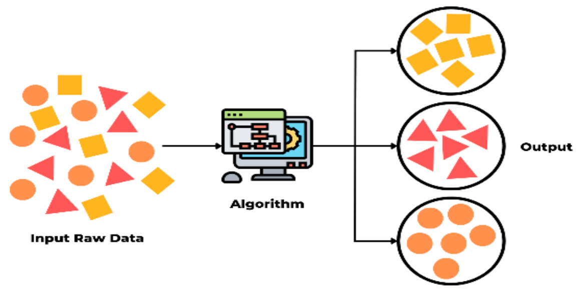

Fig. 4. Reinforcement Learning

Algorithms might potentially teach themselves to make different kinds of decisions by utilizing the reinforcement learning mentioned in Figure 4. The algorithm learns to excel in challenging and uncertain environments, allowing it to accomplish goals with ease. In reinforcement learning, an agent learns from its errors by receiving rewards or punishments, and it makes decisions by following a policy.

- Policy Gradient Methods: Rather of evaluating the worth of activities, these techniques directly enhance a policy's parameters.
- Combining Q-learning and deep neural networks, Deep Q-Networks (DQN) may be able to directly learn the right rules from high-dimensional sensory data.
- Model-free reinforcement learning methods, such as Q-learning, are used to determine the value of an action in a certain state.
- Monte Carlo Tree Search (MCTS): This way of making choices, which is common in games like Go, uses role-playing to find the best options [19].

IV. Machine Learning Algorithms

The ten most popular machine learning algorithms are listed below:

- Linear regression
- Logistic regression
- Decision tree

A. *List of Popular Machine Learning Algorithms*

1) *Linear Regression*

To further understand Linear Regression, it is helpful to think of it like sorting random logs of wood by weight . The issue is that you have no way of noting the weight of each log separately. Visually inspecting the log will help you to get a good guess of the log's weight; you can arrange its height and girth in a specific fashion which will ultimately give you a good idea of the log's weight. This is equivalent of linear regression in machine learning.

This method shows that there is a relation between the independent and the dependent factors by showing the fitted independent and dependent factor to a line. The regression line is the equation Y = a * X + b.

In this equation:

- Y: Variable That Depends
- a – Slope
- X – Independent variable
- b – Intercept

2) *2. Logistic Regression*

Logistic regression is based on independent factors to predict discrete values like 0 and 1. The possible values are usually 0 or 1. Its possible outcome can be determined via fitting your data to a logit function. The name of this method is also known as logistic regression.

The following methods are very common to enhance logistic regression models:

- include interaction terms
- eliminate features
- regularize techniques
- use a non-linear model

3) *Decision Tree*

4) The Decision Tree algorithm from the perspective of modern machine learning is one of the most popular supervised learning technique for classification problems. This works very well with dependent variables that are either continuous or categorical. This technique divides the population into two (or more) categories which are as comparable as possible using the most relevant characteristics and independent factors [19].

The researchers sought to discover if machine learning algorithms succeeded in determining loan risk as well as conventional methods. Iidentified that MLP had a greater capability at defining the risks involved in bank loans functions than RF, BayesNet, Naive Bayes (NB), and DTJ48. The model's performance on a dataset of 1,000 loans and their repayment status was assessed using conventional metrics.

To find out if a client can get a loan, we build a web app. Separating the loan data into a training set and a testing set is one of the pre-processing procedures shown in Fig. 1. The next step is to train nine ML algorithms, and then take the three best models and use them to build an ensemble model

[20]. We measure the model's efficacy using the F1 score, recall, precision, and accuracy metrics. When deciding whether or not to grant a loan, several factors are taken into consideration. The following details are required of each borrower: their income (of the applicant and any co-applicants), credit history, property, degree of education, self-employment status, gender, marital status, dependents, and length of loan[21].

V. MACHINE LEARNING APPROACHES FOR LOAN APPROVAL IN BANKING"

Machine Learning (ML) algorithms can figure out who will get a loan by looking at patterns in a set of loan decisions. This study will look at client information like age, income, loan annuity, latest credit report, business type, and length of work. To find the most important features—those that have the most effect on the prediction—we used machine learning techniques like Decision Tree, K-Nearest Neighbour, Random Forest, XGBoost, Adaboost, Lightgbm, and Random Forest [22]. We compare and evaluate these algorithms using industry-standard measures. With a 92% success rate, Logistic Regression stood out among the rest. In addition to being named the top model, its 96% F1-Score showed that it outperformed all other machine learning methods.

Using machine learning to process loan applications by banks Some things are looked at when choosing a candidate for approval in order to find out the state of the loan. When trying to evaluate loan applications and reduce the risks connected with possible borrower defaults, banks encounter a significant obstacle. Banks find this process especially onerous since they have to carefully assess the eligibility of each borrower for a loan [23]. This paper suggests a way to figure out how likely it is that a lender will agree to a loan request by using both machine learning models and ensemble learning methods together. This approach can help make the process of choosing between qualified applications more accurate. Therefore, the aforementioned issues with loan approval processes can be remedied using this approach. The approach significantly cuts down on the time it takes to authorise loans, which is beneficial for both the borrowers and the bank staff. More individuals were looking for loans at banks as a result of the industry's growth[1].

Model selection Machine Learning Approaches in Loan Approval

A. *Model Selection:*

The study "Bank Loan Prediction Using Machine Learning Techniques" used a number of different methods to choose the model. These included Ada Boosting, Gaussian NB, Random Forest Classifier, Decision Tree Classifier, and Support Vector Machine [24][25].We selected each algorithm according to its own set of advantages and characteristics. This wide range of choices made it possible to do a full analysis of the model's ability to predict loan approval outcomes. The study aimed to find the most appropriate models for the dataset's unique details by considering several algorithms; this would ensure an accurate and informed way to forecast bank loans.

1) AdaBoosting

The powerful machine learning framework known as Ada Boosting, an abbreviation for "Adaptive Boosting," increases prediction accuracy by merging the outputs of numerous simple models, most commonly decision trees, into a single robust model. One major distinction with AdaBoost is the way it handles different types of training data. Indeed, it gives cases that are more challenging to categorise a larger weight, whereas instances that are appropriately identified receive a lower weight. This is significant because it shows that the AdaBoost model is improving the intelligence of all the models in the ensemble by "learning" from cases that were hard to categorise. The flexibility to adjust to different situations is a strong point of AdaBoost. Its ability to spot and adapt to intricate data patterns makes it a powerful predictor of outcomes like bank loan approvals. Ultimately, the final model is far more precise and dependable when making predictions, as it is constructed from numerous weaker models.

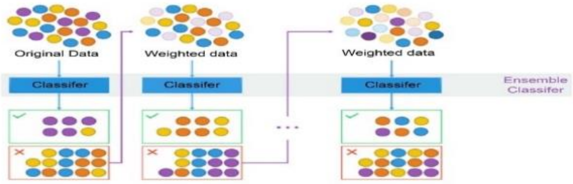

Fig. 5. AdaBoosting model architecture (1).

In Figure 5, you can see a more detailed view of the Ada Boosting model design and the weighted process of data. Ada Boosting says the accuracy was 99.99%.

2) Gaussian NB

The book "Bank Loan Prediction Using Machine Learning Techniques" focusses on a statistical classification method called Gaussian NB, which stands for "Gaussian Naive Bayes." Applying concepts from the Bayes theorem, Gaussian NB takes the class label as a given and uses it to assume that characteristics are conditionally independent [26]. A Gaussian distribution is used in this method to model how likely it is that different feature values will be found for each class when predicting bank loans. Even though Gaussian NB is based on the "naive" idea that features are separate, it usually works well, especially with continuous data. Looking at how Gaussian NB is used in this research, it's clear that it can handle a lot of attributes and use probability to anticipate how loan acceptance will go. The second part is the Gaussian NB architecture given in Figure 6.

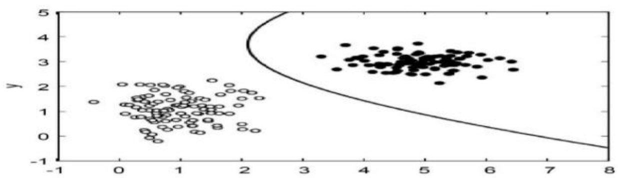

Fig. 6. Architecture of Gaussian NB

3) Random Forest Classifier

The Random Forest Classifier, which is used in "Bank Loan Prediction Using Machine Learning Techniques", is one of the important elements that are covered in it. In this method, many decision trees are merged to build a solid prediction model. Random Forest Classifier is very helpful during training as it creates many decision trees for each tree, Material for this study's complicated and heterogeneous datasets. A subset of data is trained on each tree and the final forecast for loan approval is taken to be the average of all the trees' projections. Better generalisation and less overfitting lead to a better accuracy of the algorithm's prediction.

The Random Forest Classifier architecture is depicted in Figure 7 and is responsible to use the ensemble learning to learn several decision trees on individual data sets. To obtain the final prediction, a majority vote leads to robustness, but at the same time prevents overfitting. This model got an accuracy rate of 99.98% during the loan approval procedure.

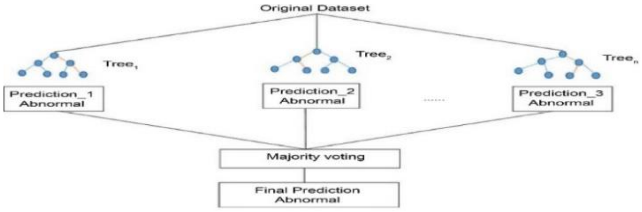

Fig. 7. Random Forest Classifier architecture (3).

4) Decision Tree

One of the simplest ML algorithms called the 'Decision Tree Classifier' is used in this project 'Bank Loan Prediction Using Machine Learning Techniques' depicted in Figure 8. Through a process of recursive feature splitting, it generates a structure resembling a decision-making tree. When it comes to predicting the results of bank loans, the Decision Tree Classifier learns on its own from datasets by looking for patterns.

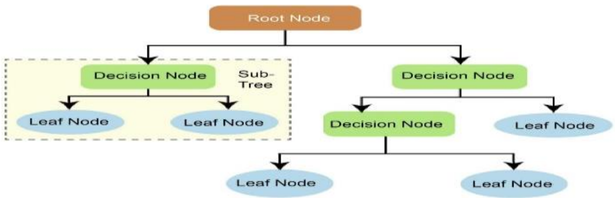

Fig. 8. Decision Tree Architecture (4).[21]

VI. Literature Review

Faster loan disbursal is one benefit that banks are reaping from the use of AI and ML for credit score evaluation. This literature analysis aims to shed light on the ways the banking industry is adjusting to mitigate different credit-related risks by gaining a better grasp of the present status of research on digital credit scoring using AI-ML methodologies. Presented below are three overarching categories into which the whole literature review falls[1].

Because of this, investigating this phenomenon is crucial. Managing loan default is a complex issue, but recent studies have revealed that there are numerous approaches to studying it. Studying the nature of the various methodologies and comparing them is critical, though, because making accurate forecasts is crucial for profit maximization. Predicting who will fail on a loan is a major area of predictive analytics[6].

A. *Traditional Method vs. Digital Method for Credit Assessment*

The 5Cs—character, capacity, collateral, capital, and conditions—are the primary subjective metrics used by traditional financial institutions to assess borrowers' creditworthiness. This method does not consider borrowers with little or no banking history or of those in rural areas. Also, this approach risks failing to cover critical detail which is key when assessing a potential borrower and therefore cannot provide a complete picture of a possible borrower. As a result, in order to reduce the number of loans that are not performing and to meet the needs of prospective borrowers, financial institutions have begun to use digital methods of credit evaluation. One option for banks is to develop their own methods of credit assessment; another is to use a third-party service, such as the Fair Isaac Corporation's FICO score, which is a credit scoring system. The FICO score has become the de facto standard for most lenders when determining a borrower's creditworthiness. Just like a person's credit score, the FICO score can vary from 300 (very low) to 850 (very good)[27].

There are five primary categories into which ML-based models fall: ensemble models, nearest-neighbor models, support vector machines (SVM), generalised line models (the most fundamental of which include logistic regression and the ordinary least square technique), Bayesian models, and so on. Using data from the Agricultural Resource Management Survey (ARMS) in 2014, the authors demonstrated and evaluated a number of ML-based models to forecast future loan demand. Using the extended features set, ML-based models outperform classic econometric approaches in terms of prediction power. On average, ML-based models outperformed the conventional econometric methods when it came to the increased features set in terms of accuracy, recall, and precision[27].

B. *Digital Channels Are Being Used by Fintech and Big Tech Companies to Offer Tailored and Rapid Banking Solutions*

When it comes to increasing access to banking services, traditional banks face obstacles. Our massive unbanked population can only be considered financially included if they have used banking services. Fintech has made great strides in reaching out to rural areas to teach people how to use their digital services. In addition, they are teaching students how to prudently put their hard-earned money to work for them. "Making rural life easier"[28] is their credo as they work. With the widespread adoption of cashless transactions brought about by demonetisation in 2016, fintech startups and large tech corporations were able to establish a foothold in the unserved and underserved rural population. Grameen Bank in Bangladesh and Ban cosol in Bolivia are well-known instances of this model of microfinance that was developed and implemented in 2005 and 2006 by non-governmental organisations (NGOs) with the goal of increasing access to formal financial services. The percentage of Kenyans with bank accounts increased by more than 100% from 26.7% in 2006 to 82.9% in 2019, thanks to Safaricom's immensely successful M-Pesa, which debuted a year later in 2007. This shift in financial innovation from a microfinance-led model to a payment-led inclusion model

C. *Research on Machine Learning Techniques Used by Different Banks Around the World for Credit Scoring: An Empirical Review*

In particular, this section explains how banks in both developed and developing countries are adapting and using cutting-edge tech based on AI and ML techniques to deal with the many credit-related risks they face. Various types of hazards are something that the majority of financial organisations nowadays face on a daily basis. Lists credit, market, operational, and liquidity risk among them. When determining a customer's creditworthiness, most previous studies have concentrated on demographic and statistical factors; however, only a small number of writers have discussed the socioeconomic influence. The writers emphasised that political swings affect economic considerations. Therefore, when evaluating credit risk, they also took political and economic aspects into account.

VII. Conclusions

The majority of the world's developing and under-developed economies have increased access to finance for rural residents as one of their top priorities. To reiterate, many marginalised groups, including young people, small-scale farmers, and others, are not allowed to participate in financial transactions; consequently, they are unable to take advantage of the many government programs, whether they be for sustainable development or related to subsidies. Banking and non-banking financial institutions alike face the monumental challenge of developing a reliable credit scoring model to incorporate these hitherto untapped areas into their lending products and services. There is a large concentration of small and marginal farmers in India, and because they are the most diverse subset of the farming population, the data collected from their farms is diverse, extensive, and sometimes incomplete. So, algorithms based on artificial intelligence and machine learning are making it possible for credit scoring. This will help people check their credit status more quickly and accurately.

Whether a bank succeeds or fails depends on how quickly and accurately it approves loans. Startups in the financial technology field have been very important in this area over the past few years, and they are now helping some traditional banks make faster and more accurate loan choices. While previous research has suggested using hybrid or AI-ML approaches to credit scoring, the true test will be whether or not financial institutions can successfully integrate these strategies on a daily basis. Future study should focus on creating models or hybrids that use machine learning-based technologies for credit scoring, using these previously collected data sets as a standard.

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