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Artificial Intelligence Based Machine Learning Application For Ascertianing Credit Eligibility

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The rapidly increasing digitization of transactions has made the banking industry dependent on artificial intelligence. Banks have to keep a vast array of consumer data to use it for various purposes in the future. Providing loans to consumers is one of the primary financial services of banks, along with many other types of services. Banks have employed several technologies including the use of Artificial Intelligence (AI) to evaluate the credit worthiness of applicants based on stored data. A branch of artificial intelligence known as “machine learning” uses data science and statistical methods to train machines using predetermined datasets. Systems create optimized models from this learning that provide the most accurate data explanations. By avoiding the use of arbitrary assumptions and limiting potential biases, it improves assessments, promotes better decision making, and aids in fraud detection. The current study focused on AI-based machine learning techniques that enable banks to build predictive models to assess the credit worthiness of potential customers.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Credit eligibility.

1.Introduction

The banking sector has become increasingly reliant on artificial intelligence as a result of the emergence of digitization of transactions. Banks are required to store a substantial amount of customer data in order to make effective use of it in the future. Lending to customers is one of the most important financial services provided by banks, along with many others. The creditworthiness of applicants has been evaluated by banks using a number of methods, including artificial intelligence (AI). AI based machines are trained using statistical techniques known as "machine learning," which is used to provide the most accurate data interpretations by creating optimised models. Improved assessment, improved decision making, and the identification of fraud may all be achieved by reducing the use of arbitrary beliefs. Using AI-based machine learning technology, banks can now create predictive models for evaluating the creditworthiness of future consumers.

In machine learning, statistical approaches are used to teach computers using an existing dataset. The systems then utilise this information to develop the most accurate models possible to explain the data. Exogenous assumptions are eliminated and biases are reduced, enabling more precise assessments and judgments (Li, J. P., et al., 2020) and various other financial applications ((Weigand, 2019; Ban et al., 2018; Buehler et al., 2019). These ML models are often used to produce projections and predictions (Wang et al., 2020; Lee et al., 2014) to analyse banks' pertinent financial worries. Moreover, Machine Learning models were more accurate at forecasting credit risk (Tang et al., 2019), bankruptcy predictions (Barboza et al., 2017), and credit card risk management (Tang et al., 2019; Barboza et al., 2017). (Butaru et al., 2016).

By eliminating human analysts and reducing mistake costs, machine learning is revolutionising the banking business. AI has created cutting-edge technology based on machine learning that identifies fraud and deceit in the process, minimising the likelihood of mistakes and analysing hundreds of documents. According to projections, using machine learning to analyses alternative data in order to determine creditworthiness will increase rapidly. Companies may desire to provide mortgages, payment plans for things, credit cards, and other loans to billions of prospective consumers with no credit history. It is reasonable for banks to consider that the more information they have about a person, the more accurately banks will be able to predict consumer behavior, such as consumers' intention to repay the loan.

Lenders may be able to make credit choices that were previously impractical by using a range of data sources and machine learning algorithms to provide an assessment of ability and willingness to repay. While this tendency may be advantageous for countries with limited credit markets, it could result in an unsustainable rise in loan balances in countries with robust credit markets. (RatnaSahay, et al 2015). The superiority of machine learning-based credit scoring models over conventional credit scoring models for evaluating creditworthiness has not been demonstrated.

Using the massive amounts of data traditional banks collect to connect mobile banking apps with banking data and artificial intelligence to aid in financial planning and forecasting may be the first step towards building a credit history.

Utilizing AI into credit scoring models has both benefits and drawbacks. Massive amounts of data can be rapidly analysed, which may result in Credit scoring algorithms that handle a wider range of credit inputs can increase the number of people for whom organisations can assess credit risk while decreasing the cost of analysing credit risks for a given individual. Review of timely payments of non-credit bills, such as those for mobile phones and other utilities, in conjunction with other data is an example of how big data may be used to improve credit rating. Due to AI, persons A loan or credit card may also be available to those without a credit history or credit score, however in the past, a lack of credit history was a limiting factor since traditional credit scoring models lack additional indicators of the propensity to repay.

It is frequently more difficult to explain a credit score and the corresponding credit decision to consumers, auditors, and management. Others have also stated that the use of new alternative data sources, such as internet behaviour or non-traditional financial data, may inject bias into credit decisions. (O'Neil, 2017).

The usefulness of these technologies depends in large part on their ability to collect historical data from a variety of borrowers and loan products. Similar to other risk models, the effectiveness of these ones depends on the availability, consistency, and quality of data on the performance of borrower-products under various financial conditions.

By collecting customer data, analysing the data using AI and data science, machine learning can help banks find ways to enhance the security of online finance, identify vulnerabilities in online systems, and mitigate threats posed by system vulnerabilities. Together, AI and machine learning can easily detect fraudulent activities and notify consumers and banks. By incorporating chatbots into their mobile banking applications, banks can guarantee that they are accessible to consumers 24 hours a day. Furthermore, by analysing client behaviour, chatbots are able to provide personalized customer service and propose appropriate financial services and products.

Additionally, banks have started using AI-based machine learning techniques to create better, safer, attractive and affordable loan options. Many banks rely heavily on the credit history, credit rating and references of other clients to establish the eligibility of any individual or business for lending.

However, one cannot completely agree that these credit-reporting systems often contain or contain errors, exclude the actual transaction data of an individual or business and incorrectly classify borrowers or creditors. Therefore, banks should automate their credit eligibility systems using modern techniques, given that an AI-based loan and credit system can analyse the behaviour and patterns of consumers with low credit history to establish their loan eligibility. Moreover, this technology alerts banks about specific activities that may increase the chances of default. In short, these technologies play a vital role in the future transformation of consumer finance. As a result, the author focused on creating a machine-learning application based on artificial intelligence to determine loan eligibility to aid banking operations.

1.2 Need & Justification of the research

Lenders across the nation are only beginning to amplify artificial intelligence and machine learning algorithms to not only better understand customer behavior but also better serve their exact requirements and preferences. The fact that the lender will request your latest credit information and, based on the score assigned to you by the credit rating agency, assess your overall creditworthiness.

In India, there are now 3 main credit rating agencies, CIBIL, Experian and CRIF Highmark, and each of them assigns you a score of 900, out of which you need to have a minimum of 750 to be smoothly approved. Now, in a traditional loan process, the lender will take at least 1 business week to first request your latest credit report from the credit rating agency, followed by actually reviewing it and arriving at your creditworthiness.

Along with this, since the entire process is manual, there might be instances where an unworthy applicant is assigned a higher credit limit, setting the stage for a default, and a worthy candidate is rejected. Lastly, in a manual process, you are always in the dark as the lender has no way of intimating you beforehand if you are eligible for the loan or not.

On the other hand, when a person apply for a Personal Loan or any such other loan through the artificial intelligence powered application, the app automatically pulls the latest credit

report from the credit bureau and, based on certain predefined criteria, instantly assesses your creditworthiness and grants you a limit.
The need & significance of the study lies in the advantage of using such artificial intelligence-based machine-learning application for ascertaining credit eligibility to assist the banking operations. It improves the manner in which banks supply services and the quality of those services. Further, the fact that the entire process will be extremely fast, easy and risk-free for both customers and the lender, and is entirely automated and transparent welcomes such applications in today`s fast moving technical world. It also increases the trust and confidentiality of the customers in their bank as they are never kept in the dark, and are fully aware of their complete eligibility for the loan right from the start.

1.3 Research Objective

The study aims to develop an artificial intelligence-based machine-learning application for ascertaining credit eligibility

2. Literature Review

According to **Russell and Norvig (1995)**, artificial intelligence (AI) machines should be able to behave and reason in a rational manner, while they also proposed a different aspect that AI machines should be able to act and think like humans.

Alan Turing's (1912–1954) presentation of the Turing machine (**1937**) (a model of the ideal intelligent computer) and formulation of automata theory were important milestones in the development of the AI field. Research by **Walter Pitts and McGulloch (1943)**, developing the MP neuron, paved the way for artificial neural network research, which was the first well-recognized AI study **(Zhongzhi, 2011; Russell and Norvig, 1995)**.

Business Intelligence (BI) is a broad term that encompasses any system infrastructure, tools, databases, applications and processes that aim to evaluate data to help system or business managers make better decisions **(Turban, Sharda, & Deleon, 2011).** Evaluate Customer Loan Appraisal, Bank Branch performance, e-banking services and retention are all great topics for applying Business Intelligence (B.I.) principles and techniques such as Data Mining (D.M.), Data Warehousing (D.W.) and Decision Support Systems (D.S.S.) to the banking industry.

In terms of information systems and technologies, the banking sector has always been a hotbed of innovation **(Shu & Strassmann, 2005). Fathi and Pasiouras (2010)** focused on bank performance profit efficiency and capacity efficiency. In addition, advanced data analysis approaches are now being used to assess social and cultural aspects influencing mobile payments **(Dahlberg, et al., 2008)** credit ratings (Marques, García and Sanchez, 2012) and financial fraud detection including credit fraud **(Ngai et al. (2011)).**

In credit scoring applications using AI based ML for assessment, it was found that there is no one-size-fits-all approach to model building **(Abdou and Pointon, 2011).** Credit risk assessment is a large topic in itself, with a considerable number of research articles in banking during the last twelve years (Marques et al, 2012).

2.1 Application of AI and Machine Learning in banking sector

- **Fraud detection and compliance**

Detecting credit card fraud is one of the most successful uses of machine learning. The use of credit card transaction data for algorithm training, back-testing, and verification. The Association of Certified Public Accountants defines fraud as any deliberate act of robbing someone of their property or money via trickery, deceit, or other unfair means. (I. Sadgali, 2018). Fraud is a latent variable, which means that it must be inferred from data as it cannot be observed directly. Therefore, although firms have access to thorough transaction histories, The ability of ML systems to make accurate fraud predictions is more difficult than that of shopping decisions (a manifest variable) (Baugess, 2017).
However, we cannot ignore the losses associated with electronic commerce. Services make electronic payments more tranquil, smooth, sufficient, and user-friendly. Organizations and banks that utilize them provide adequate security measures. To counter these challenges, however, the nuanced strategies of fraudsters continue to improve. Therefore, it is essential to enhance detection and preventive measures (B. Wickramanayake, et.al, 2020)
In order to properly oppose a scam, it is essential to comprehend the mechanics behind its execution. The device for spotting credit card fraud depends on the fraud process itself (M. Kanchana, et.al, 2020).
To accomplish this, you must provide the transaction information to the verification module, which will determine whether the details are genuine or fake. The transaction will be rejected if it is discovered to be fraudulent. If not, the deal is finalised (A. RB and S. K. KR, 2021). Fraud detection techniques using artificial intelligence and data science analysis are two examples of techniques that can be used to differentiate between the two. Fraud detection involves data mining using artificial intelligence methods, which can classify, organize, and segment data to examine millions of transactions for patterns and identify fraud.
Automated machine learning is a technique that detects fraudulent signals. There are two ways to prevent fraud: one is to detect fraud and the other is to integrate prevention into the system. The main goals of fraud detection and prevention are to initially distinguish between legitimate and fraudulent transactions, and then to prevent fraudulent behavior. To achieve this goal, historical data is used to understand user usage patterns and user behavior is reviewed to determine whether a transaction by a user is fraudulent or not. When fraud is detected by the system, fraud can be brought under control when the system is unable to identify and prevent fraudulent behavior. (2018) J. Choudhary and R. R. Popat. In supervised fraud detection systems, new transactions are classified as genuine or fraudulent based on their characteristics using the identified fraudulent and legal activities, but in unsupervised fraud detection systems, internal and external transactions are highlighted as potentially fraudulent. Point-to-point interactions can be found between supervised and unsupervised machine learning techniques. There have been many studies on various approaches to the issue of card fraud detection. These techniques include DT, K-means clustering, and ANN (O. Adepoju, et al, 2019).

- **Determining Creditworthiness**

According to **Daniel (2020)**, most loans are largely valued based on the chance of repayment by a person or business; thus, assessing the risk of default by an individual is vital for the whole industry. Even with perfect information, the task might be challenging since information

is usually missing or wrong and sometimes, both individuals and businesses lie. As such many businesses are analysing risk using AI.
Companies are now analysing an individual's whole life, including their extensive digital trail, to identify their propensity to default. Historically, lenders considered just a few variables, such as FICO score and income. Now, firms examine an individual's whole life, including their extensive digital footprint, to evaluate the likelihood that they would fail on their payments. It is referred to as "alternative data" about prospective borrowers. Extra information, according to the theory, can be particularly useful in establishing the creditworthiness of those without a typical credit history, not just for those with existing FICO scores.

❖ **Fundamental Eligibility Considerations**
As per the **Basel Committee on Banking Supervision, (2000),** the customer`s eligibility to be considered for getting a personal loan or not is critically dependent on his/her geographic location and is also contingent upon their income. The bigger the loan amount for which a person is qualified, the higher his/her income will be. Housing situationalso affects theprobability of having the loan application granted. As such a person who owns his/her own house are in a greater capacity to repay their debts on time than those who rent a property. This is because renting a property limits the discretionary income, hence diminishing the capacity to repay one` debt. Further, if someone already have a personal loan, their chances of obtaining another one are lower than if they have no other loans. Interestingly, **Basel Committee on Banking Supervision, (2000)** also claimed that the employer would also determine if their employees are qualified for a personal loan or not. As working for a well-known firm with a solid reputation gives the impression that, the job is safe. Further, the credit score and credit history will have the greatest impact on a person`s personal loan eligibility. This variable will affect the interest rate, loan length, and loan amount.
(Source: Basel Committee on Banking Supervision, 27 September 2000, 'Principles for the Management of Credit Risk', Guidelines. Available on https://www.bis.org/publ/bcbs75.htm, accessed on 20-03-2021**)**

Adhering to a dependable technique for awarding credit
Credit risk is inherent in all types of items and operations, and must be identified and managed by banks. Before launching or participating in any new products or activities, banks should ensure that the risks involved are subject to appropriate risk management procedures and controls as may be authorized in advance by the board of directors or the relevant committee **Basel Committee on Banking Supervision, (2000).**

- **Credit Scoring Applications**

AI provides a faster, more accurate assessment of a potential borrower at a lesser cost and reflects a larger variety of criteria, resulting in a more educated, data-backed choice. As compared to conventional loan scoring systems, Credit scoring performed by AI is based on more intricate and sophisticated criteria. It helps lenders to distinguish between individuals with a high risk of default and those who are creditworthy but lack a credit history. An additional benefit of the AI technology is its objectivity. In contrast to humans, machines are improbable to be partial. Applications for digital banks and loan issuance Utilize machine

learning algorithms to identify loan eligibility and present personalised options by comparing credit status with optional data such as smartphone data. (Bachinskiy 2019.)
The purpose of credit rating systems based on machine learning is to expedite loan approvals while potentially lowering risk. For many years, lenders have used credit scores to help them make decisions about who to lend money to, both personally and commercially. In the past, most credit rating systems depended on information from financial organisations about transactions and payments. These algorithms build a credit score from modest amounts of structured data using techniques such as regression, decision tree, and statistics. Using this new data collection, machine-learning methods were applied to qualitative characteristics like consumption pattern and a readiness to pay. The capacity to use more data on these characteristics allows for a more accurate, faster, and less expensive segmentation of borrower quality, resulting in a speedier credit decision (Stefan Lessmann, Bart Baesens, Hsin-VonnSeow, and Lyn Thomas, 2015). The use of personal data, however, raises additional policy concerns, such as data security and privacy. (CGFS and FSB, 2017).

3. Research methodology

This research presents a study into developing a system to predict the loan sanction probability based on a number of characteristics developed from existing database. The dataset has been gathered through a survey of bank officials on the various criterions of judging the possibility of granting loan to a customer. This investigation's goal is to look into form a machine learning model using various statistical analysis on this dataset so that an automated prediction can be provided.

3.1 Data Repository

The dataset is obtained from survey of bank officials based on a prepared questionnaire…..
The dataset contains 52 features such as Occupation, Type of Employment, Ownership status of House, Credit Score, Previous History of loan from other banks, Health Condition, Health insurance etc. Table I shows the various features.

```
'Gender', 'V 1. Age',
'V 2. Occupation (Government Employee with salary slip & ITR of last three years)',
'V 3. Occupation (Private employee Employee with salary slip & ITR of last three years)',
'V 4. Occupation (Business with IT return of last three years)',
'V 10. Ownership Status of House (Owned/Rented)',
'V 11. Previous history of loan from other banks',
'V 13. Default status', 'V 14. Minimum Net Monthly Income',
'V 15. Credit Score (CIBIL Score)', 'V 16. Collaterals/guarantee',
'V 18. Guarantor's Documents (Personal details, PAN/AADHAR Card, Employment details.)',
'V 20. Value of the Property/assets owned ', 'V 21. Credit Card',
'V 22. Saving Pattern of the borrower (NSE/LIC/Bond/Share and other investments)',
'V 24. Gold Ornaments of the borrower',
'V 25. Mobile Nos. of blood relatives of borrower.',
'V 26. Electricity Bill/Gas Bill/House tax/ Water tax, other Online paid bills etc)',
'V 27. E-commerce Transaction Frequency & Amount',
'V 28. Shopping Bills/Amount',
'V 31. Food Delivery Services Frequency & Amount',
'V 32. No. of  Friends & Followers on Facebook/Instagram/Twitter and other social media Platforms.',
'V 33. Posts/Photographs of Places visited',
'V 34. Posts/Photographs of Hotels Visited', 'V 37. Intelligence',
'V 38. Honesty', 'V 39. Character Certificate',
'V 40. Health Condition', 'V 41. Health Insurance'],
```

Table 1: Name of Features

Table 2: Assigned Weight according of the Features.

	Gender	V 1. Age	V 2. Occupation (Government Employee with salary slip & ITR of last three years)	V 3. Occupation (Private employee Employee with salary slip & ITR of last three years)	V 4. Occupation (Business with IT return of last three years)	V 10. Ownership Status of House (Owned/Rented)	V 11. Previous history of loan from other banks	V 13. Default status	V 14. Minimum Net Monthly Income	V 15. Credit Score (CIBIL Score)	...	V 28. Shopping Bills/Amount	V 31. Food Delivery Services Frequency & Amount
0	1	2	1	0	0	1	1	1	1	2	...	3	1
1	1	4	1	0	0	2	1	0	2	1	...	3	3
2	2	3	1	0	0	1	1	0	3	1	...	5	3
3	1	2	0	1	0	2	0	0	3	1	...	5	3
4	1	2	0	1	0	1	1	0	2	1	...	4	4

V 15. Credit Score (CIBIL Score)	...	V 28. Shopping Bills/Amount	V 31. Food Delivery Services Frequency & Amount	V 32. No. of Friends & Followers on Facebook/Instagram/Twitter and other social media Platforms.	V 33. Posts/Photographs of Places visited	V 34. Posts/Photographs of Hotels Visited	V 37. Intelligence	V 38. Honesty	V 39. Character Certificate	V 40. Health Condition	V 41. Health Insurance
2	...	3	1	1	1	1	4	4	3	4	5
1	...	3	3	1	1	1	1	1	1	1	1
1	...	5	3	1	2	2	5	5	3	4	4
1	...	5	3	1	3	3	5	5	3	2	4
1	...	4	4	3	5	5	5	5	5	5	5

3.2 Data Preprocessing:

Data Preprocessing is done to convert the gathered data into a meaningful form so that it can be processed by the system. Irrespective of simulation results, whether the data includes rubbish, the production still becomes garbage. Therefore, pre-processing data is a key step in data mining and machine learning. Preprocessing data is a tool array that transforms raw data into a comprehensible format. In pre-processing results, outliers are detected, views on outliers are measured, missing values established and complete and incoherence tests made. Data must be compressed or structured before they refer to machine learning algorithms. Data is standardized because the data-set systems have different measurement units available.

3.2.1 Algorithm for Data Preprocessing:

```
loanPerson = []
for i in range(0,52):
    if finalcondition[i]>152:
        loanPerson.append(1)
    if finalcondition[i]>100 and finalcondition[i]<151 :
        loanPerson.append(2)
    if finalcondition[i]>75 and finalcondition[i]<100:
        loanPerson.append(3)
    if finalcondition[i]>50 and finalcondition[i]<75:
        loanPerson.append(4)
    if finalcondition[i]<50:
        loanPerson.append(5)
print(loanPerson)
```

Table 3: The preprocessed data appears below

	V 2. Occupation (Government Employee with salary slip & ITR of last three years)	V 3. Occupation (Private employee Employee with salary slip & ITR of last three years)	V 4. Occupation (Business with IT return of last three years)	V 10. Ownership Status of House (Owned/Rented)	V 11. Previous history of loan from other banks	V 13. Default status	V 14. Minimum Net Monthly Income	V 15. Credit Score (CIBIL Score)	V 16. Collaterals/guarantee
0	50	0	0	10	10	-20	10	-10	10
1	50	0	0	0	10	0	15	10	20
2	50	0	0	10	10	0	20	10	20
3	0	20	0	0	0	0	20	10	20
4	0	20	0	10	10	0	15	10	20

V 16. erals/guarantee	V 18. Guarantor's Documents (Personal details, PAN/AADHAR Card, Employment details.)	...	V 26. Electricity Bill/Gas Bill/House tax/ Water tax, other Online paid bills etc)	V 27. E-commerce Transaction Frequency & Amount	V 28. Shopping Bills/Amount	V 31. Food Delivery Services Frequency & Amount	V 34. Posts/Photographs of Hotels Visited	V 37. Intelligence	V 38. Honesty	V 39. Character Certificate
10	10	...	3	0	0	0	0	0	0	0
20	10	...	0	0	0	0	0	0	0	0
20	10	...	0	3	0	0	0	3	3	0
20	-10	...	3	3	0	0	0	3	3	0
20	10	...	0	0	0	0	3	3	3	3

There were no null values in the data table. The graph is as shown in **Figure 1** below:

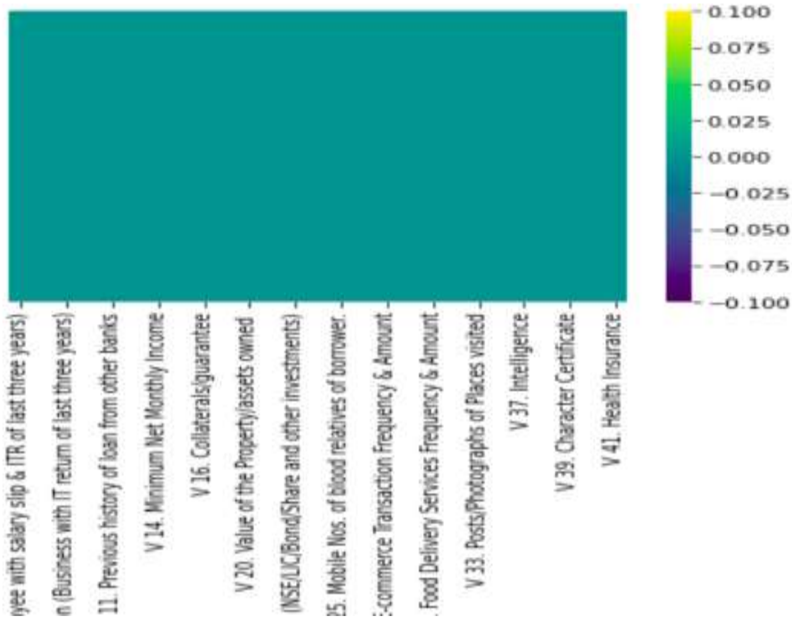
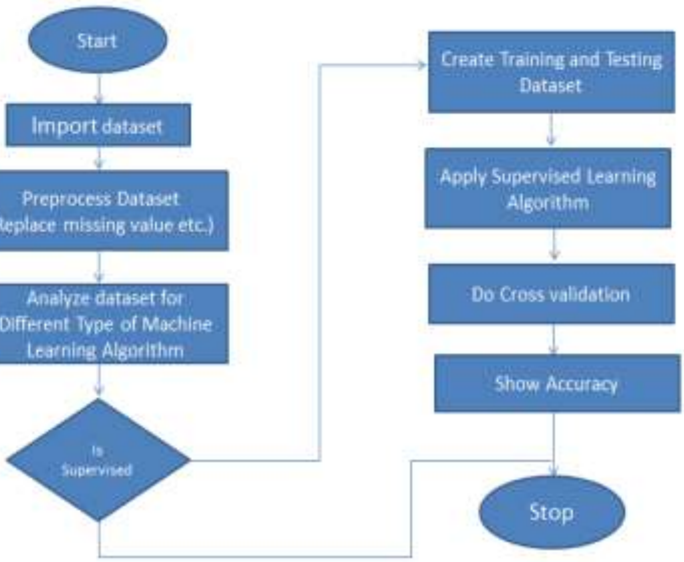


Figure 1: Graph of Null Values

4. RESULTS & DISCUSSION



Algorithm

```
for i in pr:
   if pr[i]==1:
         predictValues.append("Very High")
#           return "Very High"
   if pr[i]==2:
         predictValues.append("High")
#           return "High"
   if pr[i]==3:
         predictValues.append("Moderate")
#           return "Moderate"
   if pr[i]==4:
         predictValues.append("Low")
#           return "Poor"
   if pr[i]==5:
         predictValues.append("Very Low")
#           return "Very Poor"
```

The preprocessed dataset is then fed into the model as shown in the algorithm above. The algorithm for predicting the Probability of loan sanction is as shown below:

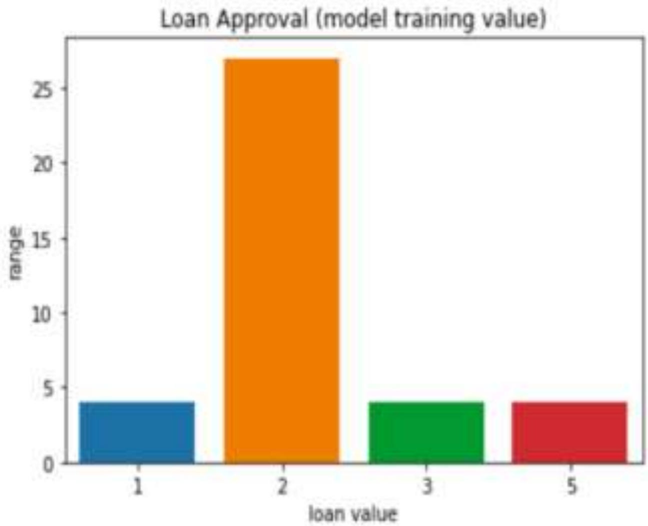


Figure 3: Loan Prediction Training Values

Figure 3: Loan Prediction Testing Values

Figure 4: Loan Approval (Model Predicted Value)

The algorithm assigns values to the data set's 52 features. Age, occupation (government employee, employee with salary slip & ITR of last three years), occupation (business, with IT return of last three years), residence (urban/rural), type of family (nuclear/joint), number of dependents, guarantor's documents (personal details, PAN/AADHAR card, employment details), etc. After analysing the basic data, we obtain the statistical analysis from which we derive the weights for them, e.g., 1, 2, 3, 4, 5. (Very High, High, Moderate, Poor, Very Poor). Numerous tools are used, such as Pandas for data analysis and in evaluating time series, Excel data sheets, and Seaborn for automatically estimating and plotting linear regression plots. Other tools include Numpy for numerical computation of the data and data analysis, image processing, and other libraries as a simple stack for such libraries.

The algorithm was developed to establish and design a system using AI and ML to stop frauds and misleading information from prospects applying for loans in the banking industry. Works with the data set that the person entered. It employs the full loan approval model. It correlates the value provided in the data sets, and according to the values and weights allocated to them, the results found produce the following final values:

1	Very High

2	High
3	Moderate
4	Poor
5	Very Poor

By carefully examining all of the customer's vertical and attributes and assessing their loan application, this AI-based IT application will assist bankers in determining the amount of credit that a potential borrower is eligible for. It also assists in determining the credit worthiness of the potential borrower through its 720-degree focus.

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