

A Method for Loan Approval Prediction Using a Machine Learning Algorithm

Vedant Shinde^[1], Pranav Sandbhor^[2], Nikhil Waghmare^[3], Satyajit

Sirsat^[4] ^[1,2,3]Student, ^[4]Assistant Professor

Department of Computer Engineering,
Nutan Maharashtra Institute of Engineering and Technology
Pune

Abstract — Many more people are seeking for bank loans as a result of the growth in the banking industry. These loans cannot all be approved. Gains from loans are what bank assets primarily make revenue from. The goal of banks is to allocate their resources towards secure clientele. Even though loans are approved by many banks these days following extensive verification and validation procedures, there is never a guarantee that the chosen consumer will be secure.

As a result, it's critical that the banking industry use a variety of strategies to identify clients who make their loan payments on schedule. The random forest technique is used in this report to classify the data. Using a training dataset, the Random Forests method creates a model. This model is then applied to test data, yielding the desired result.

Many more people are seeking for bank loans as a result of the growth in the banking industry. These loans cannot all be approved. Gains from loans are what bank assets primarily make revenue from. The goal of banks is to allocate their resources towards secure clientele.

Keywords— outlier, Prediction, loan, component, Overfitting, Safe, Bank loans, Transform, machine learning

I. INTRODUCTION

For many banks, loan distribution is their primary business activity. The loans made to clients account for the majority of a bank's revenue. These banks charge interest on loans that are given to clients.

Investing bank assets in secure clients is their primary goal. Many banks still process loans using a regressive verification and validation procedure [1].

However, as of right moment, no bank can guarantee that the client selected for a loan application is secure or not. We thus implemented a system for bank loan approval

called the Loan Prediction System Using Python in order to prevent this circumstance.

A loan prediction system is software that determines if a certain consumer is eligible and able to repay a loan.

A client's ability to repay a loan is indicated by a yes response; a negative response shows that the consumer is unable of doing so. These criteria allow us to approve loans for clients..

II. LITERATURE SURVEY

Data analysis to forecast a client's loan-based nature.

The primary goal of the report is to categorize loan clients. The report categorizes the clients based on specific criteria. Investigative data analysis is used to classify [2].

A method called exploratory data analysis examines and condenses the key characteristics of a training dataset.

Prediction of Loan Approval using Machine Learning Approach

The process known as machine learning involves building an analytical model from a learned model. Using test data, this model is applied to provide the precise outcomes

Here, the author predicted the loan using three different methods.

1. K Nearest Neighbor is one of them.
2. Tree of Decisions
3. Stochastic Forests

The primary objective of this report is to provide prompt and precise outcomes for loan approval to qualified clients. There will be a number of loan applicants in the banking industry. Verifying a customer's eligibility through paperwork is challenging. The n number of users can receive correct results from the system [3].

Ensemble model survey for loan prediction

The author of this paper built a model using the Random Forest technique. In this study, a perfect model for is identified by combining two or more classifiers. loan forecast.

By comparing two or more models and selecting the best model for improved loan prediction, the ensemble technique helps the banking industry make the best decision when approving loan applications.

III. RELATED WORK

Up until now, different institutions have handled loans using paper and pen. When the significant number of

clients apply for loans from banks These banks take a long time to grant loans. There is never a guarantee that the selected applicant will be able to repay the loan once it has been approved by the banks [4]. A lot of banks approve loans using software that they own. The current system uses data mining algorithms to approve loans; this is an outdated method of loan approval. A Generalized dataset is created by combining many data sets, and various machine learning methods are then used to provide outputs. However, these methods fall short of expectations.

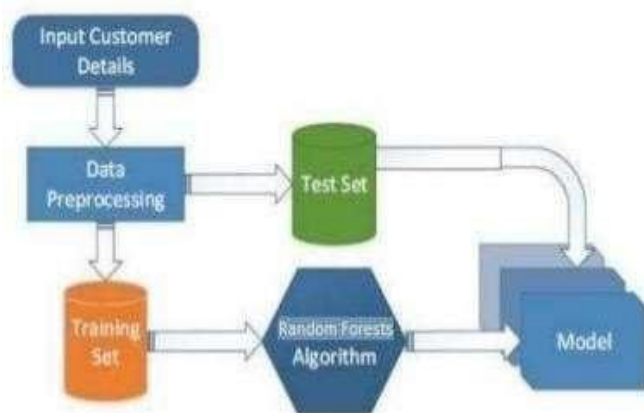
Large banks are experiencing financial troubles as a result. In order to address this problem, we provide a novel approach for loan approval.

3.1. Proposed System

Software called the Loan Approval System is used in the banking industry to approve loans [5]. Our suggested approach makes use of a machine learning algorithm. Through the process of machine learning, a symmetric model is created from an existing dataset and used to evaluate a new dataset. A test dataset and a training dataset make up the system. The model is built using the training dataset. To get the desired outcome, this model is applied to a testing dataset. The ensemble technique was employed in the model development process. Using this ensemble method, the random forest algorithm creates a model using the available training dataset.

IV. IMPLEMENTATION

Ensemble learning has been employed in the system's construction.



Architecture of Proposed Model

Fig. 1. Block Diagram of Loan Approval Prediction System

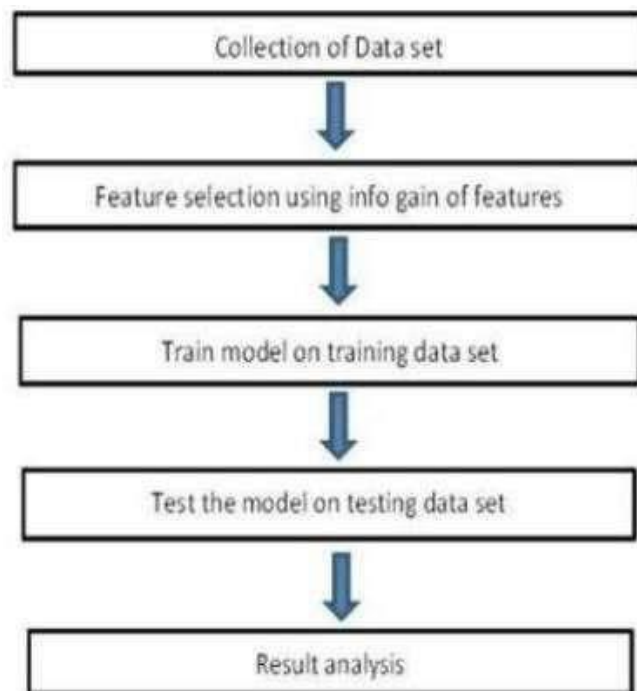


Fig.2. Flowchart Diagram of Loan Approval Prediction System

Ensemble learning

A technique called ensemble learning uses a large number of weak classifiers. To get the desired outcome, we feed these classifiers our training dataset. These classifiers might employ a variety of techniques, such as the k closest neighbor algorithm, the decision algorithm, the svm algorithm, or another learner classifier [7].

Our training dataset is fed into these classifiers, and they provide results based on their algorithm work. Ensemble learning or heterogeneous classification are terms used to describe this process. All learner classifiers may be viewed as using the same algorithm. However, all of these classifiers return the same result when we submit the identical training dataset. In order to prevent this issue, we have provided these classifiers with distinct training datasets, resulting in distinct outputs from each classifier [8]. These classifiers create a model by taking into account a number of criteria and producing an output. Every classifier may create a model based on the provided training dataset. Our training dataset is fed into these classifiers, and they provide results based on the algorithm function. Ensemble learning or heterogeneous classification are terms used to describe this process. Additionally, we may use the same approach for all learner classifiers.

However, all of these classifiers return the same result when we submit the identical training dataset. In order to prevent this issue, we have provided these classifiers with distinct training datasets, resulting in distinct outputs from each classifier. These classifiers create a model by taking into account a number of criteria and producing an output. Every classifier may create a model based on the provided training dataset [9].

Random Forest Algorithm

The Random Forest Algorithm employs the ensemble learning technique, as we have already mentioned.

Working of Random Forest Algorithm

The Random Forest Algorithm adheres to Decision Tree principles. The Random Forest Algorithm examines several decision trees and produces a result that satisfies the majority of the decision trees, whereas the decision tree algorithm produces the outcome by taking into account only one component.

The Random Forest Algorithm creates a robust model that fulfills the decision tree model's numerous nodes. This model is then used to the testing dataset to obtain the desired result [10]. First, a training dataset is needed to develop a model. From that training dataset, we take into consideration the bootstrap dataset1 subset. There are several variables in this bootstrap dataset1. We only take into account two of these factors, and from these two variables, we create a root node for the variable that yields more accurate results than the other. Using the bootstrap dataset1, we construct a decision tree in this way. We examine a different subset of the training dataset, which we'll refer to as bootstrap dataset2. In the same manner that we construct a decision tree for the bootstrap dataset 1one, we also construct a dataset for the bootstrap dataset 2. These procedures must be followed until a large number of decision trees are obtained.

Once we have a large number of decision trees, we compare them all and create a model that takes into account each decision tree in its entirety [11]. Strong Model is the name given to the resulting model. The training dataset is used to create a model in this manner.

In this format, the system uses the Random Forest Algorithm to construct a model when we input a training dataset. The model is then used to provide the necessary output when we upload a testing dataset. There are two class labels in the output: yes and no. If the answer is yes, the customer is qualified for loan approval; if the answer is no, the client is not eligible for loan approval [12]. The system produces the necessary output in this way.

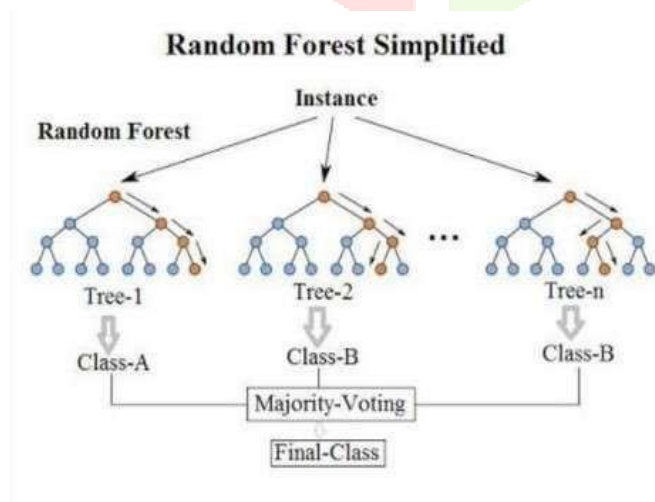


Fig. 3. Random Forest

V. DATAPRE-PROCESSING

Looking through accessible Bank Promoting informational indexes, it was found that the Bank Showcasing informational collection at Kaggle is one of the every now and again examined informational collections utilizing AI procedures [13]. Basically, there were two informational indexes at Kaggle connected with bank advertising direct missions. The full informational index has around 45,211 information examples with 20 elements, out of which 10 were numeric elements and 10 were straight out. The full informational collection was intended to be utilized for anticipating whether the bank client will buy in a drawn out store. In this exploration, the emphasis is on the client's information that is accepted to endorse a credit or not. As displayed in table 2, just a subset of the elements was utilized: age, work, conjugal, instruction, default, equilibrium, advance, and lodging [14]. By leading an underlying examination of the informational index, there were no missing qualities seen as in all the picked credits.

VI. OUTPUT

To shield framework from unapproved access, we have made administrator login module for security reason. It comprises of username and secret word. By giving the legitimate username also, secret key we can get to the framework.

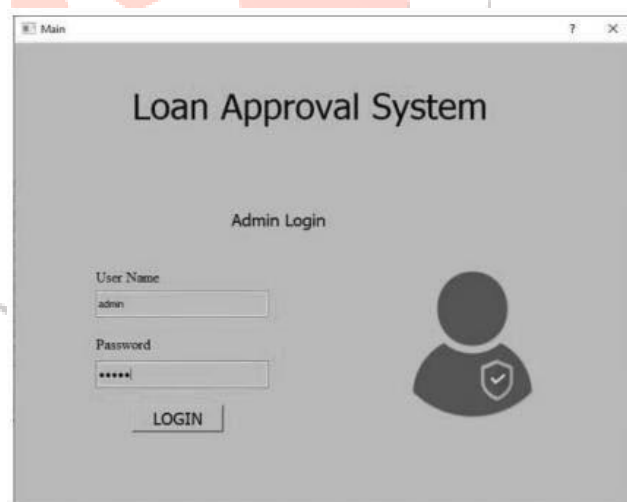


Fig 4. Admin login

The administrator home comprises of two choices:

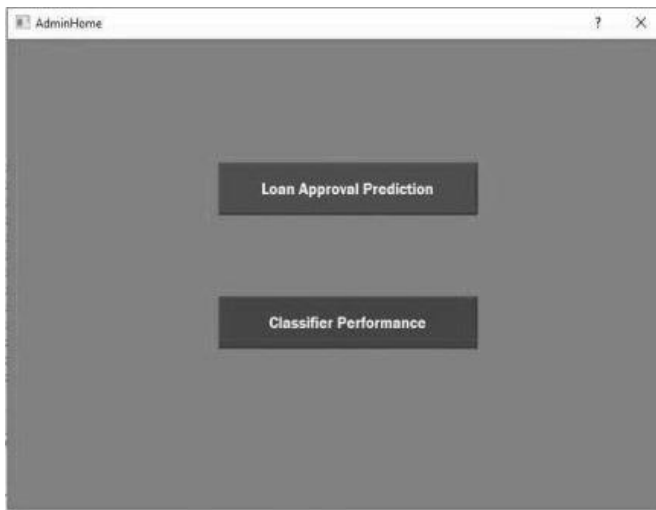


Fig 5. Admin Home

Credit Endorsement Expectation is picked for expectation of credit status though classifier execution gives the forecast after effects of three calculations:

Loan_ID	Gender	Married	Dependent	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
1	Male	No	0	Graduate	No	5900	0	36000	360	1	Urban	Y
2	Male	Yes	1	Graduate	No	4300	1500	13120	360	1	Rural	N
3	Male	Yes	0	Graduate	Yes	8000	0	57000	360	1	Urban	Y
4	Male	Yes	0	Not Graduate	No	2500	2500	94020	360	1	Urban	Y
5	Male	No	0	Graduate	No	6000	0	19940	360	1	Urban	Y
6	Male	Yes	2	Graduate	Yes	3437	4286	13407	360	1	Urban	Y
7	Male	Yes	0	Not Graduate	No	2385	1510	45675	360	1	Urban	Y
8	Male	Yes	3	Graduate	No	3036	2004	67020	360	0	Semurbani	N
9	Male	Yes	2	Graduate	No	4006	1520	98720	360	1	Urban	Y
10	Male	Yes	1	Graduate	No	11041	10966	34730	360	2	Semurbani	N
11	Male	Yes	2	Graduate	No	1000	750	55570	360	1	Urban	Y
12	Male	Yes	2	Graduate	Yes	2500	1040	11000	360	1	Urban	Y
13	Male	Yes	2	Graduate	No	8773	3000	24000	360	1	Urban	Y
14	Male	No	0	Graduate	No	11073	2040	14120	360	1	Rural	N
15	Male	Yes	0	Graduate	No	1200	1000	56717	120	1	Urban	Y
16	Male	No	0	Graduate	No	4000	0	34425	360	1	Urban	Y
17	Male	No	1	Not Graduate	No	1000	0	234000	360	1	Urban	Y
18	Female	No	0	Graduate	No	1010	0	12570	360	1	Urban	N
19	Female	Yes	0	Not Graduate	No	4807	0	426210	360	1	Rural	N
20	Male	Yes	0	Graduate	No	2000	2000	709125	360	1	Urban	Y
21	Male	Yes	0	Not Graduate	No	7600	0	456000	360	0	Urban	N
22	Male	Yes	1	Graduate	No	3055	3625	70335	360	1	Urban	Y
23	Male	Yes	0	Not Graduate	No	2000	1011	40110	360	0	Semurbani	N
24	Male	Yes	2	Not Graduate	No	1345	1017	23112	360	0	Rural	N

Fig 6. Train Data

The above Fig. 6 addresses the prepared information. The train information comprises of different traits like compensation, military status, advance records, and credit reimbursements on time and so on. As per these elements we fabricate a required model for advance expectation.

The above Fig. 7 addresses the test information. The test information comprise of different properties like compensation, military status, credit accounts aside from the advance endorsement status. The credit endorsement status is acquired. At the point when we send the test information to the model which is work from the prepared information.

Loan_ID	Loan_Status
1	Y
2	Y
3	Y
4	Y
5	Y
6	Y
7	Y
8	N
9	Y
10	Y
11	Y
12	N
13	N
14	N
15	Y
16	Y
17	Y
18	Y
19	Y
20	Y
21	Y
22	Y
23	Y
24	Y
25	Y
26	Y
27	Y
28	Y
29	Y
30	Y
31	Y
32	Y
33	Y
34	Y
35	Y
36	Y
37	Y
38	Y
39	Y
40	Y
41	Y
42	Y
43	Y
44	Y
45	Y
46	Y
47	Y
48	Y
49	Y
50	Y
51	Y
52	Y
53	Y
54	Y
55	Y
56	Y
57	Y
58	Y
59	Y
60	Y
61	Y
62	Y
63	Y
64	Y
65	Y
66	Y
67	Y
68	Y
69	Y
70	Y
71	Y
72	Y
73	Y
74	Y
75	Y
76	Y
77	Y
78	Y
79	Y
80	Y
81	Y
82	Y
83	Y
84	Y
85	Y
86	Y
87	Y
88	Y
89	Y
90	Y
91	Y
92	Y
93	Y
94	Y
95	Y
96	Y
97	Y
98	Y
99	Y
100	Y

Fig 8. Loan Status

The above Fig. 8 addresses the credit status. The credit status is acquired after the sending of test information to the model which is work from the prepared information utilizing Irregular Backwoods Calculation. The credit status comprises of Client if furthermore, advance status. It shows for a specific client credit is supported or not. On the off chance that credit status is Y (Yes) the client is qualified for endorsement of credit and in the event that it is N (No) the client isn't qualified for endorsement of credit.

VII. CONCLUSION

From the appropriate perspective on examination this framework can be involved ideal for identification of clients who are qualified for endorsement of advance [15]. The product is working great and can be utilized for all financial necessities. This framework can be effortlessly transferred in any working framework. Since the innovation is moving towards on the web, this framework has more scope for the impending days. This framework is safer what's more, solid. Since we have utilized Arbitrary Timberland Calculation the framework returns exceptionally exact outcomes [16]. There is no issue assuming there are numerous no of clients applying for advance. This framework acknowledges information for N no. of clients. In future we can add more calculations to this framework for come by additional precise outcomes.

VIII. REFERENCES

- [1] K. Hanumantha Rao., G. Srinivas., A. Damodhar., M.Vikas Krishna., Execution of Inconsistency Location Strategy Utilizing AI Calculations: Worldwide Diary of Software engineering and Media communications, Vol. 2, Issue 3, 2011.
- [2] S.S. Keerthi., For example Gilbert., Intermingling of a sum up SMO calculation for SVM classifier plan, AI, Springer, Vol. 4, Issue 1, pp. 351-360, 2002.
- [3] Andy Liaw., Matthew Wiener., Arrangement and Relapse by arbitrary Backwoods, Vol. 2, Issue 3, pp. 9-22, 2002.
- [4] Ekta Gandotra., Divya Bansal., Sanjeev Sofat., Malware Examination and Characterization: An Overview, Diary of Data Security, Vol. 05, Issue 02, pp. 56-64, 2014.
- [5] Clatter information mining instrument, <http://rattle.togaware.com/clatter-download.html>
- [6] Aafer Y., Du W., Yin H., Droid APIMiner: Mining Programming interface Level Elements for Vigorous Malware Recognition in Android, Security and protection in Correspondence Networks, Springer, pp 86-103, 2013.
- [7] J. R. Quinlan., Acceptance of Choice Tree, Machine Learning, Vol. 1, No. 1. pp. 81-106.
- [8] Viswanatha, V., Venkata Siva Reddy & R. Rajeswari. (2020). Research on state space modeling, stability analysis and pid/pidn control of dc-dc converter for digital implementation. In: Sengodan, T., Murugappan, M., Misra, S. (eds) Advances in Electrical and Computer Technologies. Lecture Notes in Electrical Engineering, 672. Springer, Singapore. DOI: 10.1007/978-981-15-5558-9_106.
- [9] Kumar, Rajiv, et al. (2019). Prediction of loan approval using machine learning. International Journal of Advanced Science and Technology, 28(7), 455-460.
- [10] Viswanatha, V. & R. Venkata Siva Reddy. (2017). Digital control of buck converter using arduino microcontroller for low power applications. International Conference On Smart Technologies For Smart Nation (SmartTechCon). IEEE.
- [11] Supriya, Pidikiti, et al. (2019). Loan prediction by using machine learning models. International Journal of Engineering and Techniques, 5(2), 144-147.
- [12] V. V, R. A. C, V. S. R. R, A. K. P, S. M. R & S. B. M. (2022). Implementation of IoT in agriculture: A scientific approach for smart irrigation. IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, pp. 1-6. DOI: 10.1109/MysuruCon55714.2022.9972734.
- [13] Arun, Kumar, Garg Ishan & Kaur Sanmeet. (2016). Loan approval prediction based on machine learning approach. IOSR J. Computer Eng, 18(3), 18-21.
- [14] Vincenzo Moscato, Antonio Picariello, Giancarlo Sperli, "A benchmark of machine learning approaches for credit score prediction, Expert Systems with Applications," Volume 165, 2021, 113986, ISSN 0957-4174, <https://doi.org/10.1016/j.eswa.2020.113986>.
- [15] Amit Kumar Goel, Kalpana Batra, Poonam Phogat," Manage big data using optical networks", Journal of Statistics and Management Systems "Volume 23, 2020, Issue 2, Taylors & Francis.
- [16] Nikhil Madane, Siddharth Nanda,"Loan Prediction using Decision tree", Journal of the Gujrat Research History, Volume 21 Issue 14s, December 2019.