Credit Risk Assessment - A Machine Learning Approach

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Abstract. Banks are foregoing their present reserves for future sources of Revenue. This source is associated with a risk called credit default risk which increases defaulting conditions called the Non-performing assets(loans) thus leading to the financial crisis. Machine Learning, a branch of Artificial Intelligence, is the upcoming technology with promising solutions to present limitations of the systems eliminating the human errors or emotions with precision by way of training and testing. The present study is focused on predicting defaulting loans using algorithms of Machine learning. The dataset is preprocessed for dropping the missing values. Further three models - Logistic Regression, KNN and XGBoost are applied for predicting defaulters based on precision, recall and F1-score. The findings of the research concluded that the XGBoost model performed best among the three models for assessment of credit risk which will waive off the crisis situation.

Keywords: Artificial Intelligence · Machine Learning · Credit Risk · KNN · Logistic Regression · XGBoost · Default Risk

1 Introduction

Credit risk is the root cause for financial crisis. Credit risk arises due to disbursement of loans by banks. For banks, loans are the primary source operating revenue in form of interest and processing fee paid by the borrower. On the basis of collateral banks provide loans to the borrowers. The repayment depends on the borrower's income generation. The crisis situation comes into picture due to uncertainty of repayments which is called credit risk or default risk [1] where the banks not only lose their revenue (interest amount) but also their principal also [2].

Credit risk or default risk can be waived off if properly predicted. Machine Learning Algorithms which is part of Artificial Intelligence, the future ruler of the technology, gives a means for assessment of credit risk. Training the system with existing cases eliminates many limitations of disbursement and recovery of loan process such as personal biases. In the present paper a prediction model is developed using Machine Learning Algorithms for credit risk assessment.

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2 Understanding the Concept of Credit Risk and Machine Learning Algorithms

2.1 What is Credit Risk?

The probable loss for lending institutions emerging due to failure of repayment of the loan by the borrower. In simple terms, a failure of contractual commitment of the borrower due to inability of repayment.[19] The following table shows the list of factors contributing to credit risk (Table 1)

Table 1. Factors contributing to Credit risk [20]

Internal	External
Inappropriate lending practices	Government interference
Limited Institutional capacity	Volatile interest rates
Credit policies	Inappropriate laws
Poor management	Massive licensing of banks
Low capital and liquidity levels	Inadequate supervision by the central bank
Direct lending	
Poor loan underwriting	
Laxity in credit assessment	

The different types of credit risk include.

1. Credit default risk - non-repayment by individual and exceeding 90 days from due date
2. Concentration risk - non-repayment by companies due to large losses of industry
3. Country risk or sovereign risk - non-repayment by sovereign states due to foreign currency commitments

Credit default risk is primarily influenced by microeconomic factors listed above; Concentration risk is influenced both by micro and macro economic factors and the Country risk or Sovereign risk is influenced primarily by macroeconomic factors.

The primary cause is inappropriate risk assessment and followed by disbursement to specific borrowers - single specific individuals, groups of individuals, companies, industries, sectors etc. leading credit concentration. Lenders can waive off credit risk through mitigation such as Risk-based Pricing, agreements called as covenants which specify - periodic report of borrower's financial status, making prepayment in case of unfavorable changes, availability of funding pool to diversify the risk, Insuring the credit and arranging for alternative credit. All the mitigation is an attempt to address the credit risk but at the primary level a prediction required to do mitigation. Credit risk analysis helps to forecast the ability of borrower's repayment which helps for further mitigation through covenants and minimizes the loss quantifiably. As part of Basel III execution these techniques help in increasing the proficiency in measuring, identifying and regulating credit risk [19].

2.2 What is Machine Learning?

Machine learning is the process of learning by machine how humans respond to the specific condition. This process basically helps in training the machine to imitate humans. This technology helps in highly vulnerable areas where human intervention is highly risky for the life of humans or creates large losses to the economy in terms of financial crisis.

Machine learning is a branch of Artificial intelligence [6] which applies algorithms to represent humans. The more the training the more is the accuracy.

In general, large volumes of flooding data (Big data) is increasing the scope of applications of machine learning algorithms due to the limited approach of humans and in particular to the Banking Industry [7] (Fig. 1 and 2).

2.2.1 Classifiers of Machine Learning

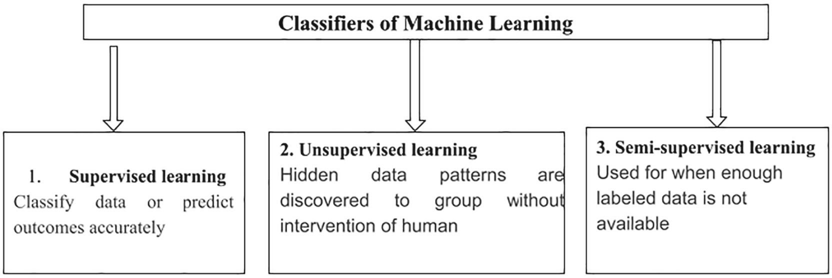


Fig. 1. Classifiers of Machine Learning [21]

2.2.2 Working of Machine Learning Algorithm

There are three main parts in the algorithm [6].

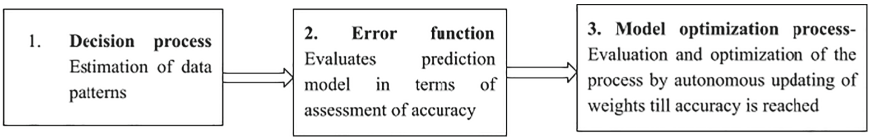


Fig. 2. Working of Machine Learning Algorithm [21]

2.2.3 KNN Model

K Nearest Neighbour algorithm is a supervised classification algorithm also a lazy algorithm no learning or decision but only similarity based classification using euclidean distance which is a proximity measure [8] (Fig. 3 and 4).

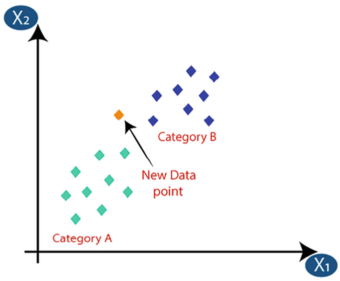


Fig. 3. Working of KNN Algorithm [24]

Algorithm of KNN.

1. Load Data - xls, csv
2. Initialise K value
3. Every sample in the training lab.

   Distance between query point & the current point is calculated.
   Distance & the index of the example are added to the ordered collection.

4. Distances& Indexes of Ordered collection are sorted in ascending order.
   1. First K entries from sorted collection are picked
   2. Labelling Of selected K entries
   3. Returns K Labels Mean in case of regression and Mode in case of classification.

2.2.4 Logistic Regression Model

It is a regression model under supervised classification algorithm criteria decision based on threshold value using sigmoid function [10].

1. High Recall or Low Precision where the number of false negatives are reduced.
2. Low Recall or High Precision where the number of false positives are reduced.

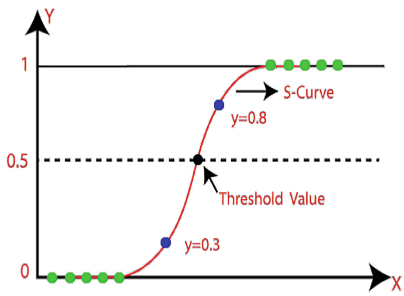


Fig. 4. Working of Logistic Regression Algorithm [26]

2.2.5 XGBoost Model

It is a powerful model under supervised learning model. The statement is validated based on.

1. Objective function
2. Base Learners

The objective function which contains a loss function and a regularization term. Further the difference between the actual and predicted values is calculated to obtain the results which gives accuracy level of the model. The loss functions include:

1. Regression problems
2. Binary classification

The base learners also called as Ensemble - a single prediction is obtained based on training and combining individuals. In the process predictions are combined so that bad predictions are eliminated and finally good predictions is formed. The key members of metrics include:

1. Root-mean-squared error (RMSE)
2. Mean-squared-error (MAE) [13]

3 Literature Review

Table 2. Literature review [3–17]

Year	Authors	Title	Methodology	Result
2022	Pontus Lindqvist Dariush Khailtash [32]	The Impact AI on Bank's Risk Management Approach	Dynamic Risk Management Framework & Multi-Level Perspective	New risks- organisational and regulatory identified with AI implementation
2021	Iryna Yanenkova Yuliia Nehoda Svetlana Drobyazko Andrii Zavhorodnii Lyudmyla Berezovska [3]	Modeling of Bank Credit Risk Management Using the Cost Risk Model [3]	fuzzy programming and symbiotic methodical support	At a very early point Predicting defaulting loans while monitoring using change of indicators
2020	Chun and Lejeune [4]	Risk-Based Loan Pricing: Portfolio Optimization Approach with Marginal Risk Contribution [4]	Statistical method	Analyzing factors help banks to minimize lending risk

(*continued*)

Table 2. (*continued*)

Year	Authors	Title	Methodology	Result
2020	Drobyazko et al.; Nosratabadi et al.[5]	Risk Management in the System of Financial Stability of the Service Enterprise. Journal of Risk and Financial Management [5]	Statistical method	No appropriate monitoring and forecasting system with respect to operating risk
2019	Kaya, Or¸cun et al. [31]	Artificial intelligence in banking	Review	Key process automation - Detecting fraud pattern, personal banking, anti-money laundering (AML)
2019	Zinisha, OS, Ivanenko, IN, and Avdeeva, RA [30]	Artificial ˙ Intelligence As A Factor To ˙ Improve Bank Eciency	Robots	Saving cost upto 87% by investing in robos than hiring employees fultime and increasing efficiency of work
2019	Sarfo-Manu, Philip & Siaw, Gifty & Appiahene, Peter. [29]	Intelligent System for Credit Risk Management in Financial Institutions	Data Mining Algorithm, Decision Tree, Domain Expert, Expert System	Rate of Accuracy 70% for predicting Client eligibility for loans
2019	Allen and Luciano [6]	Risk Analysis and Portfolio Modelling [6]	Qualitative Analysis	Financial indicators help banks to obtain information about credit risk and defaulting borrowers based on previous default history
2018	Naoyuki Yoshino and Farhad Taghizadeh-Hesary [7]	A Comprehensive method for the credit risk assessment of small and Medium-sized enterprises based on Asisn Data [7]	Cluster analysis Principal component analysis	Taking Finanical health as basis the customers of SME are grouped. Each group is unique with interest rates and ceilings of lending

(*continued*)

Table 2. (*continued*)

Year	Authors	Title	Methodology	Result
2018	Wilhelmsson and Zhao [8]	Risk Assessment of Housing Market Segments: The Lender's Perspective [8]	Statistical method	Overstating the interest rate and levy surcharges of different types helps in minimizing the risk and transferring it on to responsible borrowers
2017	Giordana and Schumacher [9]	An Empirical Study on the Impact of Basel III Standards on Banks' Default Risk: The Case of Luxembourg. [9]	Statistical method	Accuracy of the borrower assessment is important for granting a loan with grant amount
2016	Natalija KonovalovaIneta Ineta Kristovska Marina Kudinska [10]	Credit risk management in commercial banks [10]	Factor analysis	In commercial banks based on internal credit ratings there was improvement in management of credit risk
2016	Sirus Sharifi. Arunima Haldar S.V.D. Nageswara Rao [11]	The relationship between credit risk management and non-performing assets of commercial banks in India [11]	Multiple linear regression	Negative relation between growth of NPAs or loans and identification of credit risk
2015	Yoshino, Taghizadeh-Hesary, and Nili [12]	Estimating Dual Deposit Insurance Premium Rates and Forecasting Non-Performing Loans: Two New Models. ADBI [12]	PCA - Principal component analysis and Cluster analysis	Predicting Non-Performing Loans

(*continued*)

Table 2. (*continued*)

Year	Authors	Title	Methodology	Result
2014	Addo Boye Michael Kwabena [13]	Credit Risk Management in Financial Institutions: A Case Study of Ghana Commercial Bank Limited [13]	Regression model	Positive relationship between ROE and NPAs and negative relationship between lower loan losses and higher interest
2013	Orsenigo and Vercellis [14]	Linear versus Nonlinear Dimensionality Reduction for Banks' Credit Rating Prediction. Knowledge-Based Systems [14]	Quantitative methods	Identification of determinants of Banks' rating which help for assessing the creditworthiness
2007	Ravi Kumar and Ravi [15]	A comprehensive survey of the application of statistical and intelligent techniques to predicting the likelihood of default among banks and firms [15]	Statistical techniques	Prediction of credit ratings
2007	Maechler et al. [16]	Decomposing Financial Risks and Vulnerabilities in Eastern Europe [16]	Statistical method	High credit risk calls for approaches and systematic methods for forecasting and identification of risk
1999	Poon, Firth, and Fung [17]	A Multivariate Analysis of the Determinants of Moody's Bank Financial Strength Ratings [17]	Logistic regression models	Moody's ratings help in predicting value based on profitability indicators, risk and Loan provision information

From the literature review it can be summarized that all most the previous studies highlighted on prediction models of identifying credit risk based on different statistical methods, regression models, clustering analysis etc. In most of the studies indicators such as profitability ratios, Non performing assets (NPAs), ROE, Credit rating etc. are taken for study purpose. No study gave a prediction of credit risk. The present suggested model is based on machine learning algorithms for training the system with dataset and providing prediction based on Precision, Recall and F1 score (Table 2).

4 Research Problem or Gap

Default risk or credit risk is reaching its heights due to many limitations in the process of disbursement. There is no proper mechanism to forecast the risk. As the process is executed with human interventions which is having the threat of emotions, biasing etc. which is the root cause for the interrupted revenue generation and increases the collection cost. To address this machine learning models are used to predict the default probability.[18].

5 Objectives of Study

1. To understand the concept of credit risk and Machine learning algorithms
2. To analyse credit risk using machine learning algorithms

6 Research Methodology

Dataset

For the study purpose credit_risk_dataset.csv (1) Dataset is taken from Kaggle. The following table shows the description of variables (Table 3).

Table 3. Type of variables used

S. No	Variable	Variable type	Units
1	Age	numerical	Years
2	Income	numerical	INR
3	status of Home	categorical	"rent", "mortgage" or "own"
4	Experience	numerical	Years
4	Intent of Loan	categorical	"education", "medical", "venture", "home improvement", "personal" or "debt"consolidation"

(*continued*)

Table 3. (*continued*)

S. No	Variable	Variable type	Units
5	Amount of Loan	numerical	INR
6	Grade of Loan	categorical	"A", "B", "C", "D", "E", "F" or "G"
7	Rate of Interest	numerical	Percentage
8	Loan to income ratio	numerical	0 and 1
9	Default credit history	binary categorical	"Y" or "N"
10	Status of Loan (target variable)	binary, numerical	0 - no default 1- default

The data exploration and preprocessing is done in order to drop the missing values from the data. The study is based on descriptive statistics using function describe(). For visualization of the relationships, a scatterplot matrix is used. Further to find out the relation between the variables and the loan status Blox plot is used. For testing and training three algorithms - logistic regression, K-Nearest Neighbourhood and XGBoost are used (Fig. 5 and 6).

The following is the model developed:

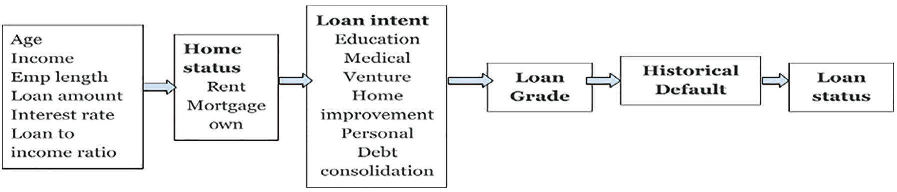


Fig. 5. Research model Source: author's proposal

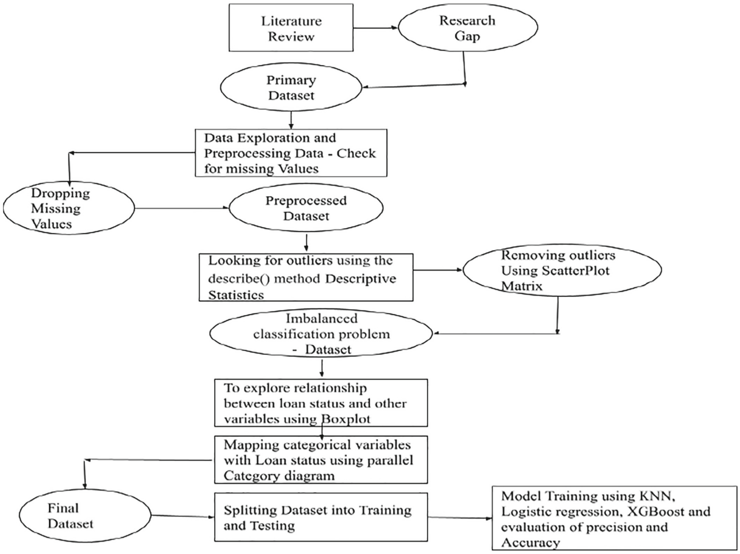


Fig. 6. Research Design Source: The author's proposal

7 Experimental results

- **Data Analysis**

Step 1: Data Exploration & Preprocessing: In this step Missing values are identified in two variables - employment length and interest rates which are considered.

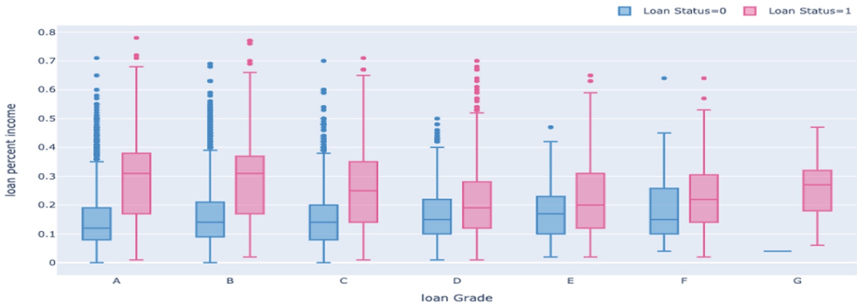
Step 2: Identifying Outliers: Using describe() and scatter plot matrix 3 outliers identified - Age, Employment length and income which are eliminated. The following descriptive statistics is calculated.

	Age	Income	Employment_Length	Loan_Amount	Interest_Rate	Loan_Status	loan_percent_income
count	28638.000000	2.863800e+04	28638.000000	28638.000000	28638.000000	28638.000000	28638.000000
mean	27.727216	6.664937e+04	4.784482	9656.493121	11.039867	0.216600	0.169488
std	6.310441	6.235645e+04	4.095491	6329.683361	3.229372	0.411935	0.106393
min	20.000000	4.000000e+03	0.000000	500.000000	5.420000	0.000000	0.000000
25%	23.000000	3.948000e+04	2.000000	5000.000000	7.900000	0.000000	0.090000
50%	26.000000	5.595600e+04	4.000000	8000.000000	10.990000	0.000000	0.150000
75%	30.000000	8.000000e+04	7.000000	12500.000000	13.480000	0.000000	0.230000
max	144.000000	6.000000e+06	123.000000	35000.000000	23.220000	1.000000	0.830000

Source: Research work

Step 3: Step 3: Generating target variable:In the dataset 78.4% are non-default cases when compared default cases meaning imbalanced classification. To handle this imbalance classification firstly, Status of Loan - Loan to income ratio is the indicator variable to identify default borrowers. Boxplot is used to draw the relationship between the loan status and other variables. From the following Boxplot figure it can be drawn that borrowers (Grade G) with low loan to income ratio didn't default and repaid their loans.

Secondly, Parallel category diagram is used to identify the relation of the categorical variables with loan status.



Source: Research work

Most of the borrowers have attained A and B as common grades while very borrowers were graded as F and G. From the home status of rent, mortgage and owners, firstly highest defaulters were rented borrowers, Secondly it is followed by the mortgage and finally by the owners with least number of defaulters. Coming to the loan intent of the borrowers majority of them took loan for the purpose of Educational loans where as for home improvement was the least. Defaulting conditions were more in case of borrowers with loan intent of consoliation of debt and expenses incurred for medical purposes. Further three models KNN, Logistic regression and XGBoost were applied to attain precision and Accuracy.

8 Result Analysis

KNN, Logistic regression and XGBoost models are used for training and testing of imbalanced dataset. The main focus is to have a common metric that is accuracy. The metrics of evaluation is based firstly on precision(ratio of true positives to total positives) where the positive symbolizes default cases, second on Recall (true positive rate - true positives to total number of elements) which give false positives predicting default or not, third F1 score gives combined score of both Precision and Recall (Table 4).

Table 4. Precision, Recall, F1 - score values based on models

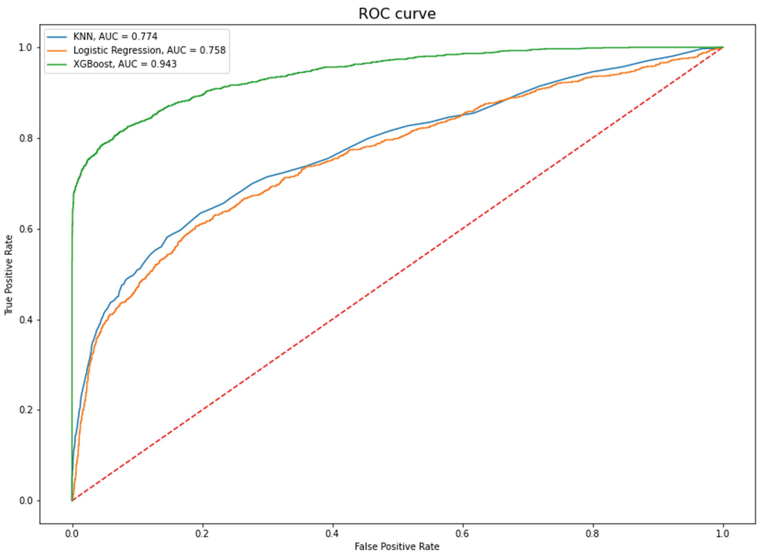
KNN Model		Precision	Recall	F1- Score	Support
	0	**84.0%**	**96.0%**	**90.0%**	**4448**
	1	**74.0%**	**38.0%**	**50.0%**	**1260**
	Accuracy			**83.0%**	**5708**
	Macro Average	**79.0%**	**60.0%**	**7.0%**	**5708**
	Weighted Average	**82.0%**	**83.0%**	**81.0%**	**5708**
Logistic Regression Model	**0**	**81.0%**	**99.0%**	**89.0%**	**4448**
	1	**79.0%**	**17.0%**	**29.0%**	**1260**
	Accuracy			**81.0%**	**5708**
	Macro Average	**80.0%**	**58.0%**	**59.0%**	**5708**
	Weighted Average	**80.0%**	**81.0%**	**76.0%**	**5708**
XGBoost Model	**0**	**92.0%**	**99.0%**	**96.0%**	**4448**
	1	**94.0%**	**72.0%**	**81.0%**	**1260**
	Accuracy			**93.0%**	**5708**
	Macro Average	**93.0%**	**85.0%**	**88.0%**	**5708**
	Weighted Average	**93.0%**	**93.0%**	**92.0%**	**5708**

Source: Research work

Table 5. Summary of Precision, Recall, F–score

	Precision	Recall	F1-Score	Accuracy
KNN Model	**74.0%**	**38.0%**	**50.0%**	**83.0%**
Logistic Regression Model	**79.0%**	**17.0%**	**29.0%**	**81.0%**
XGBoost Model	**94.0%**	**72.0%**	**81.0%**	**93.0%**

Source: Research work



Source: Research work

From the above table the result of training and testing the dataset using KNN model resulted with prediction of 74%, Recall with 38% and F1-Score with 50%. The accuracy is about 83 percent. Using Logistic Regression model resulted with prediction of 79 percent, Recall with 17 percent and F1-Score with 29%. The accuracy is about 81%. Using XGBoost model resulted with prediction of 94 percent, Recall with 72 percent and F1-Score with 81%. The accuracy is about 93% (Table 5).

From the above table and chart out of the metrics of 3 models XGBoost gave the best result of precision 94 percent, Recall with 72 percent, F1 score with 81 percent and the Accuracy of 93 percent.

9 Conclusion

Among the three prediction models - Logistic Regression, K Nearest Neighbour and XGBoost - XGBoost model gave highest accuracy - precision in assessment of credit risk. Thus it can be concluded that assessment of credit risk helps in waiving off the financial crisis. So, in real-time with 93% of accuracy the proposed prediction model can be implemented for assessment of credit risk by banks.

References

1. https://www.investopedia.com/terms/c/creditrisk.asp
2. https://www.investopedia.com/terms/d/defaultrisk.asp#:~:text=Default%20risk%20is%20the%20risk,all%20forms%20of%20credit%20extensions
3. Yanenkova, I., Nehoda, Y., Drobyazko, S., Zavhorodnii, A., Berezovska, L.: Modeling of bank credit risk management using the cost risk model. J. Risk Finan. Managem. **14**(5), 211 (2021). https://doi.org/10.3390/jrfm14050211"

4. Chun, S.Y., Lejeune, M.A.: Risk-based loan pricing: portfolio optimization approach with marginal risk contribution. Manage. Sci. **66**, 3735–3753 (2020)
5. Drobyazko, S., Barwinska-Malajowicz, A., Slusarczyk, B., Chubukova, O., Bielialov, T.: Risk management in the system of financial stability of the service enterprise. Journal of Risk and Financial Management **13**, 300 (2020)
6. Allen, D.E., Luciano, E.: Risk analysis and portfolio modelling. Journal of Risk Financial Management **12**, 154 (2019)
7. https://www.adb.org/sites/default/files/publication/473006/adbi-wp907.pdf
8. Wilhelmsson, M., Zhao, J.: Risk assessment of housing market segments: the lender's perspective. Journal of Risk and Financial Management **11**, 69 (2018)
9. Giordana, G.A., Schumacher, I.: An empirical study on the impact of basel iii standards on banks' default risk: the case of luxembourg. Journal of Risk Financial Management **10**, 8 (2017)
10. https://www.researchgate.net/publication/304669880_Credit_risk_management_in_commercial_banks
11. https://www.researchgate.net/publication/308610434_Credit_risk_management_practices_in_Indian_Banks. (Accessed 09 May 2022)
12. Yoshino, N., Taghizadeh-Hesary, F., Nili, F.: Estimating Dual Deposit Insurance Premium Rates and Forecasting Non-Performing Loans: Two New Models. ADBI Working Paper. No. 510. ADBI: Tokyo (2015)
13. Kwabena, A.B.M.: Credit risk management in financial institutions: a case study of Ghana commercial bank limited. Res. J. Fina. Account 5(23) (2014). www.iiste.org, ISSN 2222–1697 (Paper) ISSN 2222–2847 (Online)
14. Orsenigo, C., Vercellis, C.:. Linear versus nonlinear dimensionality reduction for banks' credit rating prediction. Knowl. Based Syst. **47**, 14–22 (2013)
15. Ravi Kumar, P., Ravi, V.: Bankruptcy prediction in banks and firms via statistical and intelligent techniques–a review. Eur. J. Oper. Res. **180**(1), 1–28 (2007)
16. Maechler, A.M., Srobona, M., Delisle, W.: Decomposing Financial Risks and Vulnerabilities in Eastern Europe. IMF Working Paper. Washington, DC, USA: International Monetary Fund, WP/07/248, pp. 1–33 (2007)
17. Poon, W.P.H., Firth, M., Fung, H.G.: A multivariate analysis of the determinants of moody's bank financial strength ratings. J. Int. Finan. Markets. Inst. Money **9**, 267–283 (1999)
18. https://towardsdatascience.com/a-machine-learning-approach-to-credit-risk-assessment-ba8eda1cd11f
19. https://www.educba.com/credit-risk/
20. https://journals.univ-danubius.ro/index.php/oeconomica/article/view/3027/3209#:~:text=The%20main%20source%20of%20micro,loan%20underwriting%2C%20laxity%20in%20credit
21. https://www.ibm.com/in-en/cloud/learn/machine-learning
22. https://www.springerprofessional.de/en/a-stitch-in-time-saves-nine-a-big-data-analytics-perspective/17846200
23. https://www.geeksforgeeks.org/k-nearest-neighbours/
24. https://www.google.com/search?q=KNN+Algorithm&tbm=isch&ved=2ahUKEwi3gOzVmdD3AhWZKbcAHbibCa8Q2-cCegQIABAA&oq=KNN+Algorithm&gs_lcp=CgNpbWcQAzIECAAQQzIECAAQQzIFCAAQgAQyBQgAEIAEMgUIABCABDIFCAAQgAQyBQgAEIAEMgUIABCABDIFCAAQgAQyBQgAEIAEOgcIIxDvAxAnULUKWLUKYMYaaABwAHgAgAGnAYgBlQKSAQMwLjKYAQCgAQGqAQtnd3Mtd2l6LWltZ8ABAQ&sclient=img&ei=R993YvfAJ5nT3LUPuLem-Ao&bih=880&biw=1920&rlz=1C1CHBF_enIN983IN985#imgrc=_wWUhdyKGVGvWM
25. https://www.geeksforgeeks.org/understanding-logistic-regression/

26. .https://www.google.com/search?q=logistic+regression+algorithm+in+machine+learning+pdf&rlz=1C1CHBF_enIN983IN985&sxsrf=ALiCzsbsf4mPxIBZZ8X2SkTdLl3jPkhsqQ:1652023058259&source=lnms&tbm=isch&sa=X&ved=2ahUKEwiQgLG8mdD3AhVLR2wGHR4rDBoQ_AUoAnoECAEQBA&biw=1920&bih=880&dpr=1#imgrc=LuaHnfur76i8eM
27. https://www.geeksforgeeks.org/xgboost-for-regression/?ref=gcse
28. https://www.google.com/search?q=xgboost+algorithm+in+machine+learning&tbm=isch&ved=2ahUKEwjHurjYm9D3AhWH8DgGHYOHB8sQ2-cCegQIABAA&oq=xgboost+algorithm&gs_lcp=CgNpbWcQARgBMgcIIxDvAxAnMgUIABCABDIFCAAQgAQyBQgAEIAEMgUIABCABDIFCAAQgAQyBggAEAcQHjIGCAAQCBAeMgQIABAYMgQIABAYUABYAGDPC2gAcAB4AIABcIgBcJIBAzAuMZgBAKoBC2d3cy13aXotaW1nwAEB&sclient=img&ei=ZeF3Yof0Oofh4-EPg4-e2Aw&bih=880&biw=1920&rlz=1C1CHBF_enIN983IN985#imgrc=QZ9NELxuymJ7gM
29. Sarfo-Manu, P., Siaw, G., Appiahene, P.: Intelligent system for credit risk management in financial institutions. Int. J. Artifi. Intell. Mach Learn. **9**, 57–67 (2019). https://doi.org/10.4018/IJAIML.2019070104
30. Zinisha, O.S., Ivanenko, I.N., Avdeeva, R.A.: Artificial Intelligence As A Factor To ˙ Improve Bank Eciency. Indo Am. J. Pharm. Sci. **6**(3), 6917–6919 (2019)
31. Kaya, O., et al.: Artificial intelligence in banking. Artifi. intell. (2019)
32. Khailtash, P.L.D.: The Impact AI on Bank's Risk Management Approach. In thesis report submitted to KTH Industrial Engineering and Management (2022)