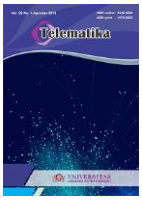
Telematika – Vol. 15, No. 2, August (2022) pp. 92-99 e-ISSN 2442-4528 | p-ISSN 1979-925X



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Telematika

Accreditated SINTA "2" Kemenristek/BRIN, No. 85/M/KPT/2020

UNIVERSITAS AMIKOM PURWOKERTO

Effect of Macroprudential Loan to Value (LTV) Policy Using the Support Vector Regression (SVR) Approach

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ARTICLE INFO

History of the article:
Received January 6, 2022
Revised August 8, 2022
Accepted August 15, 2022

Keywords:
Loan to Value (LTV)
Macroprudential
Support Vector Regression (SVR)
KPR.

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ABSTRACT

The macroprudential policy has a goal to confine the risk and price of crises systemic, especially in managing financial stability amidst the COVID-19 pandemic. One of its instruments is Loan to Value (LTV). The ratio of LTV is a ratio between the value of credit or cost that can give by Bank Conventional or Syariah towards collateral value as property. This study aims in getting to know about its influence on citizens to take *Kredit Kepemilikan Rumah* (KPR). Based on the data from Central Bank Indonesia (BI) would be found about the increasing ratio of LTV YoY-Year of Year. The data set in this study was derived from five banks with the data range being from 2014 to 2020. According to the characteristic data that will be used, thus one of the algorithms of machine learning which is Support Vector Regression (SVR) was chosen as an approach to observe this trend. By using this method, the result indicated which bank that had been influenced by the LTV ratio. The category of the bank that got impact is the bank that had the reverse influence on the credit value of home ownership, they are Foreign Bank, Mixed Bank, *Bank Persero, Bank Swasta*, and *Bank Perkreditan Rakyat*.

INTRODUCTION

Implementation of macroprudential policy from BI has a goal to mitigate and reduce risk systemic, especially in this pandemic situation. One macroprudential instrument policy is Loan to Value, namely LTV. This policy supports intermediation functions that balance, quality, and improve the efficient financial system in Indonesia. LTV is a ratio value between credit value or cost derived from Conventional Bank and loan property for which credit is given. Because of that, the effect of macroprudential LTV needs to study further.

Previous studies about machine learning particularly that consider the LTV problem emerge years ago. First, the study literature refers to research from (Goyal and Kaur, 2016) with the founding of three models for the genetic algorithm as the best model for forecasting the finance of loan risk for customers using an R programming language. Second, (Douglas et all, 2017) stated that their novel identified macroprudential policy to assess the average treated effect in adjusting two-stage of "hard-limit" policies such as LTV. Whereas, in the same year, (Lim and Nugraheni, 2017) claimed that the subprime mortgage crisis in 2007-2009 in Indonesia led to urgent research about managing non-performing ratios and prices in the housing market because they were potential sources of financial imbalance. Then, they said that LTV is an effective policy to become more persistent in the housing price cycle.

Two years later a previous study, (Niu et al, 2019) used three machine learning algorithms constructed to demonstrate the predictive performance of credit scoring social network information. Meanwhile, (Sasikirono et al, 2019) explained the effect of the LTV policy on the bank's property loan risk of Indonesia's tightening policy period to be implemented. Their research suggested that further study should be directed to measure the impact of changes in LTV on the growth of property loans. Another research in 2019 also supports our study to use a machine learning approach to research LTV. (Hani M, et all) said that a machine learning model is used to predict mortgage defaults. The improvement had been achieved according to their study. In recent years, (Dushimimana et all, 2020) confirmed that machine learning techniques can create a credit score model for airtime loans.

According to the previous research as aforementioned above, this study used an algorithm machine learning based, which is called Support Vector Machine (SVM) to learn about the LTV policy effect. This scheme is to observe the influence of LTV policies related to home loan ownership. This algorithm was first introduced by Vapnik in 1992 as a harmonious series of excellent concepts in the field of pattern recognition. The development of SVM method originally used for classification was also developed into a regression method known as Support Vector Regression (SVR) (Su et all, 2019).

Then, this study aims to measure of LTV ratio which was taken to determine the correlation between the free variable and the response of the dataset using SVR. This test is to model and estimate the influence of LTV value using the SVR method on home ownership loans in Indonesia, especially in managing and rethinking financial policy amidst the pandemic COVID-19 situation. The SVR model has advantages over the Ordinary Least Square (OLS) regression in terms of implicit utilization of nonlinear through the application of kernel functions that map features with data point vectors to higher dimension spaces allowing the use of models as in linearly separable cases. Therefore, SVR attempt to model and assess the influence of loan to value (LTV) on KPR-homeownership loans in Indonesia, then look for what types of banks are affected by its policy.

RESEARCH METHODOLOGY

1.1 Design System

The design system of this study involves normalizing the dataset step and then calculating the x and y value, as LTV and KPR data respectively, to be tested in equation 1. After that, the value of x and y in the step fitting to the data actual, which means minimizing the error during the predicted step. By the time the resulting suit the expected values, the values of x and y are plotted in the graphic.

1.2 Normalization Dataset

According to the data on The Bank Indonesia website, the data of home *Kredit Kepemilikan Rumah* or usually known as KPR in Indonesia has increased from year to year. The most mortgage value is found in Bank Persero which subsequently is a Private Bank. Both banks are important variables to determine the effect of the LTV policy on mortgages in Indonesia. Hence, this study uses the data from those banks.

The dataset used for KPR comes from Bank Indonesia. The data is taken from the website of Bank Indonesia between 2014 and 2020 with a unit of billion rupiahs. The data collected include loan to value and home ownership credit data from Persero Bank, Local Government Bank, Private Bank, Foreign, and Mixed Bank, and People's Credit Bank. The data before normalization is demonstrated in Table 1.

Table 1. Data KPR

Bank / Year	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Persero	1000	1120	1281	1494	1748	1842	1885
Pemda	1000	1112	1063	981	999	1024	1051
Swasta	1000	1009	1031	1111	1234	1279	1333
Asing	1000	1133	1171	875	795	781	757
Perkreditan Rakyat	1000	1214	1363	1386	1558	1660	1748

1.3 Support Vector Regression (SVR)

The Support Vector Machine (SVM) algorithm was first proposed by Vapnik (1995) for the classification of two categories or binomials. In the simplest form, SVM separates points from different classes, e.g., classes {+1} and {-1} with a single hyperplane of multiple-dimensional spaces that are eventually nonlinearly resolved. The optimum hyperplane is obtained through nonlinear programs, precisely quadratic programming.

Support Vector Regression (SVR) is the implementation of SVM in the case of regression. SVR is a classification method with a response variable as an ordinal variable developed into a regression method where the free variable is a numeric variable in the form of a rill and continuous number. For example, there is a set of data using equation (1).

$$D = \{(x_0, y_0), (x_1, y_1), \ldots, (x_n, y_n)\} \quad (1)$$

With a variable description in the formula:

x = Independent variable (cause)

y = Linear function with $y = k + cx$

k = Constanta

c = Regression Coefficient

n = amount of data

The variables are then used to solve the primal problem of simplification by using equations (2) and (3).

$$min_{\omega,b,\varsigma,\varsigma^*} \sim \frac{1}{2}\ \omega^T \omega + C \sum_{i=1}^{n} (\varsigma_i + \varsigma_i^*) \quad (2)$$

$$min_{\alpha,\alpha^*} \frac{1}{2}\ (\alpha - \alpha^*)^T\, Q(\alpha - \alpha^*)^1 + \varepsilon e^T(\alpha + \alpha^*)^T - y^T(\alpha + \alpha^*)^1 \quad (3)$$

With a variable description in the formula:

ω = weight

ς = data

α = alpha

ε = epsilon

Q = n from positive matrix semidefinite

e = one vector

Training vectors are implicitly mapped to higher dimensions (even to infinity) by the φ (phi) function. The decision function found in equation (4).

$$\sum_{i=1}^{n} (\alpha - \alpha^*) K(x_i, x) + \rho \quad (4)$$

With a variable description in the formula:

x = data

α = alpha

ρ = function phi

K = kernel

1.4 Loan to Value (LTV)

One goal of LTV policy is to control financial stability and mitigate systemic risk that comes from increasing the price of property. One of the objectives of LTV or FTV policy is to maintain financial system stability and mitigate systemic risks stemming from rising property prices. LTV or FTV policy also aims as a macroprudential instrument to promote a balanced and quality banking intermediation function in supporting national economic growth while maintaining financial system stability.

Therefore, the LTV policy that is made affects the down payment for property loans in Indonesia. The lighter the policy, the lighter the down payment of property loans. Illustration of LTV data can be found as Table 2.

Tabel 2. Data Loan to Value (LTV)

Year	2014	2015	2016	2017	2018	2019	2020
Data LTV	60	65	73	80	80	80.5	85

Because the KPR credit value of each bank has a different nominal, the data must be normalized, thus, each bank has the same amount of value. The KPR value that will be used calculates using equation (5).

$$KPR[x] = \left(\frac{KPR_{actual}[x] - KPR_{actual}[x-1]}{KPR_{actual}[x-1]} * KPR[x-1]\right) + KPR[x-1] \quad (5)$$

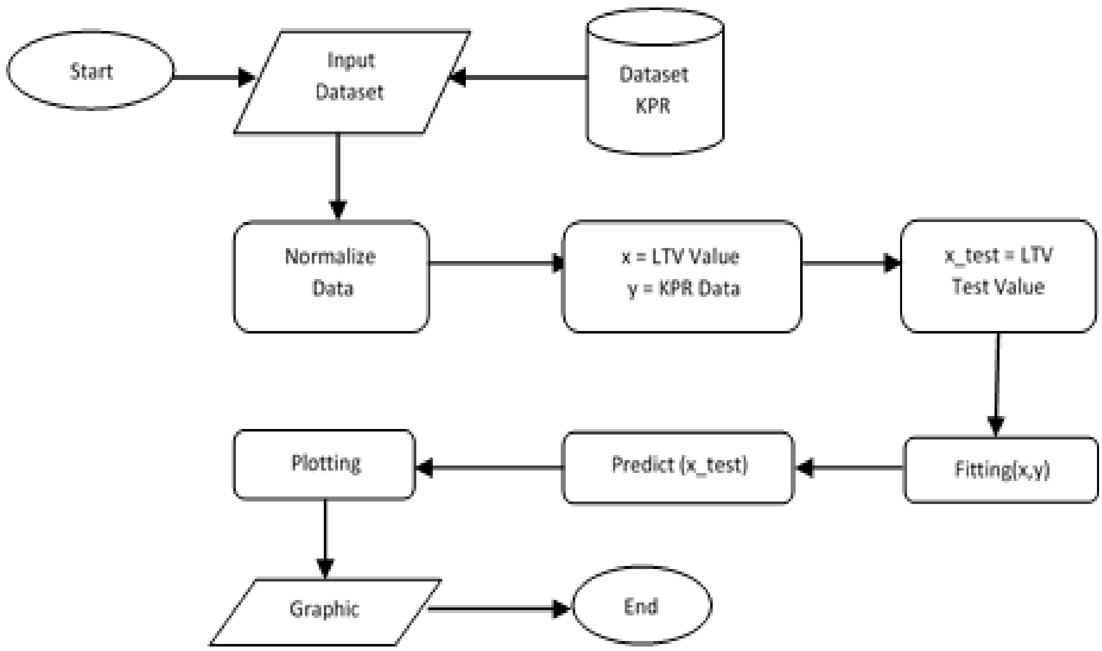

Figure 1. Block Diagram of Monitoring Ltv Policy Using SVR

RESULTS AND DISCUSSION

In this test, a measurement of the correlation between the free variable and the response of the dataset was used. This test is to model and estimate the influence of LTV values using the SVR method on home ownership loans in Indonesia, to find out what types of banks are affected by LTV policies.

Tabel 3. Description of Bank Persero Variable

Variable	Respond (Y)	Predictor (X)
Unit	Billion	Persen
Min	1000	60
Mean	1562.164	74.214
Max	1885.502	85
Std Deviation	357.5221	8.952919
Correlation between X and Y		0.968742754

In Table 3 above, it can be seen the measurement result of the correlation between free variable (X) and response variable (Y) which is 0.97 (positive), which means that there is a direct relationship between the variable of KPR and LTV ratio. This means that the better the loan to value ratio, the higher the KPR credit score. Based on those data in Table 3, the SVR algorithm then implementing a linear kernel with C equal to 1e3 to search the marginal line in classifying the bank refer to the values of x and y. After applying the SVR algorithm on the available variables, the test results are obtained in figure 2.

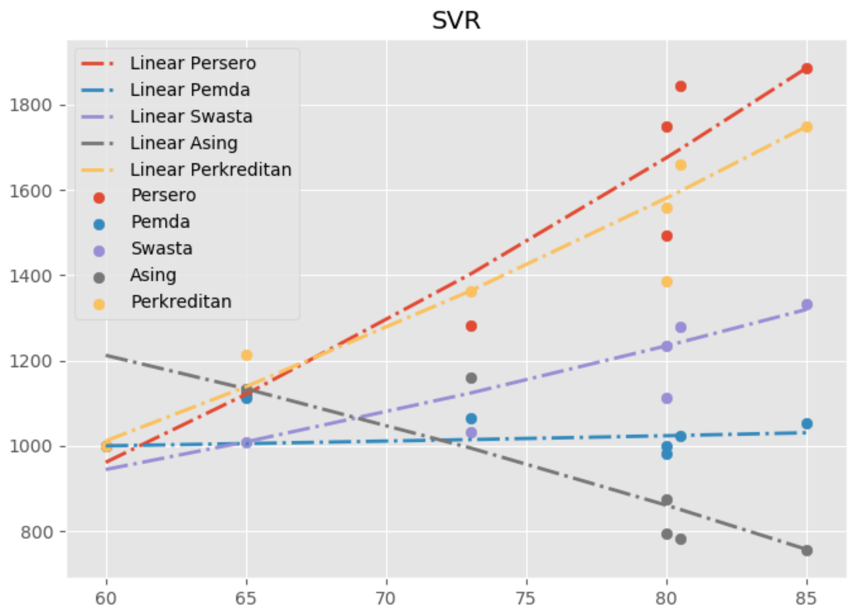

Figure 2. Regression Linear Pattern in Each Bank

The result from this approach is a linear regression prediction pattern of five bank. The label class we got here then will be the next LTV value to predict, and then after the process terminate in fitting data the result of the LTV is shown in table 4. Hence, it can be known which banks are affected by this loan to value ratio.

Table 4. New Data LTV

Year	2014	2015	2016	2017	2018	2019	2020
Data LTV	60	70	65	75	67	85	80

The expected predictive result based on the pattern obtained in figure 3 is a volatile chart with a constant pattern or trend. If there is a bank with such a chart, then the credit score of the bank's ownership is believed to be affected by the LTV ratio.

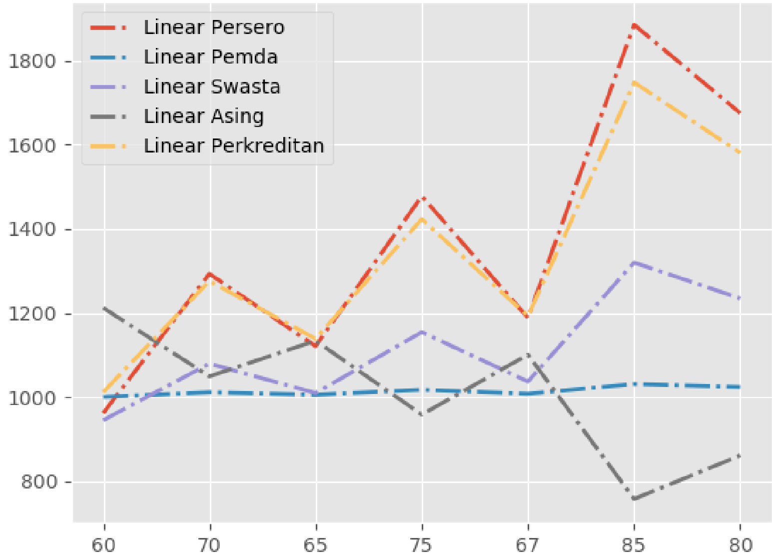

Figure 3. SVR Classification from New LTV

Based on the Figure 3, the output illustrated the fluctuation of the new data LTV in five banks. Bank Persero and Bank Perkreditan having a significant incline trend in their LTV term. Bank Swasta has the half pattern as same as the two banks above. Meanwhile, it is only occurred in Bank Asing with the sharply decline. It means LTV ratio has a negative influence, because if the LTV low then the KPR in this bank will rise. On the other hand, LTV in bank Pemda remain stable which reflect in linear line.

CONCLUSIONS AND RECOMMENDATIONS

The LTV ratio issued by Bank Indonesia (BI) from 2014 to 2020 has an influence on home ownership loans (KPR) to several banks in Indonesia. The types of banks that are believed to be affected by this LTV ratio are Persero Bank, Private Bank, and People's Credit Bank. There are also types of banks that are affected upside down by this LTV ratio, namely Foreign Banks and Mixed Banks. Bank Persero and Private Banks have the highest mortgage value of other banks. Thus, it can be concluded that the LTV ratio becomes the influence of the public to take home ownership loans (KPR). According to this conclusion, macroprudential policy with LTV instruments has an effect in reducing systemic risks, especially in 2019-2020 whilst in the condition of the COVID-19 pandemic.

For further research, it is expected to use large dataset, so that the accuracy of the influence of LTV value on home ownership loans in Indonesia getting better. To improve the application of the SVR algorithm, it is necessary to add some optimization algorithms, while still concern about empirical approach to study other policy interventions.

REFERENCES

Abdelhamid, M. H., & Tawfik Elmasry, M. (2019). *Machine Learning Approach for Credit Score Analysis: A Case Study of Predicting Mortgage Loan Defaults*. Universidade Nova de Lisboa https://run.unl.pt/bitstream/10362/62427/4/TEGI0439.pdf

Anchal Goyal and Ranpreet Kaur, February 2016, Accuracy Prediction for Loan Risk Using Machine Learning Models. International Journal of Computer Science Trends and Technology (IJCST) – Volume 4 Issue 1.

Bank Indonesia. Rasio Loan to Value atau Financing to Value (LTV/FTV). Retrieved from Bank Indonesia: https://www.bi.go.id/id/ssk/Instrumen-Makroprudensial/LTV-FTV DP/Contents/default.aspx

Cortes, C., Vapnik, V. (1995). Support-vector networks. Mach Learn 20, 273–297. https://doi.org/10.1007/BF00994018

Douglas K et al, November 2017, Loan-to-value policy and housing finance: effects on constrained borrowers, Paper produced as part of the BIS Consultative Council for the Americas (CCA) research project. https://www.bis.org/publ/work673.pdf

Dushimimana, B., Wambui, Y., Lubega, T., & McSharry, P. E. (2020). Use of Machine Learning Techniques to Create a Credit Score Model for Airtime Loans. *Journal of Risk and Financial Management*, *13*(8), 180. https://doi.org/10.3390/jrfm13080180

E. Chandra Blessie and R. Rekha, November 2019, Exploring the Machine Learning Algorithm for Prediction the Loan Sanctioning Process, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-1. https://doi.org/10.35940/ijitee.A4881.119119

Efrizoni, L. (2021). Prediction Model Grade Point Average using Backpropagation Neural Network and Multiple Linear Regression. *Telematika*, *14*(1), 33–46. https://doi.org/10.35671/telematika.v14i1.1113

Ganstrom D and Abraham J, 2019, *Loan Default Prediction using Supervised Machine Learning Algorithms*, https://kth.diva-portal.org/smash/get/diva2:1319711/FULLTEXT02.pdf

Goyal, A., Kaur, R., & Research Scolar. (2013). Accuracy Prediction for Loan Risk Using Machine Learning Models. *International Journal of Computer Science Trends and Technology*, *4*(1). Retrieved from www.ijcstjournal.org

de Araujo, D. K. G., Barroso, J. B. R. B., & Gonzalez, R. B. (2020). Loan-to-value policy and housing finance: Effects on constrained borrowers. In Journal of Financial Intermediation (Vol. 42, p. 100830). Elsevier BV. https://doi.org/10.1016/j.jfi.2019.100830

Lim, C., & Nugraheni, S. (2017). Loan-to-Value Ratio and Housing Price Cycle: Empirical Evidence From Indonesia. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan*, *18*(2), 225. https://doi.org/10.23917/jep.v18i2.4846

Zhu, L., Qiu, D., Ergu, D., Ying, C., & Liu, K. (2019). A study on predicting loan default based on the random forest algorithm. In Procedia Computer Science (Vol. 162, pp. 503–513). Elsevier BV. https://doi.org/10.1016/j.procs.2019.12.017

Maharesi, R, (2013), Penggunaan Support Vector Regression (SVR) pada prediksi Return Saham Syariah BEI, Bandung: PESAT (Psikologi, Ekonomi, Sastra, Arsitektur & Teknik Sipil). https://core.ac.uk/download/pdf/231285662.pdf

Niu, B., Ren, J., & Li, X. (2019). Credit scoring using machine learning by combing social network information: Evidence from peer-to-peer lending. *Information (Switzerland)*, *10*(12). https://doi.org/10.3390/INFO10120397

Peter J. Morgan, Paulo José Regis, and Nimesh Salike, March 2015, *Loan-to-Value Policy as a Macroprudential Tool: The Case of Residential Mortgage Loans in Asia*, ADBI Working Paper 528.

Ramanjani R, September 2017, *Machine Learning Classification: Prediction of Loan Approval*, Machine Learning Classification: Prediction of Loan Approval – Rajivs geeky stuff (wordpress.com)

Sasikirono, N., Sumanto, S., Made Sudana, I., Meidiaswati, H., & Mandiri Sekuritas, P. (2019). 267-Loan-to-Value Policy and Property Loans Risk in Conventional Commercial Banks of Indonesia. *International Research Journal of Business Studies |, 03*. https://doi.org/10.21632/irjbs

Su, Moting, Zongyi Zhang, Ye Zhu, Donglan Zha, and Wenying Wen. (2019). "Data Driven Natural Gas Spot Price Prediction Models Using Machine Learning Methods" Energies 12, no. 9: 1680. https://doi.org/10.3390/en12091680

Ereiz, Z. (2019), *Predicting Default Loans Using Machine Learning (OptiML)*, 2019 27th Telecommunications Forum (TELFOR). https://dx.doi.org/10.1109/TELFOR48224.2019.8971110