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# Designing a Smart Model for Granting Banking Facilities Based on Big Data, Macroeconomic Variables, Sanctions, and Economic Shocks

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**ABSTRACT**

The granting of bank facilities and the targeting and identification of suitable customers by banks is a serious concern. The non-repayment of granted loans by customers can severely damage the profitability of banks, leading them to move towards proprietorship and economic activity, which ultimately results in increased inflation and many other economic problems. Based on the problem mentioned, the aim of the present research is to design an intelligent model for granting bank facilities based on big data, considering macroeconomic variables, sanctions, and economic shocks. To design this model, six macroeconomic variables, shocks, and sanctions were included in the model. The model was evaluated using four machine learning algorithms: multiple regression, support vector machine, decision tree, and random forest, based on customer data from the banks in the country. The results indicate that the highest accuracy and lowest error belong to the random forest algorithm, with 93% and 0.12%, respectively, followed by the decision tree with the best performance. The third rank belongs to the support vector machine, and the last rank belongs to linear multiple regression. The most influential variable is economic shock with 33%, sanctions with 15.8%, and inflation with 15% in the second and third ranks of importance. Subsequently, economic growth, unemployment rate, and Gini coefficient have relatively less influence, estimated to affect loan repayment or the number of unpaid loans by 9%, 10%, and 11%, respectively.

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## 1) Introduction

Loan repayment behavior is an important issue that can determine whether or not bank facilities are granted (Owen, 2025). Bank managers review credit granting decisions based on this, as the most important income for banks comes from granting loans (Liu et al., 2025). However, due to the high number of non-performing loans, banks generally turn to economic proprietorship, which has been anticipated by many economic experts (Ghasemi et al., 2022; Sierra et al., 2024). Many factors and variables affect the granting of bank facilities, and much research has focused on this topic, with each study discovering different factors. Among these, the role of macroeconomic variables is significant and undeniable, and through these variables, many events and dependent variables, including loan repayment behavior, can be explained and described (Alagic et al., 2024).

In Iran, there are specific conditions such as sanctions, which make the mere examination of macroeconomic factors irrelevant to the issue of granting facilities and repayment behavior. Sanctions are an important factor that, according to some domestic economists, have negatively affected the economy by up to 50% and led to a decrease in GDP. Since research based on sanctions is not abundant due to the small number of sanctioned cases globally, it is important to examine the effect of this component on repayment behavior or on the number of non-performing loans. Despite sanctions, economic shocks have occasionally attacked the country, leading to an increase in the exchange rate and, consequently, severe inflation in the country, a clear example of which was observed in 2012, 2018, and 2020, when the inflation rate grew by up to 40% and caused a decrease in the value of the national currency. In the 1990s, specifically in 1995, the country also experienced 49% inflation, which cannot be described as an economic shock trend due to its decrease in subsequent years.

Therefore, it can be said that, overall, the combination of macroeconomic variables, sanctions, and economic shocks can become a model for explaining the granting of bank facilities by banks. Based on it, decisions regarding the granting of facilities can be made and loan repayment behavior can be predicted. This is what the researcher aims to do in the present study. In this research, based on six variables—economic growth, unemployment rate, inflation rate, Gini coefficient, economic shock, and sanctions—an estimate of loan repayment behavior is provided, and an intelligent model for granting bank facilities can be presented accordingly. In this regard, machine learning algorithms are used for the accurate estimation of results.

The main issue of the present research is the emergence of economic shocks and sanctions as exogenous factors in the country's economy, which can have a significant impact on macroeconomic variables, and this effect has been repeatedly observed in different historical periods, with currency jumps being a significant result. The aim of the present research is to discover whether economic shocks and sanctions can affect loan repayment and whether a model can be designed in this regard to intelligently grant bank facilities.

The structure of the present article is such that the theoretical foundations and literature review are first presented; then, the methodology, analysis, and finally, the conclusion are provided.

## 1) Literature Review and Research Background

Macroeconomic variables are defined as important variables that influence and are influenced by the economic conditions of a country, holding the highest level of importance and impact according to university professors and top economic managers of a country. The most important macroeconomic variables include gross domestic product, national expenditure, national capital formation, general price level or inflation, employment level or unemployment, budget deficit, foreign debts, boom and recession, Gini coefficient, and interest rate (Chehreh & Sarabadani, 2024; Zhang et al., 2025). However, among the mentioned variables, GDP growth, unemployment rate, inflation rate, and Gini coefficient have received more attention in research literature, and their impact on various dependent variables has been repeatedly investigated. Some studies have also considered the interest rate as an important macroeconomic variable. Therefore, these variables can be examined as influential factors on various dependent economic variables.

Economic sanctions are activities or actions imposed by one or more international actors (sanctioning parties) against one or more other countries (sanctioned targets) to punish these countries, with the aim of depriving them of certain exchanges or compelling them to accept specific important norms (from the perspective of the sanctioning parties) (Javed, 2024; Mohammadian & Aslani, 2022). Here, "sanctioning party" refers to a country (or an international group) that is the author or publisher of the sanction scenario although more than one country may participate in enforcing the blockade. "Target" refers to the country or countries that are the primary the target of sanctions. Economic sanctions can include various forms of trade barriers, tariffs, and transaction restrictions (Al Maruf et al., 2024).

Economic sanctions against Iran were imposed in May 1980 by the Jimmy Carter administration in retaliation for the seizure of the US embassy by students following Imam Khomeini. These initial sanctions intensified in the 1980s, particularly in 1984 and 1988, by the Reagan administration. However, a new round of sanctions against Iran by the US was imposed during the Clinton administration in 1994 and 1995. The status of these sanctions continued until 2006, but it was in this year that secondary sanctions, which went beyond the initial US sanctions, were imposed under the pretext of Iran's nuclear program. These sanctions were imposed after Iran's case was referred to the Security Council and were gradually intensified by the European Union and the Security Council. Although the UN and Security Council sanctions were suspended in 2016 due to the signing of the JCPOA, US and EU sanctions were not lifted even with the JCPOA. With the emergence of Trump administration on November 4, 2018, sanctions under the title of maximum pressure, were approved and have continued to date.

Economic shocks are defined as unexpected events capable of rapidly affecting a country's economy. These shocks can originate from internal or external factors that hit the supply or demand side, and their consequences manifest as changes in production, prices, employment, and other macroeconomic variables. In our country, due to the imposition of oppressive sanctions mentioned above, significant economic shocks have occurred, the most important of which are the economic shock of summer 2012, the economic shock of summer 2018, and the economic shock of 2020. The economic shock of summer 2012 was due to the imposition of Security Council sanctions on July 1, 2012, which led to a threefold jump in the exchange rate in the country. In the second economic shock, due to Trump's withdrawal from the JCPOA, another economic shock occurred, ultimately leading to a threefold increase in the exchange rate in the country. Finally, the 2020 shock occurred due to the COVID-19 pandemic, which led to a twofold jump in the country’s exchange rate.

Given the above concepts regarding economic variables, economic shocks, and sanctions, the following section introduces the most important research studies examining the effects of macroeconomic variables on loan repayment behavior. Research gaps are identified in this review.

Javed (2024) assesses how inflation affects loan repayment rates and financial institution stability. Sangweni and Takawira (2024) examine the effect of changes in macroeconomic factors on banks' lending behavior. Fajariyanto and Wasiaturrahma (2024) explore the effect of institutional quality and macroeconomic variables on non-performing loans. Krasovytskyi and Stavytskyy (2024) predict mortgage default using machine learning techniques. Al Maruf et al. (2024) incorporate behavioral factors into loan default prediction using a literature review on social, economic, and psychological risk indicators. Sierra et al. (2024) conduct a comparative analysis of macroeconomic indicators in optimizing credit risk prediction. Ojarikre et al. (2024) examine the effect of macroeconomic variables on non-performing loans in Nigeria. Mensorale and Odumuyiwa (2024) investigate the prediction of borrower loan repayment rates using machine learning. Alagic et al. (2024) utilize machine learning algorithms to enhance credit risk analysis. Abi (2025) employs machine learning algorithms for credit scoring and loan default prediction based on financial and transactional data. Owen (2025) examines the effect of macroeconomic indicators on credit risk using Bayesian hierarchical models. Kheneifar and Amiri (2025) propose a new hybrid model for predicting loan default in marine finance based on topographic data analysis and machine learning. Zhang et al. (2025) predict loan default using machine learning algorithms. Peykani et al. (2025) consider the effect of macroeconomic shocks on non-performing loans and credit risk in the Iranian banking system using time-varying vector autoregression. Liu et al. (2025) highlight macroeconomic determinants of credit loss prediction.

**Table 1. Literature Review**

| Machine Learning | Economic Shocks | Sanctions | Macroeconomic Variables | Granting Bank Facilities | Smart Model | Objective | Year | Researchers |
|---|---|---|---|---|---|---|---|---|
| | | | ✓ | ✓ | | Assessing the impact of inflation on loan repayment rates and financial institution stability | 2024 | Javed |
| | | | ✓ | ✓ | | Investigating the effect of changes in macroeconomic factors on banks' lending behavior | 2024 | Sangweni & Takawira |
| | | | ✓ | ✓ | | The effect of institutional quality and macroeconomic variables on non-operational loans | 2024 | Fajariyanto & Wasiaturrahma |
| ✓ | | | ✓ | ✓ | | Predicting mortgage default using predictive machine learning techniques | 2024 | Krasovytskyi & Stavytskyy |
| | | | ✓ | ✓ | | Predicting loan default using a literature review on socio-economic and psychological risk indicators | 2024 | Al Maruf et al. |
| | | | ✓ | ✓ | | Comparative analysis of macroeconomic indicators in optimizing credit risk forecasting | 2024 | Sierra et al. |
| | | | ✓ | ✓ | | Investigating the effect of macroeconomic variables on non-performing loans in nigeria | 2024 | Ojarikre et al. |
| ✓ | | | ✓ | ✓ | | Predicting borrowers' loan repayment rates using machine learning | 2024 | Mensorale & Odumuyiwa |
| ✓ | | | ✓ | ✓ | | Using machine learning algorithms to improve credit risk analysis | 2024 | Alagic et al. |
| ✓ | | | ✓ | ✓ | | Using machine learning algorithms to score credit and predict loan default based on financial and transactional data | 2025 | Abi |
| ✓ | | | ✓ | ✓ | | Investigating the effect of macroeconomic indicators on credit risk using Bayesian hierarchical models | 2025 | Owen |
| ✓ | | | ✓ | ✓ | | Predicting loan default in offshore financing based on topographic data analysis and machine learning | 2025 | Kheneifar & Amiri |
| ✓ | | | ✓ | ✓ | | Predicting loan default using machine learning algorithms | 2025 | Zhang et al. |
| | ✓ | | | ✓ | | Investigating the effect of macroeconomic shocks on non- | 2025 | Peykani et al. |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | performing loans and credit risk in the Iranian banking system | | |
| ✓ | | | ✓ | ✓ | | Forecasting credit losses by considering macroeconomic determinants | 2025 | Liu et al. |
| ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | Designing a smart model for granting banking facilities based on big data, macroeconomic variables, sanctions, and economic shocks | | The present research |

Based on the literature review conducted, it can be observed that despite numerous studies in the field, no research has investigated the impact of three categories of variables, macroeconomic variables, economic shocks, and sanctions, on customer loan repayment, and subsequently, presented a model for smart bank loan disbursement. Such a study is not found in the research literature, indicating a research gap that the current study aims to innovatively address.

## 2) Research Methodology

The current research is applied and developmental in terms of its objective, as it presents a smart model for bank loan disbursement. The research is quantitative in nature. The statistical population and study period for the current research span from the beginning of 1386 to the end of 1403 SH. The data is monthly, and considering the 17-year study period, it comprises 204 months. It should be noted that the number 204 refers solely to the study period, meaning the period starts from 1386 and extends to the end of 1403 SH. However, the bank customer records within this period amount to over 10,000 records, which is a clear example of big data. Therefore, the data volume is not 204, but rather pertains to over 10,000 records of customer loan histories over a 204-month period.

On the other hand, it should be mentioned that the study period was chosen due to the presence of economic crises and shocks, as well as a period during which the highest level of sanctions was imposed against our country by the US, the European Union, and the United Nations, and also due to high fluctuations in macroeconomic variables.

The variables studied include four macroeconomic variables. These variables are the inflation rate, unemployment rate, economic growth, and Gini coefficient. The reason for selecting these variables is their high impact and their tangible presence in the economic society. Furthermore, these variables are subject to change across different periods. In contrast, a variable such as interest rate showed minimal changes during the study period and was therefore excluded from the analysis. Calculating other macroeconomic variables is also generally difficult and requires high accuracy in data collection. However, the four variables of economic growth, unemployment rate, Gini coefficient, and inflation rate can be collected from information centers, including the website of the National Statistics Center of the country.

Regarding economic shocks and sanctions variables, dummy variables were used, such that periods subject to economic shocks are represented by one, while other periods are represented by zero. Additionally, the intensity of sanctions is shown as a nominal variable based on both cases in the study. Table 2 presents the characteristics of these variables.

**Table 2. Research Variables**

| Row | Variable title | Variable symbol | Variable type | Variable scale |
|---|---|---|---|---|
| 1 | Inflation rate | X1 | Input | Quantitative |
| 2 | Gini coefficient | X2 | Input | Quantitative |
| 3 | Unemployment rate | X3 | Input | Quantitative |
| 4 | Economic growth | X4 | Input | Quantitative |

| Row | Variable title | Variable symbol | Variable type | Variable scale |
|---|---|---|---|---|
| 5 | Economic shock | X5 | Input | Binary |
| 6 | Sanctions | X6 | Input | Ordinal |
| 7 | Number of unpaid loan | Y | Output | Binary |

Regarding the nominal variables of sanctions and economic shock, which are binary in nature, during the study period, the years and periods affected by inflation due to sanctions and economic shock have a value of one. For example, the years 2012, 2018, and 2020, as well as the currency shock of 2022, specifically November and January 2022, are considered periods of economic shock. In total, periods of currency jumps and periods of turbulence, such as the stagflation in summer 2012 and 2018, are considered periods of economic shock. The years of intensified sanctions, 2011 to 2013 and 2018 to 2024, are considered periods subject to sanctions. The variables of the present research can be depicted in the following schematic model.

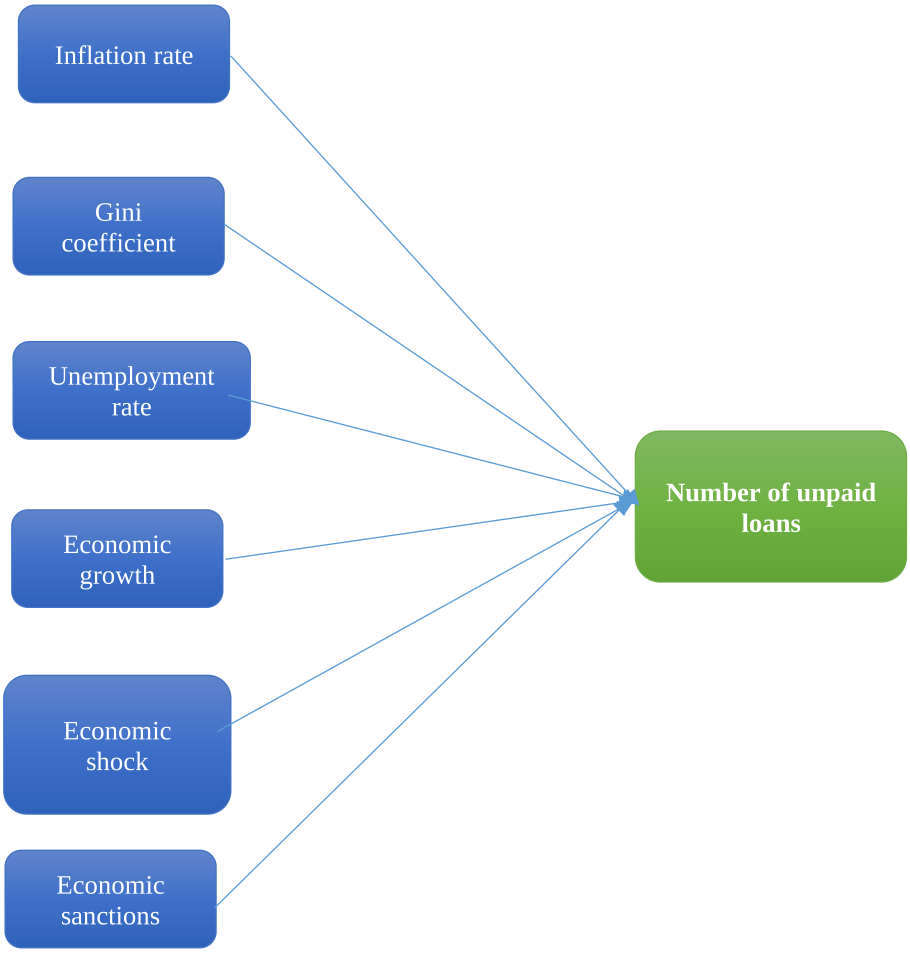


**Figure 1. Conceptual Model of the Present Research**

To implement the above model in Figure 1, regression machine learning algorithms are used, as the goal is to estimate and predict the number of unpaid loans in Iranian banks. Therefore, the algorithms used include multiple regression algorithms, which are the most common algorithms in regression calculations, as well as support vector machine, decision tree, and random forest algorithms. The results of these algorithms are evaluated based on their accuracy and error rates. The higher the accuracy of the algorithms and the lower their error rate, the better their performance. It should be noted that accuracy and error criteria are used in the present research as the algorithms used aim to estimate and predict, rather than classify. If the goal were classification, a confusion matrix would have to be used; however, the present research aims to estimate accuracy and error. The following formula is used to calculate the error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)2 \qquad (1)$$

In the above relationship,

N: sample size

$Y_i$: actual value

$\widehat{Y}_i$: predicted value.

The index used to calculate accuracy is the Mean Absolute Error index, which is calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \widehat{Y}_i\right| \qquad (2)$$

In the present study, the sole objective was to use and evaluate the application of machine learning algorithms in designing the proposed model. The purpose of using the multiple regression algorithm was merely to prove the high capability of other three machine learning algorithms, which can be demonstrated by proving the superiority of these algorithms over machine learning algorithm in terms of multiple criteria. The aim of the current research was not to utilize econometric approaches, but to only consider the capability of machine learning algorithms.

## 3) Data Analysis

This section deals with data analysis. As described in the methodology section, four machine learning algorithms—multiple regression, support vector machine, random forest, and decision tree—are used to estimate the number of unpaid loans or defaults on bank loans. Based on the six variables, the model is implemented, and the accuracy and error rates are determined, considering the regression objective of the model rather than variable classification, to identify which algorithm has greater capability for better estimation. First, the error results are presented. Prior to the analysis, data distribution, separated into training, validation, and test data, is presented in Table 3.

**Table 3. Distribution of Data by Training, Validation, and Test Data**

| Row | Data type | Split percentage |
|---|---|---|
| 1 | Training | 70% |
| 2 | Validation | 15% |
| 3 | Test | 15% |

In order to validate the presented model, the K-Fold Cross-Validation method was used.

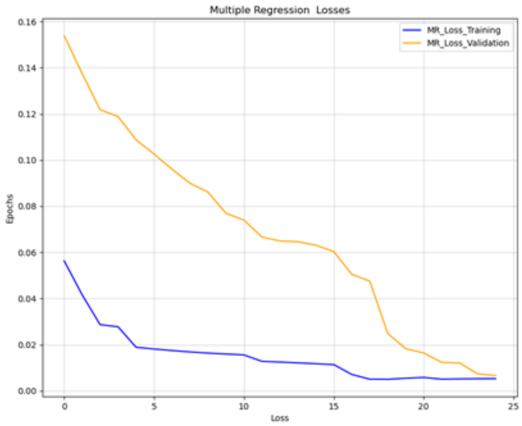


**Figure 2. Multiple Regression Training Validation Error**

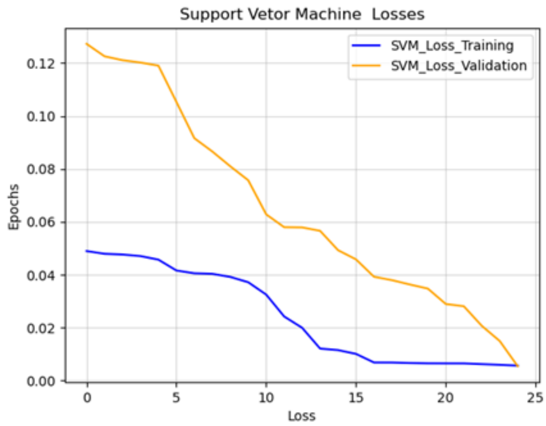


**Figure 3. Validation Error and Support Vector Machine Training**

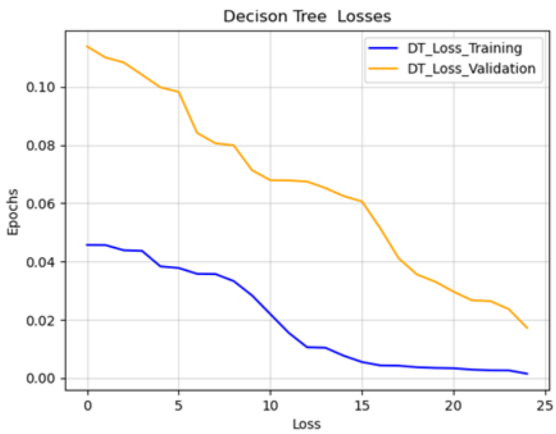


**Figure 4. Decision Tree Validation and Training Error**

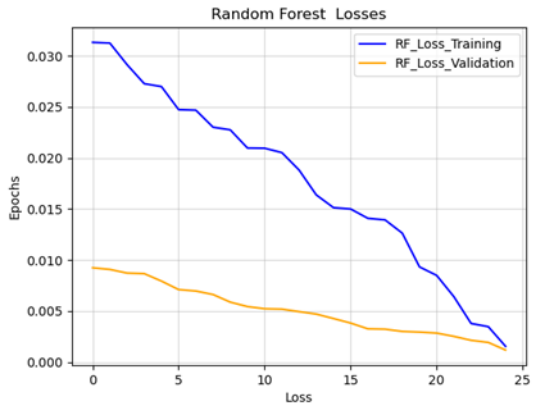


**Figure 5. Validation and Training Error of Random Forest**

In Figures 2 to 5, two forms of validation and training data converge are observed. Rather than data validation, data test can also be used, but in general, the condition for the correct functioning of the convergence algorithm is the validation and training forms, which is clearly evident in all 4 Figures. The second condition for the proper performance of the algorithms is the decreasing nature of the shapes, as the error shapes must be decreasing to show the decrease in the amount of estimation error. Figures 2 to 5 are only to demonstrate the correct performance of the algorithm and more detailed results are presented in the following tables.

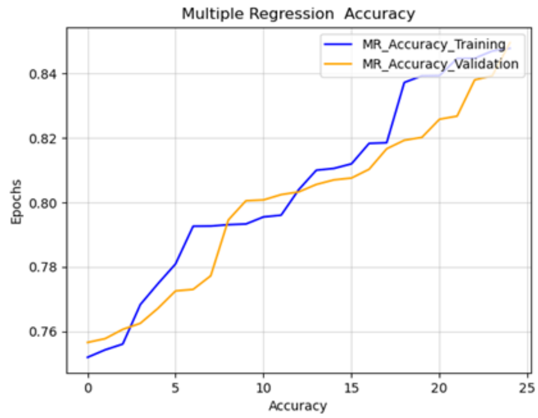


**Figure 6. Accuracy of Validation and Training of Multiple Regression**

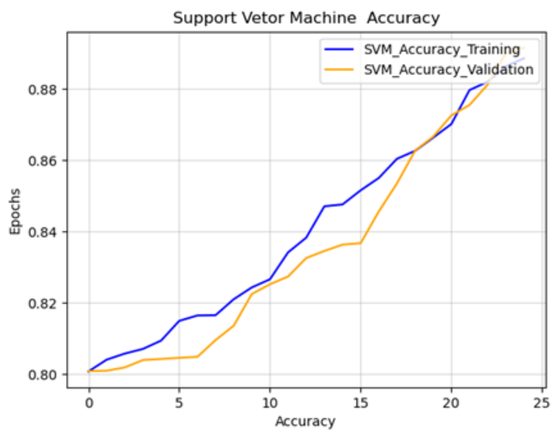

**Figure 7. Accuracy of Validation and Training of Support Vector Machine**

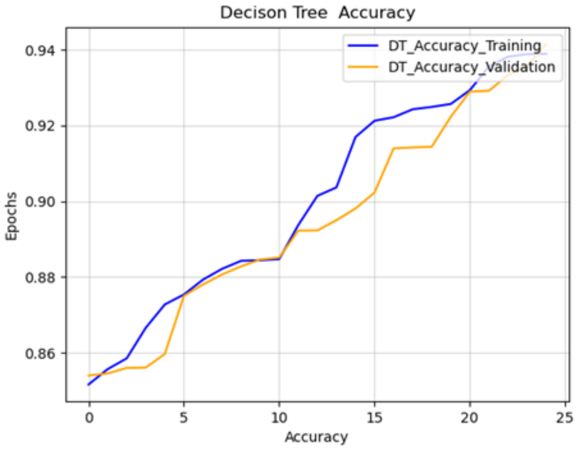


**Figure 8. Accuracy of Validation and Decision Tree Training**

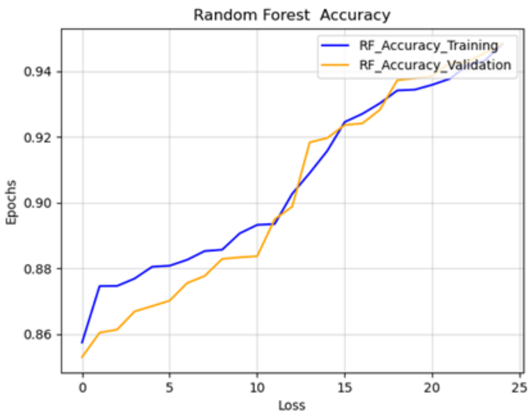


**Figure 9. Validation and Training Accuracy of Random Forest**

Figures 6 to 9 estimate the accuracy of each algorithm. As can be seen from the validation and training data presented in Figure 4, both enjoy convergence and are also of an ascending nature, which are two conditions for proving the correct performance of the algorithms in different iterations. Therefore, all four algorithms were able to estimate both the model and the accuracy appropriately; however, to achieve a more accurate viewpoint, the results are presented separately for each algorithm in Table 4.

**Table 4. Comparison of Algorithms in Terms of Accuracy and Error**

| Algorithm | Accuracy | Error |
|---|---|---|
| Multiple Linear Regression | 0.803 | 0.0056 |
| Support Vector Machine | 0.0838 | 0.0052 |
| Decision Tree | 0.915 | 0.0014 |
| Random Forest | 0.938 | 0.0012 |

The results indicate that the random forest algorithm, with more than 93% accuracy, has the highest accuracy in predicting or estimating the presented model and shows that the six macroeconomic variables, economic shock, and sanctions were able to estimate the number of non-performing loans to a significant level. In other words, the 6 variables presented in the current research model have an impact of up to 93% on the failure to repay the loan or default in it and can explain it. Figures 9 and 10 present a comparison of the accuracy and error of the algorithms.

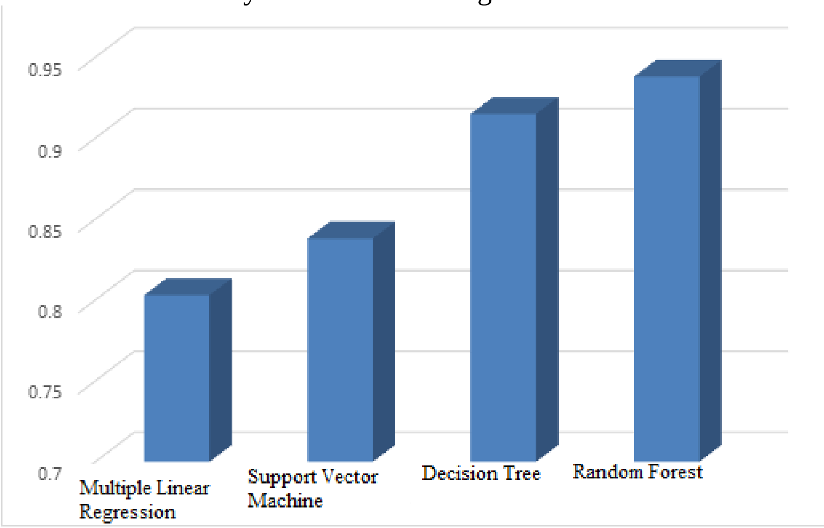


**Figure 10. Comparison of Algorithms in Terms of Accuracy**

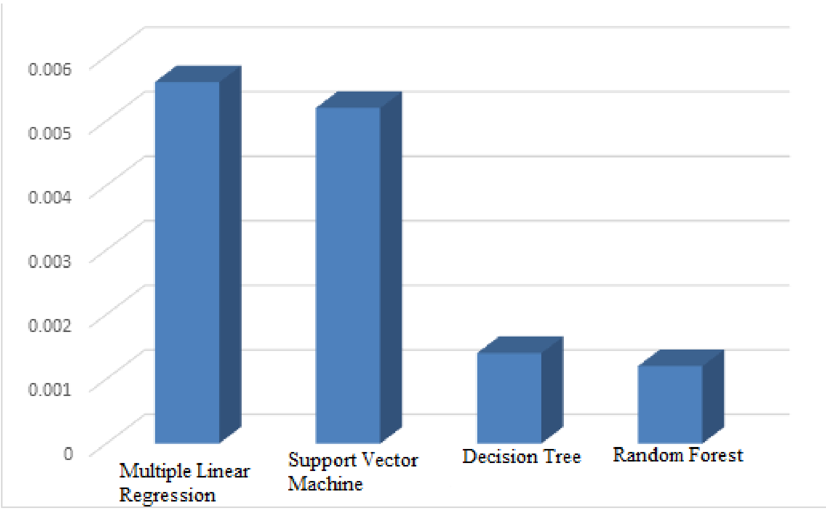


**Figure 11. Comparison of Algorithms in Terms of Error**

Based on Figures 10 and 11, the highest accuracy and the lowest error are related to the random forest algorithm, followed by the decision tree with the best performance. The third rank relates to the support vector machine, while the last rank relates to the multiple linear regression. Therefore, the most efficient algorithm in the present study is the random forest, which has been proven in many similar studies. This is because the highest accuracy and lowest error are achieved by this algorithm, and the decision tree is in the second place with a small distance.

Subsequently, the variables are compared in terms of their effectiveness and the contribution they make to the R value of each algorithm. The results are presented in Table 5.

**Table 5. Comparison of Each Variable Contribution to the R Value of Each Algorithm**

| Algorithm | Inflation rate | Gini coefficient | Unemployment rate | Economic growth | Economic shock | Sanctions |
|---|---|---|---|---|---|---|
| Multiple Linear Regression | 0.12 | 0.06 | 0.07 | 0.09 | 0.31 | 0.153 |
| Support Vector Machine | 0.13 | 0.06 | 0.08 | 0.09 | 0.32 | 0.158 |
| Decision Tree | 0.15 | 0.08 | 0.1 | 0.1 | 0.33 | 0.155 |
| Random Forest | 0.15 | 0.09 | 0.1 | 0.11 | 0.33 | 0.158 |

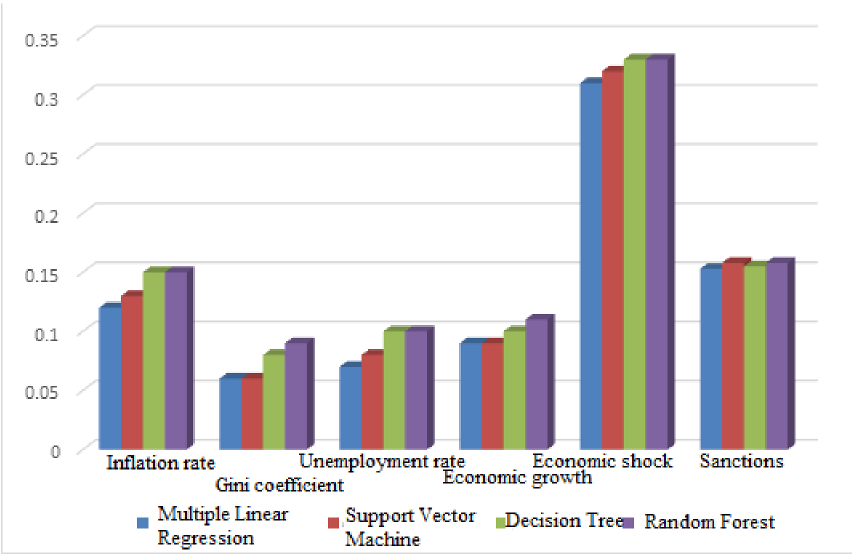


**Figure 12. Comparison of Each Variable Contribution to the R Value of Each Algorithm**

Figure 12 shows the contribution each variable makes to the R value, which is the coefficient of prediction or determination of each variable. The most influential variable is economic shock, which has the greatest impact based on the random forest algorithm, which is the most valid algorithm in the present study. The impact of this variable and its contribution to the R value was estimated by the random forest algorithm to be 33 percent. The ranking is related to sanctions, which has an importance of 15.8 percent, followed by inflation, which has an effect of 15 percent. The variables of economic growth, unemployment rate, and Gini coefficient have an effect of 9, 10, and 11 percent, respectively on loan repayment or the number of unpaid loans.

**5) Conclusion**

In this study, a model for granting bank facilities based on big data was presented. The big data included the number of unpaid loans in Iranian banks. To design the model, six economic variables were presented in the model, four of which include macroeconomic variables in addition to one economic shock variable and one economic sanction variable. The results were obtained using four machine learning algorithms that sought to estimate the number of unpaid loans. Using these algorithms, it can be seen that all six variables have a high impact on the bank's failure to repay customers. This is while the economic shock variable has the greatest impact by a large margin compared to other variables. Sanctions are in the second place in terms of impact, followed by inflation in the third place.

Based on these results, economic shocks, entering the country due to their effect on the exchange rate and the increase in the general level of prices, inflation, and uncertainty, can seriously threaten loan repayment by customers and have a 33% impact among all existing variables. Additionally, the role of sanctions as a second factor is undeniable, and despite some viewpoints that consider sanctions ineffective in the Iranian economy, the results of this study indicate that sanctions are of second importance and that they can lead to non-repayment of loans, indicating that sanctions have a direct impact on the prosperity of businesses, production, and even on the normal lives of people in the country.

As expected, inflation at 15 percent shows a significant effect, but the effect of economic shocks and sanctions is greater. However, the present study expected this effect to realize regarding inflation. Other factors such as unemployment, economic growth, and the Gini coefficient have less impact, and therefore, their impact is more indirect, as economic growth indicates the so-called enlargement of the economic pie. The smaller the economic pie, the more it can negatively affect loan repayment. On the other hand, the Gini coefficient is an indicator of economic justice in society; the lower it is, the more positive the effect on the economy, thereby affecting loan repayment. In other words, it can be said that the Gini coefficient has a direct relationship with the vulnerability of low income deciles in loan repayment. The higher the Gini coefficient, the more likely it is that individuals with low income deciles will have problems repaying loans. Therefore, the effect of the Gini coefficient can be interpreted as high.

Bank managers can use the present research model to estimate non-performing or unpaid loans of their respective banks. It should be noted, however, that the presented model is general and can be examined at the regional and provincial levels. Since repayment conditions may be possibly different in each province, the present research model can be examined in different environmental and geographical contexts. Because environmental conditions can affect the results of the present study, the results cannot necessarily be generalized and expanded to different banking areas. On the other hand, other variables can be added to the current research six-variable model, which is suggested for future research. Artificial or sociological variables can complement the current research model and overcome its limitations.

## Resources


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