Research Article

Development of a credit risk evaluation system using multilayer neural networks

Abstract

This paper deals with the development of a credit risk assessment system using multilayer neural networks. The main objective of this work is to provide a decision support tool for risk assessment, considering relevant variables in the process. To achieve this objective, the backpropagation algorithm and the Adam optimizer were used to train the model. In terms of materials and methods, a training and validation data set including relevant financial information of credit applicants was used. A multilayer neural network was implemented that made predictions and calculated the loss using the categorical cross-entropy function. The results obtained during the development of the system showed a favorable performance and a satisfactory level of accuracy in identifying and classifying different levels of credit risk. However, it is emphasized that the system does not provide absolute results; human intervention is recommended as a last resort for decision making.

Keywords: credit Risk, ANN, credit rating, financial assessment

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Introduction

Currently, credit risk refers to the evaluation performed by a banking entity to classify a person applying for credit. These systems evaluate the credit behavior or credit history of the applicant, considering variables such as delinquent accounts, balance of other loans, monthly income, demographic data, among others.[1] With the Covid-19 pandemic, the problem of credit risk assessment has increased due to the large number of credit applications, some of which are from people with bad credit history or who request amounts greater than their payment capacity, which has generated deficiencies in the assessment of default risk and losses for financial institutions.[2]

The seriousness of this problem lies in the double impact it has both for financial institutions, which face greater losses due to the high delinquency rates that could result from poor assessment, and for potential borrowers, who may face unjustified rejections due to insufficiently accurate assessment systems.[3] This problem not only affects the financial stability of institutions, but can also hinder access to credit, a crucial tool for welfare and economic development.

Faced with this problem, the adoption of new cost-effective technologies could enable financial institutions to have decision support systems for credit granting. Credit risk evaluation systems based on artificial intelligence and machine learning have emerged as a viable alternative to improve evaluation processes and reduce the percentage of loss probability in loans; studies and research on the subject have shown that the adoption of such technologies for evaluation significantly improves the results of evaluations.[4] However, these solutions depend on factors such as data availability, data processing standards, and variables used, which can affect the results of the systems and their efficiency.[5]

The motivation for designing a solution lies in the possibility of overcoming these current problems and providing a more efficient and accurate credit risk assessment tool. This solution not only benefits financial institutions by reducing their risk exposure, but could also expand access to credit for individuals and businesses, which could ultimately stimulate economic growth. The purpose of this article is to propose a credit evaluation model that combines the necessary variables with the opportunities offered by new technologies to improve these evaluation processes. This proposal addresses the implementation of a credit risk assessment system based on multilayer neural networks, explaining how this system can overcome current challenges and improve the accuracy and efficiency of credit risk assessment and proposing a credit assessment model that considers the variables necessary for such assessment to have the required accuracy.

During the development of the proposal, the results obtained showed a promising performance and a satisfactory level of accuracy. However, it is important to note that these results are not 100% accurate in all situations. Instead, the importance of human intervention as the ultimate decision maker is recognized.

The article is organized in a sequential manner, the Materials and Methods chapter will detail the state of the art of the subject, the problem and the proposed solution, detailing each of them, then, the following chapter of Results and Discussions will describe the results obtained from the proposal made and will conclude with an analysis of the results, and, finally, the last chapter will present the conclusions and propose recommendations for future research.

Methodology

This chapter seeks to cover the existing theory and research related to the subject in order to understand the proposed solution and to present all the studies related to the field of credit risk assessment.

Credit risk assessment is a field of study used to determine the probability that a borrower will default on payment obligations and aims to minimize the risk of default and protect the lender's interests. For this purpose, various factors are analyzed, such as the borrower's credit history, repayment capacity, current financial situation and other relevant factors.[6] It is from this that different research has given rise to different credit risk assessment systems that use various techniques and methods to determine the level of risk and allowing the timely identification of potential risk factors is what could be incurred by the applicant.

The classification of these systems can be done in different ways, considering the statistical model used, the interaction with the environment and its functionality. In terms of the statistical model, there are systems that use logistic regression to estimate the probability of credit default based on predictor variables, and systems that use discriminant analysis to estimate the probabilities of belonging to different credit risk categories.[7] In terms of interaction with the environment, systems can be classified as autonomous, which operate without direct interaction with the external environment and use predefined statistical models and parameters; adaptive, which constantly adjust to changes in the environment by updating their models and parameters; benchmarking-based, which compare credit performance with predefined external standards; and human-interactive, which combine statistical models with human intervention in the credit risk assessment process. In terms of functionality, systems can be classified as unidimensional, which focus on a single dimension of credit risk; multidimensional, which consider multiple dimensions of credit risk; predictive, which use statistical models and predictive analytics to estimate future credit risk; and rule-based, which use predefined rules and criteria to assess credit risk and generate feedback on the outcome.[8]

The creation of credit risk assessment systems can have multiple benefits in different aspects. From an economic point of view, these credit risk assessment systems can help financial institutions make informed decisions on lending and interest rate setting, which can reduce the risk of default and protect the lender's interests by minimizing the risk of default, credit risk assessment systems can help financial institutions maintain financial stability and solvency, which in turn can contribute to overall economic stability. Similarly, from a social point of view these credit risk assessment systems can help protect borrowers from excessive financial burden, as financial institutions can make more informed decisions about lending and setting interest rates by protecting borrowers from excessive financial burden, credit risk assessment systems can help reduce the risk of poverty and social exclusion. So also, from a research point of view, the creation of credit risk assessment systems can be the subject of research and development, which can contribute to the improvement of techniques and methods used in credit risk assessment research on credit risk assessment systems can also contribute to the understanding of the factors influencing the risk of default and the identification of new ways to minimize that risk.

Several machine learning libraries, such as Scikit-learn, TensorFlow and Keras, are used to develop these systems. Among them, Scikit-learn is a Python library that offers a wide range of classification and regression algorithms, including SVMs, and provides tools for data preprocessing and model performance evaluation.[9] TensorFlow, on the other hand, enables the construction of highly complex and accurate neural network and Deep Learning models, and is capable of running models on a variety of devices and platforms.[10] Keras focuses on speed of experimentation and ease of use, offering a large number of neural network layers, activation functions, and classification optimizers.[11]

From this analysis, it can be inferred that a credit risk assessment system is composed of processes, tools, and criteria used to analyze and measure the probability of default by a borrower on a loan or credit. These systems are based on the collection and analysis of financial, credit and other relevant variables to determine the level of risk associated with a specific loan applicant.

The development of credit risk assessment systems involves the use of different methods for each aspect of system development beyond software implementation technologies such as software development methodology, such as agile methodologies. These provide a flexible, feedback-focused approach to software development that allows for rapid changes in system design and functionality during the development process. Agile methodologies, unlike traditional methods, emphasize collaboration, adaptability, and continuous delivery of value to the end user,[12] and the credit analysis method. Employed in these systems emulates the evaluation processes performed by credit experts. One approach frequently used in this context is the Financial Statement Analysis Method. This method consists of examining in detail the applicant's financial statements, including the balance sheet, income statement and cash flow. Various financial techniques and ratios are used to assess the applicant's financial health and, therefore, its creditworthiness.

Continuing with the process of implementing credit risk assessment systems, a crucial consideration is the selection of algorithms for credit evaluation and rating. Within these algorithms, Support Vector Machines (SVM) are a relevant option. These algorithms are used to categorize samples into two or more classes, which is useful in the context of credit assessment to predict whether an applicant represents a risk to the organization. SVMs operate by finding the hyperplane that best divides the samples in the feature space, which maximizes the distance between categories.[13]

In addition to this, Neural Networks are also used which are algorithms that are inspired by the workings of the human brain, they can be employed in credit evaluation to make predictions based on complex data patterns. These algorithms use multiple layers of interconnected nodes to process data and make predictions.[14] Similarly, Random Forest algorithm also plays an essential role in these systems. This algorithm combines multiple decision trees into an ensemble for sample classification. Each tree in the Random Forest is trained with a random sample from the data set, and the predictions from all the trees are combined to give a final classification.[15]

Finally, XGBoost can be used to predict the credit risk probability of applicants. This algorithm, based on predictor variables such as income, credit history and age, requires historical training data to adjust its parameters and tune the model to the specific characteristics of credit applicants.[5] The credit risk assessment process is a crucial element in the operation of financial institutions, as it makes it possible to determine the credit applicants' ability to pay and minimize the risks associated with lending.[16] However, this process is complex and presents significant challenges that require careful attention by credit assessment experts. A point to consider within this problem is that many of the processes to verify the level of risk associated with the loan, focuses the evaluation on the financial category such as credit history, level of indebtedness, among other indicators, which, although they provide a frame of reference during the evaluation, there are other categories that can improve the outcome of the evaluation allowing to reduce the level of risk associated with the evaluations.[2]

From a theoretical perspective, credit risk assessment is based on financial models and theories that seek to quantify and predict default risk. These models take into account variables such as credit history, level of indebtedness and other financial indicators, which can provide a clear view of the creditworthiness and payment capacity of the credit applicant.[16] However, although these theoretical models are useful, they do not always consider non-financial factors that can influence credit risk, such as consumer behavior, the general economic context and market conditions. In addition, theoretical analysis can sometimes be limited by the lack of historical data and the difficulty of modeling uncertainties and unforeseen events.[2] From a practical perspective, the development of credit risk assessment systems based on AI and deep learning presents specific challenges. On the software side, the design and implementation of machine learning and deep learning algorithms can be complex. Developers must choose the right algorithm for each specific task, and it must be able to handle the unique characteristics of credit data, which can include a high degree of variability and noise.[2] In addition, algorithms must be able to learn from large volumes of data and make accurate predictions in real time, which may require advanced optimization and model fitting techniques.[17] From a hardware point of view, AI-based credit risk assessment systems may require significant computational resources. Deep learning model training can be processor and memory intensive, and may require specialized hardware, such as graphics processing units (GPUs) or distributed computing systems. The hardware must be able to support the workload without compromising system performance or user experience.[18]

Considering the exposed problematic, the need arises to develop an evaluation model that incorporates new categories with the objective of obtaining improved results in the process. This implies the search for additional variables and more complete criteria for a more accurate and effective credit evaluation. By expanding the evaluation categories, we seek to address the applicant's evaluation processes in a more complete manner. The proposed model consists of 3 categories:

1. **Financial Category:** Within this category, variables that are directly related to the applicant's economic and credit situation within the financial system are considered. The variables in this category are defined by the information provided by the applicant such as monthly income, monthly expenses, among others; and variables are provided by financial institutions such as credit rating, debt history, among others.
2. **Socioeconomic Category:** This category considers variables within the applicant's social and economic context, in order to determine certain payment capacities in relation to the loans requested.
3. **Personal Category:** Within this category, variables are considered that allow the specialist to know the applicant's information in order to know his or her individual payment capacities, such as age, marital status, among others.

Based on this, Table 1 shows the evaluation model described along with the categories and associated variables:

Table 1 Shows the evaluation model described along with the categories and associated variables

	Evaluation model	
Categories	**Variable**	**Description**
Finance	Monthly income	Records compliance with previous payments and debts of the applicant.
	Monthly Expenditures	The amount of money the applicant spends monthly on basic needs and financial commitments.
	Requested Amount	The amount of money that the applicant wishes to obtain as a loan.
	Loan Time	The time in which the applicant agrees to repay the loan, including interest.
	Weighted Rating in the last year	The weighted rating granted by the SBS
	Unpaid debts, punished or in legal dispute	If you have active debts in the financial system that are reported as unpaid.
	Negative information reported	If you present information registered in SICOM
	Closed Checking Accounts	If you present checking accounts closed by any financial institution
	Canceled Credit Cards	If you present credit cards canceled by any financial institution
Socioeconomic	Job type	The nature of the applicant's employment (for example, salaried, self-employed, unemployed).
	Time spent in employment	The length of time the applicant has been employed in their current job.
	Education level	The level of education achieved by the applicant (for example, high school, college, graduate).
Staff	Civil status	The applicant's marital status (for example, single, married, divorced).
	Number of dependents	The number of people who are financially dependent on the applicant.
	Age	The age of the applicant in years.
	Housing History	The applicant's residency history, including whether they are a homeowner, renter, or living with relatives.
	Purpose of the loan	The reason the applicant is applying for the loan (for example, debt consolidation, home purchase, education, business).

The categories mentioned above describe a series of variables within the evaluation model that would improve the credit risk evaluation process. These variables provide a more complete and detailed perspective of the repayment capacity and risk profile of the applicants. However, it is important to note that, although these variables contribute significantly to the evaluation, they are not a guarantee of a completely effective evaluation and the role of the expert remains fundamental in the final decision-making process. Despite the incorporation of the aforementioned categories and variables, it is necessary for the expert to analyze and evaluate each case individually, considering additional factors and exercising professional judgment.

In order to improve the accuracy and efficiency of credit risk assessment, the implementation of a system based on multilayer artificial neural networks is proposed. Based on this, a conceptual model of the solution is shown in Figure 1. This proposal seeks to take advantage of the power of machine learning and the information processing capacity of neural networks to make more accurate and reliable predictions about the payment capacity of applicants.

Multilayer artificial neural networks are computational models that simulate the functioning of neural networks in the human brain. These networks are composed of interconnected layers of artificial neurons, where each neuron performs mathematical computations and transmits information through weighted connections. As the system is trained with training data, the connections between neurons are adjusted to optimize the prediction process.

The choice of multilayer artificial neural networks as the basis of our system is due to their ability to recognize complex, nonlinear

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patterns in data sets. By training the system with a historical data set that includes financial and credit information, the neural network can learn to identify correlations and hidden patterns that can be used to predict the ability to pay of new applicants. The proposed system will leverage information gathered from the financial, socioeconomic, and personal variables mentioned above. These variables will serve as input data for the multilayer neural network system, which will process the information and generate a prediction of the applicant's ability to pay and level of credit risk.

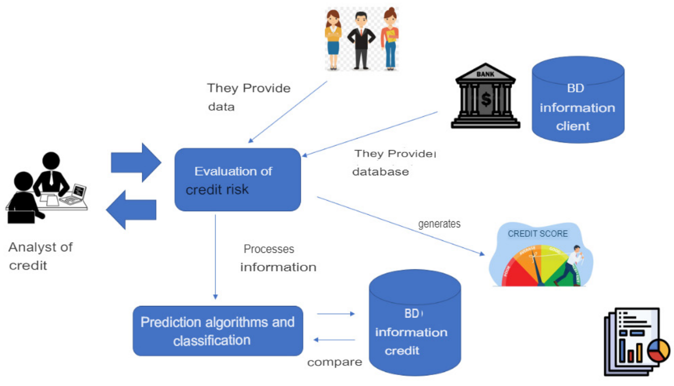

Figure 1 Conceptual solution model.

For the development and construction of the classification model from the multilayer neural network approach, a graphical example is shown in Figure 2 to exemplify the multilayer neural network model:

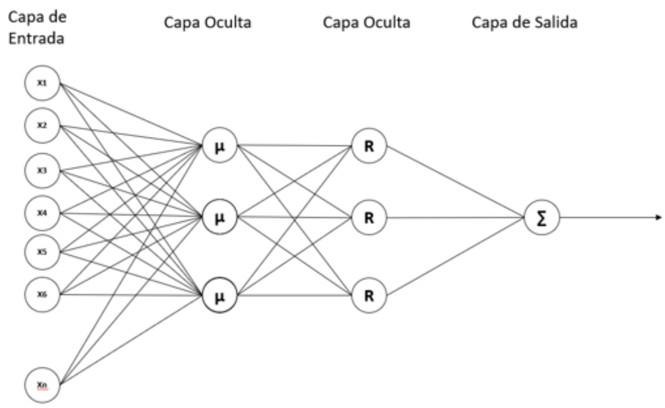

Figure 2 Proposed multilayer neural network model.

Input Layer: The input variables are related to the variables presented in the evaluation model and are shown in Table 2.

Table 2 Definition of input variables

	Inputs variables	
Categories	**Variable**	**Variables (Xn)**
Financial	Monthly income	x1
	Monthly Expenditures	x2
	Requested Amount	X3
	Loan Time	x4
	Weighted Rating in the last year	X5
	Unpaid debts, punished or in legal dispute	X6
	Negative information reported	X7
	Closed Checking Accounts	X8
	Canceled Credit Cards	X9
Socioeconomic	Job type	x10
	Time spent in employment	X11
	Education level	x12
Personal	Civil status	X13
	Number of dependents	X14
	Age	X15
	Housing History	X16
	Purpose of the loan	X17

Hidden Layers: In this layer two main functions are performed, the first one processes the product of the weights assigned for each evaluation criterion by the corresponding input value dependent on the category using the required formula (Table 3).

The second function is the activation function, which for the proposal is the ReLU function that allows to improve the outputs of the neurons by means of the following formula (Table 4).

Output Layer: This layer performs the Sofmaz function for the final processing of the sets of values to convert them into probabilities by means of the following formula (Table 5).

Based on the calculations defined for the algorithm processing, a table of ranks is defined in order to analyze the result and grant a credit rating to the applicant. This table is shown below Table 6.

Table 3 Calculation in hidden layers

Producer of the variables			
Categories	**Variables (Xn)**	**Weights (Wi)**	**Calculation**
	x1	0.11	
	x2	0.11	
	X3	0.11	
	x4	0.11	
Financial	X5	0.12	
	X6	0.11	$\sum_{n=1}^{9} W_{(i*X_n+b)}$
	X7	0.11	
	X8	0.11	
	X9	0.11	
	x10	0.34	
Socioeconomic	X11	0.33	$\sum_{n=10}^{12} W_{(i*X_n)}+b$
	x12	0.33	
	X13	0.2	
	X14	0.2	
Personal	X15	0.2	$\sum_{n=13}^{17} W_{(i*X_n)}+b$
	X16	0.2	
	X17	0.2	

Table 4 Calculation of activation in the hidden layers

Variable Activation Function				
Categories	**Variables (Xn)**	**Weights (Wi)**	**Calculation**	**ReLU function**
	x1	0.11		
	x2	0.11		
	X3	0.11		
	x4	0.11		
Financial	X5	0.12	$\sum_{n=1}^{9} W_{(i*X_n)}$	$f(x)=max(0,x)$
	X6	0.11		
	X7	0.11		
	X8	0.11		
	X9	0.11		
	x10	0.34		
Socioeconomic	X11	0.33	$\sum_{n=10}^{12} W_{(i*X_n)}$	$f(y)=max(0,y)$
	x12	0.33		
	X13	0.2		
	X14	0.2		
Personal	X15	0.2	$\sum_{n=13}^{17} W_{(i*X_n)}$	$f(z)=max(0,z)$
	X16	0.2		
	X17	0.2		

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Table 5 Calculation of the Softmax function at the output layer

Evaluation criteria	
Classification rank	**Result**
0.00 ≤ R(score) ≤ 0.35	Low risk
0.35 < R(score) ≤ 0.70	Medium risk
0.70 < R(score) ≤ 1	High risk

Table 6 Performance evaluation table

Variable output function		
Categories	**f(x)**	**Softmax function**
Financial	1.58	$R = \frac{e^{1.58}}{(e^{1.58} + e^{1.34} + e^{1.8})}$
Socioeconomic	1.34	$R = \frac{e^{1.34}}{(e^{1.58} + e^{1.34} + e^{1.8})}$
Personal	1.8	$R = \frac{e^{1.8}}{(e^{1.58} + e^{1.34} + e^{1.8})}$

The model is trained using the backpropagation algorithm and the Adam optimizer. During training, predictions are made on the training set and the error of these predictions is calculated using the categorical cross-entropy function. The Adam optimizer adjusts the weights and biases in the direction of the loss slope using gradient descent, taking into account recent changes in the weights and the adaptive learning rate.

The training process consists of several stages. First, feedforward is performed by passing the input data through the network to obtain a prediction. Then, the error is calculated using the mean square error loss. Next, backpropagation is performed by propagating the error backward through the network, calculating the partial derivatives of the error with respect to the weights of each layer. Finally, the network weights are updated proportionally to these partial derivatives, controlling the update rate by the learning rate defined in the Adam optimizer.

Results

Based on the proposal developed and to validate the results, we will present the results obtained by simulating an evaluation with synthetic data collected, from which we expect to receive as output a low credit risk rating. The following table shows the variables that will be entered in the layer as input data (Table 7).

Table 7 Input data by variable

Input data		
Categories	**Variables (Xn)**	**Input value**
	x1	2
	x2	2
	X3	1
	x4	1
Financial	X5	4
	X6	1
	X7	1
	X8	1
	X9	1
	x10	2
Socioeconomic	X11	1
	x12	1
	X13	2
	X14	2
Personal	X15	2
	X16	2
	X17	1

Hidden Layers: The following table will represent the calculations of weights and activation using the formulas described above Table 8.

Output layer: The following table will represent the calculation in the output layer using the ReLU function and the product of the output by the weight of each category and will result in a summation of this multiplication (Table 9).

Table 8 Processing of the variables in the hidden layer

Calculation in the hidden layer				
Categories	**Variables (Xn)**	**Weights (Wi)**	**Calculation**	**Activation function**
	x1	0.11		
	x2	0.11		
	X3	0.11		
	x4	0.11		
Financial	X5	0.12	$\sum_{n=1}^{9} w_{(i*X_n)} + b = 1.58$	$f(x) = max(0, 1.58)$
	X6	0.11		
	X7	0.11		
	X8	0.11		
	X9	0.11		
	x10	0.34		
Socioeconomic	X11	0.33		
	x12	0.33	$\sum_{n=10}^{12} w_{(i*X_n)} + b = 1.34$	$f(x) = max(0, 1.34)$
	X13	0.2		
	X14	0.2		
Personal	X15	0.2	$\sum_{n=13}^{17} w_{(i*X_n)} + b = 1.8$	$f(x) = max(0, 1.8)$
	X16	0.2		
	X17	0.2		

Table 9 Processing in the output layer

Output layer results				
Categories	**f(x)**	**Softmax function**	**Weight by category**	**Result**
Financial	1.58	$R = \frac{e^{1.58}}{(e^{1.58} + e^{1.34} + e^{1.8})} = 0.3297$	0.4	0.13189547
Socioeconomic	1.34	$R = \frac{e^{1}.34}{(e^{1.58} + e^{1.34} + e^{1.8})} = 0.2593$	0.3	0.07781449
Personal	1.8	$R = \frac{e^{1.8}}{(e^{1.58} + e^{1.34} + e^{1.8})} = 0.4108..$	0.3	0.12326391
			Result	0.33297387

With the value obtained we proceed to compare it with our evaluation criteria, which is presented in the following Table 10.

Table 10 Test results

Comparison of the result			
Classification rank	**Result**	**Obtained value**	**Classification**
0.00 ≤ R(score) ≤ 0.35	Low risk		
0.35 < R(score) ≤ 0.70	Medium risk	0.33297387	Low risk
0.70 < R(score) ≤ 1	High risk		

Discussion

From the above result it can be seen that, as expected, the classification obtained was Low Risk, this rating indicates to the officer that based on the data provided the applicant has a low probability of incurring in payment problems. Although the result is as expected, it is important to note that the results provided by the system should not be considered absolute, but rather as a support tool for decision making in risk assessment. The credit risk assessment system has shown promise in identifying and classifying different levels of risk associated with credit applicants. However, it is essential to keep in mind that credit risk assessment is a complex process involving multiple variables and external factors that can influence the financial solvency of individuals or companies.

Conclusion

The implementation of the credit risk assessment system based on multilayer neural networks has demonstrated acceptable efficiency in the identification and classification of risks associated with credit applicants and the results obtained support the usefulness of this approach as a support tool in the decision-making process. Similarly, through the use of multilayer neural networks and the ReLU and Softmax activation functions, an accurate representation and prediction of credit risks has been achieved, thus demonstrating the efficiency of the model for cases where the volume of data and processing capacity is reduced; it should be noted that for larger or more complex data volumes it would be necessary to use and combine different prediction models that can support such level of processing. In addition, models were created for data entry, validation and processing, which for the proposal allowed to represent a correct flow of information to perform the evaluation, it is recommended to consider other modules that allow to improve the collection, flow or functionality of the system.

On the other hand, it is important to note that there are areas for improvement that could further enhance the effectiveness of the system. First, it is recommended to consider the inclusion of a model that involves a larger number of variables relevant to risk assessment. By expanding the set of variables considered, the system can capture a completer and more accurate picture of the financial situation of loan applicants. In addition, it is suggested to work on improving and expanding the training datasets used in the system. A completer and more updated dataset can increase the system's ability to recognize relevant patterns and improve the accuracy of predictions. Also, attention should be paid to the quality of the data and a thorough cleaning and validation process should be performed. Another aspect to consider for future research is the hardware used for data processing. Suitable hardware, with superior processing capabilities, would allow for greater speed and efficiency in the execution of the system, which could lead to even more accurate and faster results. This change would imply a new study and analysis for the choice of prediction models.

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Conflicts of interest

The authors declare that there is no conflict of interest.

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