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Supervised Learning Algorithms for Non-Life SCR Ratio Forecasting

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Abstract

The solvency is measured by the Solvency Capital Requirement (SCR). This study seeks to determine the best financial ratios to forecast SCR because it is significant. There is seasonality, data jumps, and shifts in insurance indicators, which make prediction of SCR difficult. Different machine learning algorithms are applied to the insurance market in this research to see how well they can describe and predict the SCR ratio. Gaussian process regression, ensemble methods, regression decision trees, stepwise regression, and neural networks were used as supervised learning techniques to find the most suitable method to predict SCR. According to our analysis of nonlife insurance data from Romania between 2016-2020, debt ratio, reserve adequacy, receivables, and liquidity are among the key indicators that should be considered when forecasting SCR. These findings can be useful for policymakers, regulators, actuaries, and professionals involved in risk management or the insurance industry.

Keywords: general insurance, machine learning, risk prediction, solvability capital requirement ratio.

JEL Classification: G22, G28.

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1. Introduction

The regulation of the insurance industry proved to present gaps in the 2007-2009 financial crisis, hence new laws were created for the protection of consumers. One of the laws which were set following this amendment was carried out is the Solvency II Directive, that entered into force in 2016 as a legally binding regulatory framework for all the insurers conducting activities in the EU and requests them to maintain a sufficient level of capital to steer clear from being declared insolvent.

Solvency II demands an insurance or reinsurance company to keep enough sufficient solvency capital as specified by different risk levels at a 99.5 percent level of confidence over one year. These include non-life underwriting risk, market risk, credit risk, and operational risk, amongst others that constitute the SCR. Moreover, compliance with SCR will assure the client about the financial soundness of the firm, including its capacity to meet all liabilities, with the penalty of closure by order of the authority in case of a breach at the firm's end.

The financial health of any insurance company may be viewed against the eligible equity in comparison with the SCR, which provides something known as the SCR ratio.A ratio below 100% suggests some financial instability in that not enough funds are set aside to cover losses above such a point, which hints at the lack of adequate reserves to cater for such situations. Therefore, accurate estimation of how much below or above this benchmark level might turn out true becomes very important not only for policymakers but also for regulators themselves, thus necessitating the development of different predictive models in relation to forecast accuracy.

This study employs machine learning algorithms when dealing with solvency capital requirement ratio predictions, something that has increasingly gained recognition within the insurance sector over past years, given the changing business landscape driven mainly by digitisation processes like automation, among others. Our main objective here is, therefore, twofold: first, we seek to identify those financial indicators that are highly correlated vis-a-vis SCRs; second, we evaluate performance diverse ML techniques under a similar context previously mentioned. For instance, some useful ratios could include receivables turnover rate, liquidity ratio, debt service coverage reserves to policyholders, etc. Based on this approach, supervised learning methods such as stepwise regression, decision trees regression, Gaussian process ensemble methods, and neural networks will be applied, thus providing information on the prediction precision levels of SCR according to different machine learning algorithms.

The purpose of this paper is to examine the applicability of machine learning algorithms in predicting solvency capital requirement ratios within the insurance sector. We intend to identify financial ratios that are most predictive of the solvency capital requirement and evaluate various machine learning techniques' performance under this setting. Our results can improve risk-based supervision and provide useful information for practitioners and regulators alike.

Our research work contributes largely towards literature development in relation to the use of machine learning algorithms, especially when it comes to predicting Solvency Capital Requirement (SCR). Through the identification of key financial indicators such as receivables; liquidity; debt ratio; and reserve adequacy, among others, we offer insights concerning what should be taken into consideration while trying to come up with accurate forecasts on SCRs so that they can be used effectively during decision-making process by different stakeholders involved like investors, managers, or even policymakers at large. Moreover, our methodology involves the employment of various supervised learning methods, including stepwise regressions, decision tree regressions, and Gaussian processes ensemble neural networks, which highlights benefits brought about through the application of these models within areas like SCR forecasting where more accuracy is required. Furthermore, this research provides practical implications for those working in the insurance industry who may wish to use these findings so as to avoid falling into financial distress themselves or failing to protect the stability of firms under their watch.

2. Problem Statement

The Solvency Capital Requirement Ratio (SCR) has been an important gauge of insurance firms' financial health, leading to many investigations into developing accurate predictive techniques. Several studies have reviewed different methods, ranging from traditional statistical approaches to advanced machine learning algorithms, to correctly predicting SCR ratios.

2.1 Traditional Methods

Moreno et al. (2020) used a dynamic panel data model to analyse the solvency of Spanish insurers and found that solvency margins were positively correlated with profitability and underwriting risk but inversely related to company size, reinsurance usage, long-tail businesses, and life insurance specialisation. They also observed that economic downturns tend to reduce solvency margins. Caporale et al. (2017) assessed insolvency risk in UK nonlife insurers and pointed out that interest rates, liquidity, profitability and leverage – along with macroeconomic factors – were significant determinants of insolvency risk based on traditional risk factors alone. Hejazi et al. (2017) demonstrated how neural networks could estimate SCR for variable accidents, showing potential for machine learning in this area. They stressed that machine learning can take into account the complicated interdependencies among accounting indicators leading to better SCR forecasts.

2.2 Machine Learning Approaches

Machine learning algorithms are a notable improvement compared to classical statistical methods, that are frequently based on means, standard deviations, normal distributions, and linear regressions. Despite being advantageous, the traditional approaches may lack the capability to pinpoint low-risk factors or to showcase linkages on different levels. In contrast, flexible detailed machine learning methods like regression trees, ensemble methods, and neural nets offer more versatile ways of analysing data.

Henckaerts et al. (2021) utilized a tree-based machine learning approach in predicting both frequency and severity of an insurance portfolio and demonstrated superiority to traditional GLM models. Their work demonstrated the fact that gradient boosting and random forest algorithms usually lead to better predictions of the damage frequency and less painful problems compared to a GLM model. Another example is by Wüthrich, 2020, who applied the neural models to price general insurance and greatly surpassed the performance of generalized linear models (GLM). Fauzan and Murfi, 2018, compared several ensemble learning methods for predicting car damage: the XGBoost AdaBoost Stochastic Gradient Boosting and Random Forest. They found out that the algorithm used was XGBoost, and it gave higher levels of accuracy compared to other methods. Further, the findings of Weerasinghe et al. (2016) also reported that the neural networks produce the best estimates when car damage is predicted.

2.3 Regularisation and Feature Selection

To address overfitting and multicollinearity issues in linear regression models, various regularisation techniques such as ridge regression, lasso, and elastic net are used. When there is no clear economic intuition for selecting relevant factors, stepwise regression is a popular choice for feature selection. This automatically selects the most significant predictors for the dependent variable, in this case SCR. Hejazi and Jackson (2017) integrated a neural network calculation of SCR with portfolio estimation. A comparison of the the performance of variable anomalies was made between them. Castellani et al. (2021) simulated life insurer SCRs using deep learning models and support vector machines, further illustrating the success of advanced machine learning techniques in this domain.

3. Research Questions / Aims of the Research

The main goal of this study is to understand the effectiveness of various machine learning algorithms in predicting the solvability capital requirement (SCR) ratios for insurance companies. Research seeks to improve the accuracy and dependability of SCR forecasts about SCRs by identifying financial ratios that are most predictive of them, which would therefore contribute to effective risk-based supervision and robust regulation within the insurance sector. To elaborate on the problem statement, this research addresses the following questions:

What are some key financial indicators used by organisations when forecasting solvency capital requirements (SCRs)? This inquiry tries to find out what the main pointers that heavily affect SCRs, thus giving insight into the necessary elements for ensuring financial stability in the insurance industry.

How accurate are different types of machine learning algorithm in predicting an SCR ratio? The question assesses the performance of stepwise regression analysis methods, regression decision trees, Gaussian process regression models, ensemble methods, and neural networks, which were used in trying to forecast the ratio.

Can we use ML models to detect financial insolvency earlier than traditional statistical methods applied in insurance firms? This query investigates if such an ability exists, by comparing the predictions of those two approaches regarding potential vulnerability areas within insurance firms, thus allowing timely regulatory interventions.

What should be done practically when applying machine learning algorithms to predict SCR ratios for supervisors and practitioners working within insurance companies? This inquiry looks at ways to implement the results from this investigation under real-world conditions to enhance monitoring systems designed to promote the soundness of financial organisations, particularly those involved with insurance undertakings.

Since they focus on verifying how well these machines work, three hypotheses tested during this research:

Machine learning algorithms significantly outperform traditional statistical methods when predicting an SCR ratio: Here, it was suggested that more advanced techniques could give better results in terms of precision or reliability than the usual means.

Receivables (Debtors), liquidity (Quick Ratio), Debt Ratio (Debt Equity), and reserve adequacy are the Key Financial Ratios for predicting the SCR Ratio. This hypothesis indicates that some selected financial indicators should have a high impact on solving capital requirement forecasting.

Early detection of financial impairment in Insurance Companies is improved through Machine Learning Models: It was proposed under this hypothesis that regulatory authorities would be able to act faster if they used machine learning algorithms as compared to traditional ones, since the former can detect potential instability quickly.

Through these hypotheses and research questions, it is anticipated that there will be a better understanding of how machines work in the insurance industry, especially when predicting SCR ratios for the solvency capital requirement.

4. Research Methods

This study involved using an annual data set in the Romanian nonlife insurance sector between 2016 and 2020 as a basis for analysis. Initially, more than 40 accounting indicators were scrutinised for analysis in this dataset. The pre-processing of the data was performed to ensure that it was of high quality and consistency by removing duplicates, examining outliers and treating them, and handling missing data, among others. The z scores were calculated to standardise the values across all variables. The preliminary analysis used a stepwise regression method in which those indicators that had the least or no explanatory power toward the SCR ratio were removed. This helped address collinearity problems inherent in any such data set. We then applied three techniques of regularisation, namely lasso regression, ridge regression, and elastic net, to choose the most important variables. Lasso assigns small weights to zero, hence making it easy to identify important variables, while ridge keeps them small and elastic net removes weight variables while reducing the influence of others.

The initial set of indicators that were selected for further testing with machine learning algorithms include:

- Profitability Ratio: Profit (loss) divided by gross premiums underwritten;
- Combined loss ratio: Recorded losses plus expenses divided by underwritten gross premiums;
- Receivables Indicator: The sum of reinsurance recoveries receivable balances insurance intermediaries' receivables plus reinsurance receivable balances divided by total assets;
- Liquidity Indicator: Total liquid assets divided by short-term liabilities;
- Debt Ratio: Total assets divided by total liabilities;
- Reserves Indicator: Sum changes RBNS+IBNR /sum RBNS+IBNR;
- Runoff ratio: adequacy ratio/ loss reserves;
- Equity Quality: Equity / Subordinated Liabilities.

To estimate the SCR ratio, we employed various supervised machine learning algorithms, including decision trees, Gaussian process regression ensemble models, neural networks, etc. Decision trees are hierarchical models that make predictions based on the best predictor at each node, while regression trees reduce the variance of response variables at each successive node, generating numerical predictions. We trained regression trees with different splits and we found that a tree with 8 splits provided the most accurate predictions. Cross-validation was used to assess model performance and avoid overtraining.

The Gaussian process regression (GPR) models represent the response by means of a probability distribution over functions. To handle non-smooth datasets more efficiently, we used an exponential kernel and achieved an R-squared value of 43%, which is comparable to the best-performing decision trees in regression. The response in Gaussian process regression is modelled using a probability distribution in function space. GPR models are nonparametric probabilistic kernel-based models.

Given a training dataset $(x_1,y_1),(x_2,y_2),\ldots(x_n,y_n)$ and a new test input x_*, GPR predicts a distribution for all possible values of y_* for x_*. A GPR model connects this data to the output with some Gaussian noise. After seeing the data, we revise our belief to obtain another Gaussian (posterior) process. We want to compute the mean and covariance (or kernel) for this posterior. With the Gaussian process framework, the posterior distributions are also Gaussian. We can make predictions about new points using the mean and covariance of this posterior distribution. In our case, an exponential kernel was used because, depending on which type you choose, it will consider different functions when building up your model within GPR, which gave us better results as it might be more appropriate while dealing with non-smooth datasets. The exponential kernel is defined as

$$k(x,x') = \exp(-(\|x-x'\|)/\lambda) \tag{1}$$

Where x and x' are input data, $\|x-x'\|$ is the L1 norm for Manhattan distance between the input data and is a length scale parameter for the width of the kernel.

4.1 Ensemble Models

Ensembles like bagging, random forests, and gradient-boosting machines can overcome these challenges because of the sensitivity of decision trees to training data. An ensemble method refers to a supervised learning technique that combines predictions from many machine learning algorithms. These models are able to produce better outcomes by gathering weak "learners" outputs into one strong model. There are a variety of methods for aggregating learners, also known as algorithms, some of which include bagging trees, random forests, and boosting trees, among others. In this algorithm, bootstrapped samples are used from the data set; at every node, a random subset of factors is selected and thresholds are randomised. Bagging trees take a sample of data and replace it, creating new datasets called bags. The algorithm samples with replacement, meaning that some data are repeated while others are left out. And then, n times, the process is repeated until an ensemble of n replicates is done, just like in bootstrapping. Training in each replica created a model for each, and accuracy was tested on each model. Boosting is an algorithm similar to ensemble techniques, but predictions are made sequentially under the assumption that each submodel corrects mistakes.

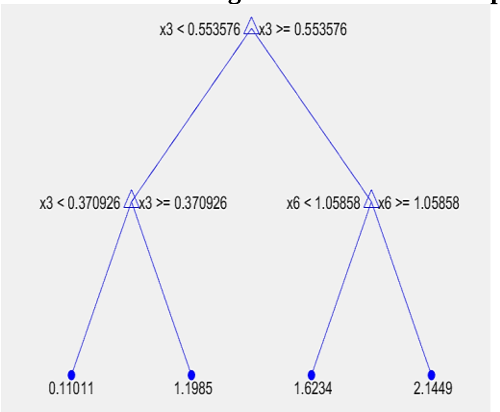
Artificial neural networks (ANNs) are supervised learning models that can learn relationships between input and output datasets, especially when such relationships are complicated or nonlinear in nature. A neurone computes a weighted sum over multiple inputs and then passes it through a nonlinear activation function, such as a threshold activation filter, to produce output. To amplify outputs from individual neurones, they need to be combined together within the network representation. The network itself can be thought of as a multivariate function that maps the input data set to an output vector. Neural networks have found useful applications within the insurance industry, among other sectors. There are different types of neural networks, depending on their capability to handle complex datasets. For our study, we employed feedforward two-layer neural networks for supervised regression. We adjusted the two-layer feedforward network in the hope that it might yield better performance than previously tuned ensembles. The data set was split into training, validation, and testing sets. After training, MSE and R-squared can be used to evaluate the network performance.

5. Findings

5.1 Regression Trees

A range of 3 to 8 splits has been used for training regression trees. The regression trees with 8 and 3 splits are presented below. This binary tree predicts the range of SCR ratio from the branching of the data. The first decision is whether the indicator of receivables is less than or greater than 0.56. If it does, follow either the left or right branch until you find the predicted SCR values. What this tree shows is that according to a company’s low level of accounts receivables, its poor position of solvency can be predicted more accurately (explained by logic).

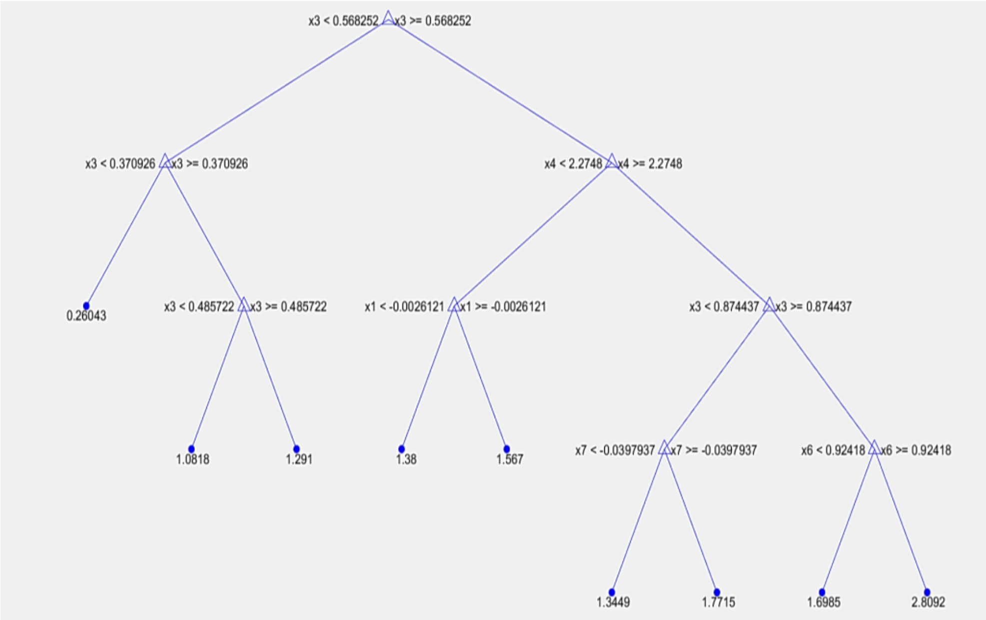
Figure 1. Partitioned Regression Trees with 3 Splits



Legend: Rentability (x1), the inverse of the combined loss rate (x2), Receivables/Total Assets (x3), Liquidity indicator (x4), Indebtedness ratio (x5), Adequacy of Reserves (x6), Runoff (x7), Quality of own funds (x8).
Source: authors' calculation.

In a partitioned regression tree with 8 splits, the receivables indicator is still the best predictor of low SCR values, but it supplies more information for other SCR values. Thus, a higher receivables indicator joined by higher values for liquidity and a higher adequacy reserve indicator will predict a high value for SCR ratio, which translates into a very good solvency position for the companies.

Figure 2. Partitioned Regression Trees with 8 Splits



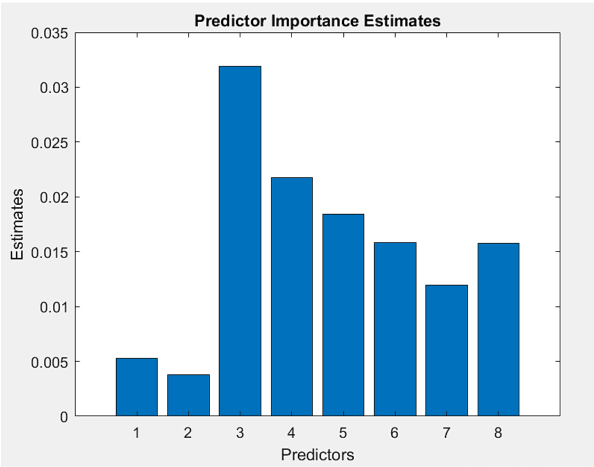
Source: authors' calculation.

Machine learning has some methods commonly used to reduce overfitting. These are cross-validation, bagging, random subspace, random forest, and boosting. Bagging decision trees do better regularisation than single decision trees that have been pruned. This regularization technique works well with models because it decreases the variance and increases the learning bias. An algorithm in machine learning divides sample data into three sets—training set, validation set, and test set—thus developing alternative strategies to increase model complexity. The test set also functions as an out-of-sample forecast tool by showing how good the model, or mixture of models, that has been chosen in advance is.

From our initial results of partitioned trees with 3 and 8 splits, we have chosen to do a cross-validation with a regression tree with a maximum number of splits equal to 8. Cross-validation, in this instance, is a procedure used for out-of-sample test performance, with repeated random sub-sample increments, achieved by dividing the dataset into equally sized folds used as validation sets, with the rest as training sets. This method is useful in estimating the predictive accuracy of a fitted tree.

We grew unbiased trees by specifying the use of curvature tests to divide predictors. We did a bar graph comparison regarding estimated predictor importance where the most important predictors selected by the regression tree. among the other 8 indicators shown above include receivables, liquidity, indebtedness, as well as adequacy of reserves, whose significance levels are displayed in the next figure with the tallest bars representing highly significant predictors selected by regression tree.

Figure 3. The importance of predictors

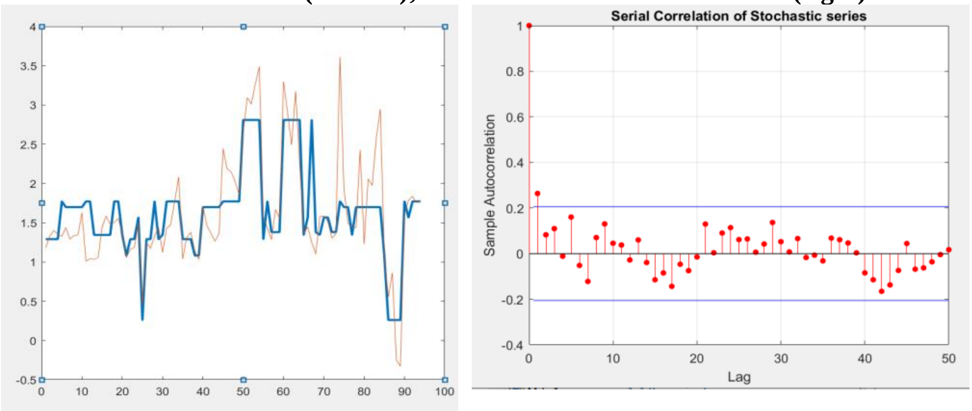


Source: authors' calculation.

The resubstitution mislaid for the most appropriate regression tree amounted to 17.8%, and it is the mean square error between predictions and actuals computed on given samples. If the error is high, then this shows that an underfit has occurred because predictions are too far from targets, while if it is too low, we may be over fitting our estimates to the sample.

The graph below shows how far off predictions were from reality as well as the self-correlation of errors in estimated trees with 8 splits. By considering the serial autocorrelation in residuals, one can observe that some autocorrelation still exists between these two variables. .

Figure 4. Partitioned Regression Trees with 8 Splits: predicted SCR (blue line) versus actual SCR (red line); Autocorrelation of the residuals (right)

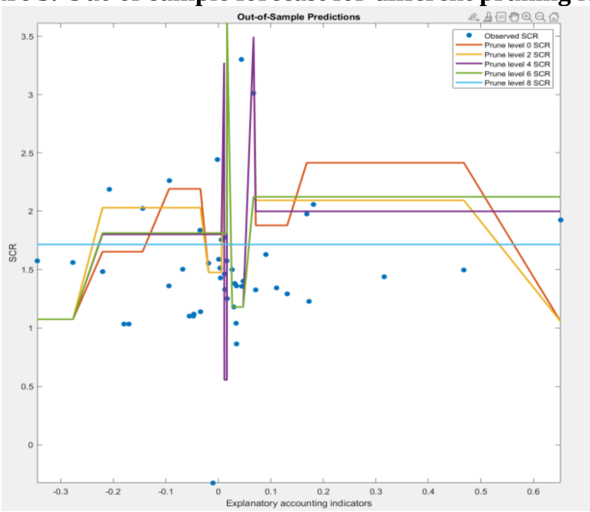


Source: authors' calculation.

We fitted the model again with only three splits and the results are poorer. The resubstituting error increased to 32%. This implies that a smaller model cannot explain SCR since it underfits the data. Out of the partitioned trees with 3 and 8 splits, the best regression tree has 8 splits and an R-squared of 43%.

We did an out-of-sample forecast for the regression tree for different pruning levels between 2 and 8 variables. For each pruning level, we predicted SCR and compared the results with the actual data.

Figure 5. Out-of-sample forecast for different pruning levels



Source: authors' calculation.

A higher pruning level implies fewer explanatory factors. As shown in Figure 4, the results indicate that only four explanatory levels are optimal to explain the largest variation of the SCR. The final explanatory variables chosen from the initial data set of eight variables are receivables, liquidity, indebtedness, and the adequacy of reserves.

Therefore, the regression trees with 8 splits showed that the receivables indicator was the most important predictor of the SCR ratio, supported by higher values for liquidity and reserve adequacy indicators. The 3-split tree was less effective, with a re-substitution error of 32%, indicating underfitting.

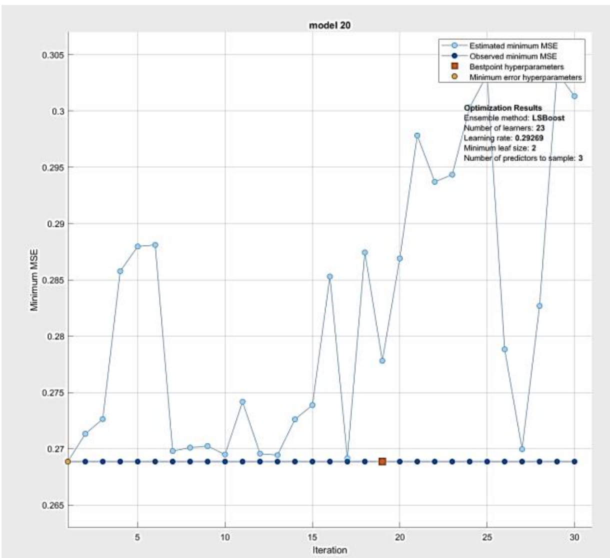
5.2 Gaussian Process regression

The GPR model with an exponential kernel achieved an R-squared of 43%. This result was on par with the best regression trees, strengthening the effectiveness of the selected indicators.

5.3 Ensemble Models

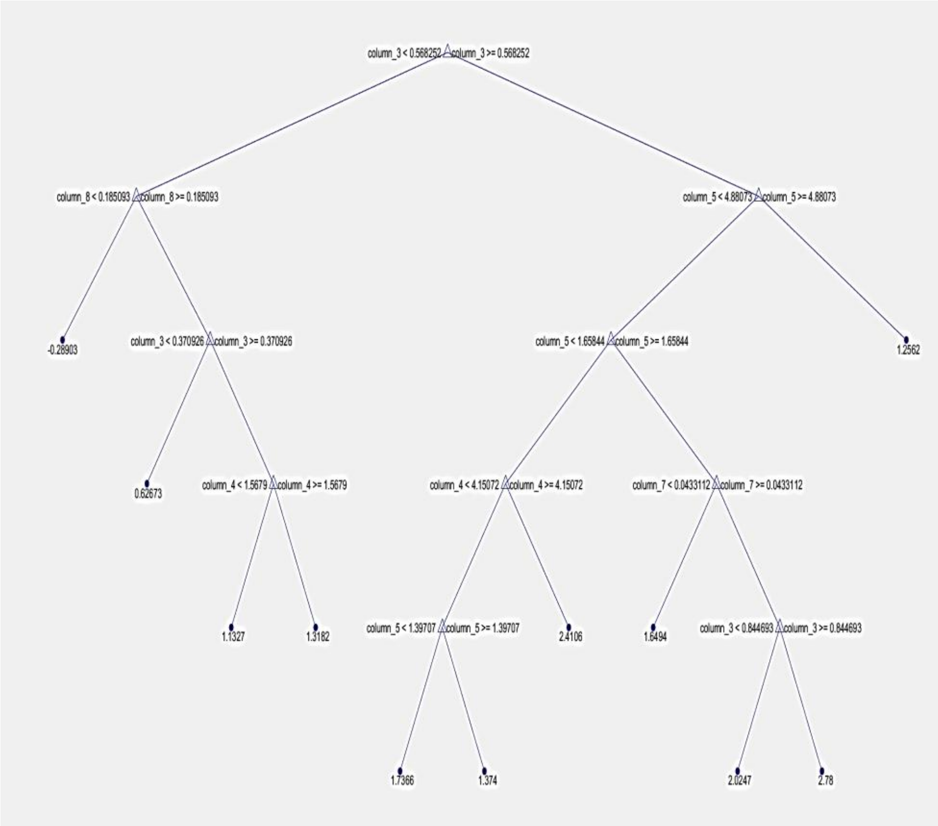
The highest R-squared of 54% is provided by boosting trees among ensemble methods. The model recognised accounts receivable, liquidity, debt, and reserve sufficiency as the most significant predictors. The best method was the boosting tree method with 23 learners. The minimum leaf size ranged from 1 to 47, and 1 to 8 predictors were taken into account during this process. The ensemble tree is presented below and confirms previous findings that an account receivables indicator is the best predictor of a firm's low SCR ratio. Trained Ensemble can be used to predict SCR.

Figure 6. Minimum MSE plot for trained ensembles



Source: authors' calculation.

Figure 7. Trained Ensemble (R-squared 54%)

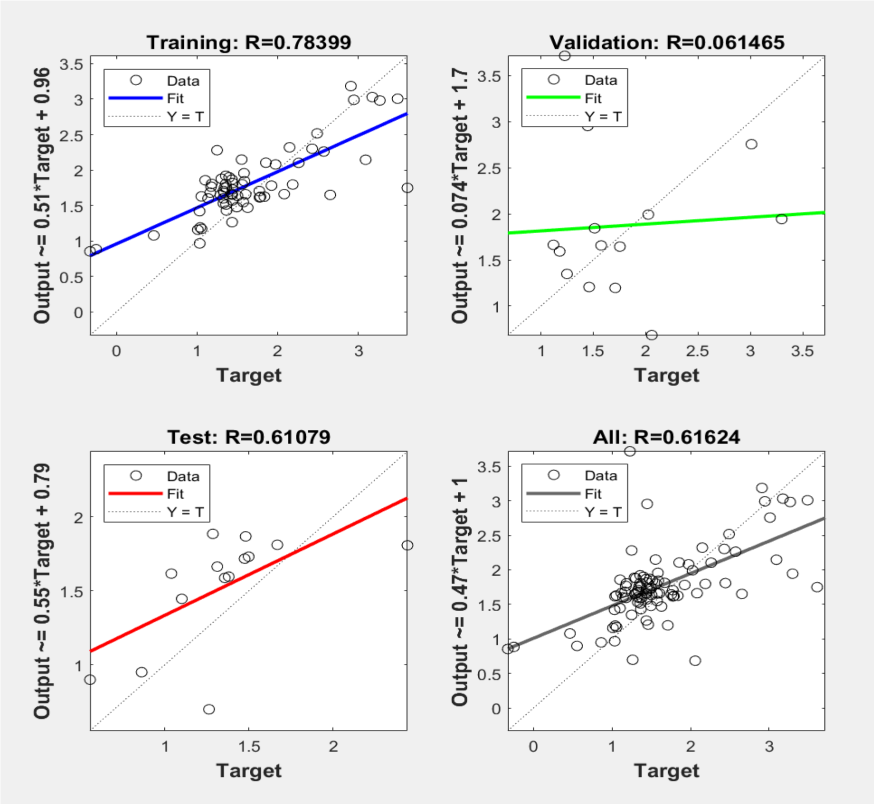


Source: authors' calculation.

5.4 Neural Networks

The graph illustrates the results of the neural network in all three stages: training, validation, and testing. The trained neural network trained recorded an R-squared coefficient of 62%, representing the best results obtained with the machine learning algorithms used in this study. These results indicated slightly superior performance to the ensemble methods (R-squared of 54%). Artificial neural networks (ANNs) are capable of modelling complex non-linear relationships. In this study, we used a two-layer forward network and split the data into sets for training, validation, and testing. The best performing neural network achieved an R-squared coefficient of 62%, outperforming all other models tested. This result highlights the superior ability of artificial neural networks to capture complex relationships in data. The network performance was consistent throughout the training, validation, and testing stages.

Figure 8. Neural network for SCR ratio



Source: authors' calculation.

5.5 Predictor Importance

The majority of the models selected for this study showed that assets, current ratio,, debt ratio and reserve adequacy are the most significant indicators. Models were evaluated based on mean squared error (MSE) and R-squared values. Neural networks performed the best, followed by ensemble models and regression trees. The cross-validation process confirmed the stability of these models, reducing the risk of overtraining and ensuring reliable predictions.

The findings indicate that machine learning algorithms such as neural networks and ensemble models can greatly enhance the accuracy of SCR ratio forecasts. These models provide useful tools for insurance practitioners and regulators to actively monitor and manage the financial health of insurance companies. Precise prediction of SCR ratios can support early identification of deteriorating financial conditions with timely regulatory interventions.

Drawing on a few core indicators, the paper proposes a simplified approach to risk-based supervision that could simplify regulation while maintaining sound financial control. Empirical results strongly support hypothesis 1. Various machine learning techniques such as decision trees, Gaussian process regression, ensemble methods, and neural networks have shown better performance in predicting SCR ratios than traditional methods. In particular, the neural network achieved an R-squared value of 62%, which is relatively high, indicating good predictive ability, among other things Ensemble methods especially boosting trees, also did well with an R-squared value as high as 54%. This suggests that machine learning algorithms can detect complex patterns or relationships between different variables, which may be missed by conventional statistical modelling techniques. Our findings thus validate our hypothesis that machine learning algorithms significantly outperform traditional methods when it comes to forecasting the SCR ratio.

Hypothesis 2 was confirmed through consistent identification of receivables liquidity indebtedness and reserve adequacy as being the most significant predictors across various models Decision trees, for example, an eight-split tree identified these factors as important towards accurate prediction achievement Similarly, ensemble approaches along with Gaussian Process Regression highlighted their relevance due to them being consistently more influential during prediction stage Bar graphs comparing importance levels within predictors further underscored the centrality of these financial ratios in determining SCR ratio Therefore our study affirms that those key financial ratios are strong predictors necessary for correct forecasts about the SCR ratio.

The performance of models and implications for regulatory practice validate Hypothesis 3 Machine learning models, particularly neural networks and ensemble methods, have brought about not only higher predictive accuracy but also better capabilities for early detection. Superior performance metrics (eg, R-squared values) show that these models can recognise signs of deteriorating financial condition earlier and more accurately than traditional methods. Ability to handle large volumes or variety of data sets by machine learning provides deeper insights into financial health, thereby enabling timely interventions by regulators. Hence, study findings strongly support hypothesis that ML improves early detection of FI in ICs.

These hypotheses, being shown to be true, have a number of implications in the real world. Initially, the fact that machine learning models have been shown to be superior means that regulators and insurance companies should adopt them as part of their risk assessment systems. Integrating these advanced methods into their frameworks would enable more accurate and timely monitoring of financial health, and thus overall market stability. Second, the discovery that key financial ratios are significant predictors emphasises the need for regulatory practice to focus on those indicators. Regulators can foresee and mitigate probable risks in a better manner by closely observing the receivables, liquidity, leverage, and reserve adequacy. Last but not least, there is an enhancement in the ability of machine learning models to conduct early detection, that stands as an irreplaceable tool for regulators who intend to act beforehand. This approach can help prevent insurance companies from going through periods of financial crisis, thereby safeguarding policyholders' confidence in the insurance industry.

6. Conclusions

The aim of this paper was to use machine learning algorithms in selecting indicators and predicting the Solvency Capital Requirement (SCR) ratio within Romanian nonlife insurance market. We were primarily interested in modelling certain relationships between some insurance indicators with deterioration of solvency positions among nonlife assurance firms.

We employed various supervised learning techniques such as regression decision trees; ensemble methods like Gaussian process regression; neural networks, etc., using an annual data set from 2016-2020 years inclusive. The analysis revealed key indicators for forecasting SCR ratio including receivables, liquidity, debt ratio, and reserve adequacy, the most important one being receivables indicator which is defined as summing up reinsurance recoveries together with all types of receivables related to insurance activities and then dividing it by total assets.

Based on empirical results obtained during this study, we can say that traditional statistical approaches were outperformed by machine learning models, thus confirming its superiority over other methods when it comes to SCR ratios predictions. Among all tested models, the neural network showed the best predictive performance having an R-squared value equal to 62% followed by ensemble model, which achieved R-squared value of 54%. These findings clearly show that the machine learning algorithm has the ability to capture complex patterns better than any other statistical method known so far while also improving accuracy in predictions.

The solvency levels unexplained by macroeconomic factors, market size, and business lines suggested the need for further investigations in these areas.

These findings have implications not only for insurance regulators but also for policy makers, actuaries, as well as professionals in the field of insurance and risk management. Incorporating machine learning models into their risk assessment framework will enable them to monitor financial health more effectively, thus making it possible for early intervention with appropriate regulations. What this study shows is how much impact can be made on analytic capabilities within the insurance industry through the use of machine learning.

While this research provides strong evidence supporting use of machine learning, there are few limitations worth considering. For instance, data used were specific to Romanian non-life assurance market; hence results cannot be generalised directly without additional validation from other markets. Also, the study period between 2016-2020 may not cover long-term trends and variations.

Further studies could take another angle such as different regions across the globe or extend the time frame, thereby enhancing external validity besides looking at integration deep learning models among others, which may improve early detection abilities as well accuracy in prediction.

To sum up, the investigation confirms that machine learning algorithms can forecast SCR ratios; it shows which financial indicators are strong predictors and demonstrates that these models enable earlier detection. The observations made have important implications for regulation as they help make insurance industry oversight more precise and anticipatory in nature.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors utilised ChatGPT to enhance readability and language clarity. Following the use of this tool, the authors meticulously reviewed and revised the content as necessary and assumed full responsibility for the final content of the publication.

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