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The Assessment of Early Warning for Insurance Company Using Machine Learning Methods

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Highlights

- This paper focuses on the prediction of insurance solvency with machine learning.
- A wide range list of financial ratios is used.
- Early warning model predicts well the capital requirement ratio one year in advance.

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Abstract

Developing an early warning indicator is essential to strengthen the financial structure and take necessary precautions in a non-life insurance company. This paper aims to implement machine learning techniques on financial ratios to estimate the capital requirement ratio and investigate the solvency of an insurance company. For this purpose, the historical ratios of insurance companies in an emerging market are considered in accordance with the regulator's solvency requirements. The ratios collected based on the performances of insurance companies in Türkiye are studied in two cases based on the number of features to be included in to four machine learning algorithms. "Full" data set with 69 and "Boruta" implemented data set with 33 ratios are employed to depict the efficiency of methods in predicting the early warning state of the company in terms of their capital requirement ratio predictions. Additionally, the assessment of these predictions to be utilized as an early warning indicator is performed. The findings illustrate that proposed early warning model predicts well the capital requirement ratio one year in advance. Moreover, among four ML methods, XGBoost achieves a prediction accuracy of 85% for estimating the state of the solvency in an insurance company compared to the other algorithms.

1. INTRODUCTION

Insurance companies are periodically monitored and controlled by supervisory and regulatory authorities and their stakeholders because of their essential duty on the social system and economy. Insufficient financial stability of the company will have many consequences, which may even endanger the economic stability. Therefore, it is crucial for regulators, decision-makers, and investors to have knowledge about the company's financial robustness to take preventive actions. Especially due to the global economic crisis, early warning mechanisms become important to aid analysts and policymakers to anticipate potential distress and take preventive measures [1].

Early warning models can help regulatory and supervisory authorities start a guaranteed and timely transaction, prioritize evaluations for pre-review planning with the best use of audit resources, and identify problematic sections or potential risks in institutions [2,3]. Many statistical and mathematical models are employed to define an early warning structure which are, mostly and essentially, data-driven [4-12]. Moreover, the ratio analysis, which is an important ingredient in early warning detection, enables decision-makers to depict the companies' economic and financial structure, profitability, and operational position by identifying significant connections between the dependent and independent financial statement items.

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The literature offers that Beaver [13] and Altman [14] are counted as the peers employing financial ratios to estimate the failure of the banks. With the same approach, the reduction in business failure prediction period is introduced by Deakin [15]. Accounting ratios enable to reliably and accurately forecast the collapse of businesses by using feature selection methods like Principal Component Analysis (PCA) [16]. Using some methods such as logit, linear and non-linear regressions are shown to be successful to estimate failure with a high prediction rate [5,7,10,17-20]. Some Machine Learning (ML) methods like Neural Networks (NN), Random Forest (RF) [21,22] and Logistic Regression are supported with feature selection methods such as Discriminant and PCA, which can be taken as the early steps of implementing ML methods to improve the prediction accuracy [4,5,7,9,10,23]. The NN method focused on the insurance companies indicates that this method is effective at identifying potential insolvency with elevated predictability [4,24]. Moreover, Gradient Boosting Machine (GBM) is also used in insurance pricing, insurance loss cost modeling, and prediction [25-27]. Genc [5] analyzes the robustness of non-life insurance companies in Türkiye with 14 financial ratios using multiple regression and logit. Its modification with longer time duration and additional methods such as the Bayesian approach is found superior to traditional methods [10].

In the insurance business, the financial ratios are manifold and constitute the backbone to illustrate the company's financial strength and robustness. Some of those also may show variation depending on the type of insurance and line of business. The risk classification of all ratios exposes the stability mostly in five tracks. These are financial, non-life, operational, profit, and solvency risks whose subcategories expand to ten risk classes including credit, liquidity, market, reinsurance, underwriting, technical provision, reputational, operational, profitability, and capital risks [5,13,28]. Considering the variety in the ratios, it gains importance to evaluate how ML improves the predictability of insurance companies' solvency based on their historical performance in accordance with financial ratios. A successful algorithm that determines the pattern concerning the past year's performance will be a guiding indicator as an early warning. It is worthwhile to see to what degree and under what circumstances ML methods, data transformation techniques, and feature selection methods can be utilized in insurance ratio analyses to detect financial robustness. The most commonly known ML methods, RF, NN, GBM, and eXtreme Gradient Boosting (XGBoost) are taken into account. Since three out of four compared methods are decision tree-based, Boruta, which is also a decision tree-based feature selection method, is employed. We aim to reveal the best performing ML method to develop a strategy, to determine the ratios which are contributory to the solvency of the company. To achieve these goals, we consider an emerging market as a case study. In the light of yearly historical data, collected from the insurance sector in Türkiye within the time frame of 2011-2020, we aim to determine a scale to the set as an early warning indicator with the aid of prespecified ML algorithms.

Türkiye as a case study is striking since the insurance market has developed immensely in the last three decades through new reforms starting by the end of the 90s. On the other hand, the market is sensitive to the volatility in financial markets and shocks due to the economic policies. Recent currency crises are excluded as their implications are expected to be high in the next fiscal year.

We consider ratios that are selected based on regulatory requirements as well as the ones accounted for in the US and EU frameworks. The subrogation of these ratios with respect to the risk they are associated with refers to the risk ordering on the company base. ML methods applied with the feature selection method, Boruta, are compared within and between levels with the original set to illustrate the influence of those methods on risk prioritization. Along with the 69 ratios, the capital requirement ratio (CRR) is regarded as the dependent variable due to its role in determining the solvency of the company in Türkiye’s insurance regulators. The solvency indicator based on CRR levels is categorized by the regulator and has four intervention levels, whose details are given in Section 5. The performances of ML methods are investigated through minimum errors and high accuracy rates analyzed also with respect to the regulatory conditions.

The paper is composed of six sections. A short description of the ML algorithms and implemented feature selection method is given in section 2. The list of ratios, as well as a brief description of Türkiye’s insurance market and its regulations in section 3. Section 4 emphasizes data implementation in proposed Early Warning Model. The accuracy improvement with respect to the feature selection method is given in terms of performance measures. Section 5 contains the proposed early warning assessment, and capital requirement impact. Section 6 finalizes the paper with concluding comments.

2. MACHINE LEARNING ALGORITHMS

ML becomes useful in many disciplines due to its practicability to handle the models in wider and larger dimensions. The algorithms aim to learn a model from a labeled data set for prediction purposes. Among many other advantages, ML copes with correlation contrary to multivariate regression, which is adversely affected by collinearity [29].

Before implementing ML methods, the most appropriate variables are chosen using grid search methods to determine the best algorithm. Afterwards, the analyses are run with respect to the parameters of the best model. The data set is split into train and test subsets with a certain proportion at which the performance measures are compared to find the best fitting method. Data splitting may vary depending on the size, characteristics, and structure of the data. Generally, 80% of the overall data is taken as train and the rest is set as the test data [30].

Among many others, as a feature selection method, Boruta enables us to select which variables in the data set are important or unimportant, as an essential step for ML [31]. Boruta iteratively eliminates the traits determined by a statistical test to be less important than random samples [32]. It compares the relevance of random probes to actual attributes to assess their significance [33]. The machine learning methods employed in our study except NN, utilize the decision tree framework. For this reason, it is advisable to opt for the Boruta feature selection approach, which similarly operates under the decision tree logic.

ML can be accomplished using two primary approaches: unsupervised methods that work with unlabeled data and supervised methods. One well-known ML method is RF, which is a decision tree algorithm requiring relatively few parameters that are effective in a wide range of data sets. After a large number of decision trees are generated, the most popular class is selected [34]. NN is often the best choice for a given problem, but they have some drawbacks. They can be slow, they are difficult to interpret, and they tend to work better with categorical data than with numerical data. However, NN is still a powerful tool for ML. A neuron is a mathematical function that takes multiple numerical inputs and produces a single numerical output. Neurons are organized into layers, and the outputs of all neurons in one layer become the inputs to all neurons in the next layer [35]. The first layer is the input layer, the last layer is the output layer, and there are one or more hidden layers in between. The hidden layers learn how to change their weights to minimize the loss function for every example of training [35,36]. GBM is another type of decision tree algorithm that can be used for regression and classification tasks. In this method, the key concept is boosting, which is a flexible nonlinear regression procedure that contributes to improving trees' accuracy [35,37]. Gradient based optimization reduces the loss function in terms of training data by using gradient computations. It has more parameters and requires a bit more effort to tune than RF, but it may achieve somewhat stronger outcomes but yield easily overfit if it continues to give more trees [35]. XGBoost is a popular gradient boosting framework that combines an efficient linear model solver and an algorithm for decision tree learning. It supports various objective functions, such as regression, ranking, and classification [38]. XGBoost employs parallel tree boosting, which efficiently and accurately resolves many data scientific problems. It is widely regarded as one of the best gradient boosting frameworks available today, thanks to its scalability in handling various scenarios. This achievement is attributed to significant technological advancements and algorithmic optimizations [39].

3. FINANCIAL RATIOS AND TÜRKİYE’S INSURANCE SECTOR

Quantities or ratios can be compared with industry standards, the same measurement from a previous age, a competitor's organization, or previously specified quantities in economic analysis. To make the best use of accounting data, it is vital to choose the correct strategy. Even while ratio research can yield a lot of insights, focusing solely on one financial ratio can be misleading. Even though it is the best, a ratio is not always a measure of the organization's health, position, or performance; it may even be a sign of certain risks if it performs poorly for a certain fiscal year [28]. Therefore, the classification of ratios in risk groups involves various risks based on projected price or probable effect, probability of occurrence, and necessary countermeasures.

Generally, the success and failure definition on the performance of the company is taken as an illustrative indicator in many analyses [4,5,7,10]. The capital adequacy ratio is the best representation of the insolvent status of the insurance firms [9,40]. The dependent variable of the early warning system for the European insurance sector is the market stress index that includes both the effects of Credit Default Swap (CDS) spikes and equity price crashes [11].

The classification of ratios is done with respect to risk types. These are (i) Financial, (ii) Profit and Solvency, (iii) Non-life, and (iv) Operational risks, which are also categorized according to their sub-risks. Credit, liquidity, and market risks are accounted for under financial risks; capital and profitability risks are enlisted under the profit and solvency risks; reinsurance, technical provision, and underwriting risks are the sub-risks of the non-life risks, operational and reputation risks constitute the operational risks. With respect to these classifications, the selected ratios are listed and presented in Table 1. All sub-risks in each class are detailed, referring to the ratios commonly accounted for financial stability. Some of those may be classified under other sub-risks. Although a ratio can belong to several different risk categories, we list it under the risk category that is the closest match. Among 70 indicators, non-life risk group contains the largest number of ratios (26), followed by Profit and Solvency (19) and Financial (17) risks. As emphasized, these ratios are selected in accordance with international practices: US, EU, and insurance sector in Türkiye. As the regulator's solvency measure for intervention in Türkiye is Capital Requirement Ratio (CRR), it is considered to be the dependent variable. In addition, the ratios written in bold in Table 1 indicate the ratios that ML methods consider as important. The ratios marked with an asterisk (*) in the abbreviation column in Table 1 indicate the ratios chosen by the Boruta method. As depicted, Boruta considers at least two financial ratios important under each sub-risk. Table 1 also highlights the ratios that hold the greatest significance within the model, namely Equity/Total Payables, Cash Ratio, Financial Leverage Ratio, Operating Expenses/Gross Written Premiums, Net Premium Receivables/Total Assets and Financial Profitability, all of which are shown in bold.

3.1. Türkiye's Insurance Sector

Having an increasing demand in the last decades, Türkiye's insurance sector is restructured through many reforms. By 2021, 41 non-life insurance companies, 21 life and pension companies, and 3 reinsurance companies operate in Türkiye. As of 2021, non-life insurance companies generate a gross premium of 87.60 billion TL (6,56 billion USD), a technical profit of 7.29 billion TL (0.55 billion USD), and a loss ratio of 80.5% (TL/USD exchange rate is 13.353 as of 31.12.2021 announced by Central Bank of Republic of Türkiye) [41]. In comparison to the year earlier, gross premium and loss ratio climb up to 28% and 22%, respectively, and decrease in technical profit with an amount of 1%. Foreign companies constitute more than half of the insurance market. A recent amendment in law, the change the state of the Insurance Regulator become a government independent identity. Insurance and Private Pension Regulation and Supervision Authority (SEDDK) is established by October 2019. It is worth to mention, the establishment of private pension insurance in 2003 has its own way to constitute the second pillar in the Social Security System in Türkiye. Agricultural Insurance Pool (TARSIM) and Turkish Natural Catastrophe Insurance Pool (TCIP-DASK) are pioneering examples of their kinds and contribute immense initiatives in the insurance sector. With the recent developments and reforms, it is aimed to reduce the regulatory difficulties in the sector. Moreover, adaptation to IFRS17 is an ongoing issue in both industry and regulators.

Table 1. *Risk groups and their related financial ratios*

Risk Type	Sub-Risk	Financial Ratio	Abbreviation
Financial Risks	Credit Risk	**Net Premium Receivables / Total Assets**	**X2***
		Premium Collection Ratio	X3*
		Doubtful Receivables / Total Assets	X19
		Financial Leverage Ratios	**X57***
		Receivables Cycle Ratio	X63*
		Collection Ratio	X67
	Liquidity Risk	Liquid Assets / Total Assets	X1*
		Cash Ratio	**X21***
		Assets Covering Technical Provisions / Technical Provisions	X22
		Current Ratio	X58*
		Tangible Assets / Total Assets	X61
		Current Assets / Total Assets	X68
		Change in Liquid Assets	X69
	Market Risk	Investment Properties / Total Assets	X23
		Assets in Foreign Currency / Liabilities in Foreign Currency	X30*
		Non-Current Assets / Long Term Liabilities and Equity	X62*
		Market Risk	X70
Profit and Solvency Risks	Capital Risk	Total Reserve / Net Premium	X8*
		Total Reserve / Liquid Asset	X9
		Gross Premiums Written to Equity	X15*
		Net Premiums Written to Equity	X16*
		Capital Requirements Ratio	X27
		Equity / Total Payables	**X28***
		Changes in Equity	X29*
		Self-Financing Ratio	X59*
		Tangible Assets / Equity	X60*
	Profitability Risk	Profit / Paid Capital	X5*
		Technical Profit / Net Written Premium	X10
		Total Income / Total Assets	X11*
		Return on Investment	X24
		Return of Assets	X25*
		Technical Profit / Gross Written Premium	X26
		Non-Life Technical Income / Non-Life Technical Expense	X56
		Financial Profitability	**X64***
		Economic Profitability	X65*
		Return on Equity	X66*

Continues Table 1. *Risk groups and their related financial ratios*

Risk Type	Sub-Risk	Financial Ratio	Abbreviation
Non-Life Risks	Reinsurance Risk	Payables on Reinsurance Operation / Equity	X7
		Reinsurance Share / Gross Premium	X12*
		Share of Reinsurance of Provisions / Equity	X20*
		Net Paid Losses / Gross Paid Losses	X33
		Changes in Retention Ratio	X34
		Reinsurance Rate of Return	X35
		Reinsurance Risk Ratio	X36*
		Share of Reinsurance of Paid Losses / Gross Paid Losses	X46
		Share of Reinsurance / Gross Provision for Outstanding Losses	X47
		Share of Reinsurance Provision for Transferred Outstanding Losses / Provision for Transferred Outstanding Losses	X48
	Technical Provision Risk	Change in Required Provision for Outstanding Losses / Available Provision for Outstanding Losses	X37
		Gross Provision for Outstanding Losses / Equity	X38*
		Net Provision for Outstanding Losses / Equity	X39*
		Change in Provision for Outstanding Losses	X40
	Underwriting Risk	Gross Loss Ratio	X4
		Premium Production / Coverage	X6*
		Net Loss Ratio	X13
		Net Loss Ratio / Gross Loss Ratio	X14
		Change in Net Written Premiums	X17
		Change in Gross Written Premiums	X18
		Motor Portfolio Share	X32*
		Gross Paid Losses / Gross Written Premiums	X44
		Change in Gross Provision for Outstanding Losses / Gross Written Premiums	X45
		Net Paid Losses / Net Written Premiums	X49
		Net Outstanding Losses / Net Written Premiums	X50
		Combined Ratio	X54
Operational Risks	Operational Risk	Net Expense Ratio	X31
		Operating Expenses / Gross Written Premiums	**X51***
		Net Commission Ratio	X52*
		Operating Expenses / Net Earned Premiums	X53
	Reputation Risk	Premium Production Per Personnel	X41*
		Gross Compensation Payment Ratio	X42
		Net Compensation Payment Ratio	X43
		Market Share	X55*

4. THE STRUCTURE OF EARLY WARNING MODEL

We propose that an insurance company's solvency state can be predicted for the fiscal year is influenced by its ratios in the prior year. Therefore, a prediction on the current year's CRR with the assumption that independent ratios (variables) are influential on company's solvency for next year, can be used as an early warning indicator. In other words, under this assumption, as the CRR has a one-year time lag for all companies, the solvency state can be predicted one year in advance.

The annual reports of the Insurance Association of Türkiye are used to gather historical information for active non-life insurance businesses in Türkiye between 2011 and 2020 [41]. Due to the changes in the regulations over the years, the structure of new companies or acquisitions, and changes in the indicators in the balance sheet and the content of income statements, cause obstacles in calculating some of the ratios. For example, financial ratios of some companies that stopped premium production or that have started their activities in current year cannot be calculated. For this reason, we consider the most persistent and stable period, which causes a reduction in time period as another obstacle. However, trusting on the ability of some ML algorithms, we proceed with the most possible representative data sets. In this case, data set includes 70 ratios observed from 47 unique companies, resulting in 375 observations over ten years period. CRR (dependent variable) and the remaining 69 ratios of active companies (independent variables) are organized in panel data of 375 rows, which constitute the base for the analyses. The software R is employed in the assessments whose steps are summarized in Algorithm 1. The study is restricted to non-life insurance companies as they often offer yearly premiums and collaterals, and their policy terms are shorter than those of life insurance. The companies that do not produce premiums voluntarily and the ones whose premium production is halted by the regulator are not included in the analyses. We predict the CRR values realized ahead in reference to 2019 observations of the companies actively operating in 2019 and 2020. By this way, the proposed model allows us to have information about the company's financial state one year in advance.

Algorithm 1. *ML on ratio analysis*

Step 1: Split 'Full' data as train and test subsets
Step 2: Apply Boruta on the features
Step 3: Create two data sets: 'Full' & 'Boruta'
for $i = 1, \dots, 4$ do ML methods
  Step 4: Find the best parameters using a grid search on the train set
  for $i = 1, \dots, 4$ **do** Full and Boruta data sets
    Step 5: Find performance
    Step 6: Compare predictions with actual values in test group using administrative measure levels
  end for
end for

Based on the dependent variable of CRR, we identify the most significant features using Boruta, which reduces to 33 ratios to be confirmed as "important" (green boxplots), 23 ratios as "unimportant" (red color), and 13 variables as "tentative" attributes (Yellow color) (Figure 1). Ratios confirmed as "important" constitute the new data set to be taken into account in the analyses. Boruta is based on a decision tree approach, which is better able to deal with the chosen ML approaches, hence analyses do not incorporate commonly used feature selection techniques like PCA or factor analysis.

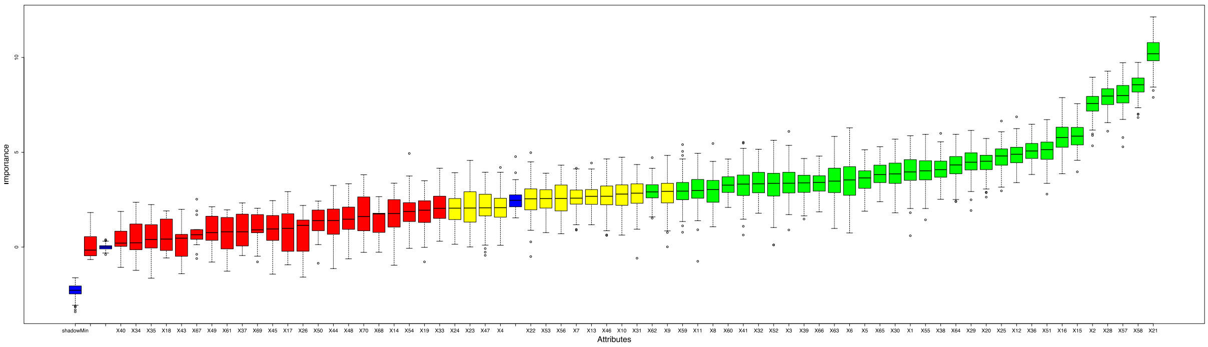

Figure 1. *Boruta feature selection for the attributes*

Based on this selection stage, we perform analyses on two sets of variables for comparison reasons. This is mainly due to having a small sample size and identifying the feature selection method's reliability. These are (i) the whole set of features named as "Full Data" and (ii) the reduced set of features selected by Boruta called "Boruta Data". In order to apply ML methods, we estimate the required parameters using Grid Search at the training subset of Full Data that is the most widely used strategy for hyper-parameter optimization, to find the parameters with the least errors with respect to different values. RF, NN, GBM, and XGBoost parameters and their results are summarized in Table 2.

Table 2. *Grid Search parameters of ML methods*

RF		NN	
Used Hyper-Parameters	Selected Parameters	Used Hyper-Parameters	Selected Parameters
max depth	15	activation	Tanh
mtries	7	epochs	1000
ntrees	100	hidden	[50, 50, 50, 50]
GBM		XGBoost	
Used Hyper-Parameters	Selected Parameters	Used Hyper-Parameters	Selected Parameters
col sample rate	1	col sample rate	0.2
learn rate	0.1	learn rate	0.1
max depth	9	max depth	5
ntrees	100	ntrees	50
sample rate	1	sample rate	1

Afterwards, ML methods are applied with these selected parameters on both sets (Full and Boruta). Then, test and train performances of all methods are compared using Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) and for both Full and Boruta Data, the minimum value in each row is denoted in bold (Table 3). RMSE, MSE and MAE formulas are representing as follows when y_j's are actual values and $\hat{y}_j$'s are predicted values

$$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{n}(y_j-\hat{y}_j)^2}{n}}, \tag{1}$$

$$\text{MSE} = \frac{1}{n}\sum_{j=1}^{n}(y_j-\hat{y}_j)^2, \tag{2}$$

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j-\hat{y}_j|. \tag{3}$$

To enhance comprehension of error values, it is worth noting that the mean value of the predicted CRR value is 1.6210, while the standard deviation is 0.7246. Performance parameters such as RMSE on test set show that XGBoost yields the smallest errors (0.3722) for Full data set, followed by GBM for Boruta data set (0.3844). For training performance, nearly all methods remain close to each other, however, the smallest RMSE value is achieved at GBM with Boruta data set. As a result, when the RMSE values are checked, it is seen that the ML methods with the best performances are XGBoost for Full data with 69 independent ratios and GBM for Boruta data with 33 independent ratios. In the Full Data set, XGBoost method has the lowest RMSE, MSE, and MAE values for testing. Also, NN has the lowest RMSE and MSE values for train, but XGBoost values are also close to NN. In Boruta Data set, GBM method has the lowest RMSE, MSE and MAE values for both train and test sets.

Table 3. *The performances of ML methods for Full and Boruta sets*

Performance		Full Data				Boruta Data			
		RF	NN	GBM	XGBoost	RF	NN	GBM	XGBoost
RMSE	Train	0.2524	0.1764	0.1793	0.1894	0.2417	0.2848	**0.1720**	0.2266
	Test	0.4009	0.5853	0.4450	**0.3722**	0.4139	0.5793	0.3844	0.4033
MSE	Train	0.0637	0.0311	0.0321	0.0359	0.0584	0.0811	**0.0296**	0.0514
	Test	0.1607	0.3426	0.1980	**0.1386**	0.1713	0.3356	0.1478	0.1627
MAE	Train	0.1592	0.1416	**0.0731**	0.1353	0.1518	0.1997	0.0830	0.1595
	Test	0.2833	0.4382	0.3426	**0.2683**	0.3025	0.4345	0.2807	0.2870

5. ASSESSMENT OF EARLY WARNING STRATEGY

The regulation on measurement and assessment of capital requirements of insurance and reinsurance companies and pension companies is issued by the Ministry of Treasury and Finance of the Republic of Türkiye. This regulation has been prepared to protect insurance and reinsurance companies' financial health, secure customer rights, and ensure stability in the sector. The regulation establishes the framework for determining, evaluating, and managing the capital adequacy of insurance and reinsurance companies. It plays an essential role in maintaining their financial strength and ensuring stability in the sector. Within the scope of the regulation, criteria related to capital adequacy measurements, risk management, and capital management activities of companies have been determined.

The required capital can be calculated using two different methods. In the first method, required capital consists of the sum of the results calculated for the non-life, life, and pension branches. For non-life branches, the highest equity among the premiums and claims basis is accepted as required capital. In the second method, the sum of the amounts found as a result of the calculations of required capital, asset risk, reinsurance risk, outstanding claims reserve risk, underwriting risk, and exchange rate risk. The company's required capital is the highest among the required capital calculated by the first and second methods [42].

The regulation also determines the authority of the Ministry of Treasury and Finance to take the necessary measures in case of a decrease in the capital adequacy of insurers. These measures may include options such as raising capital, restricting operations, or liquidating companies. According to regulation of Türkiye’s insurance sector, the regulator takes administrative measures concerning the company's performance based on the predetermined CRR level. These are classified into five stages I to V: (I) “Intervention” stage, if CRR is less than 33%, (II) “Emergency Take Precaution” stage if CRR remains within 33% - 69.99%, (III) “Take Precaution” stage when CRR lies within 70% - 99.99% and “Self-evaluation” stage if CRR is between 100% - 115%, and (V) “Sufficient” if CRR is higher than 115%. These scales are pronounced based on the Regulator's internal evaluations with respect to the historical experience on insurance companies.

Based on the estimated and realized $\mathbf{CRR}$ values, we set a rescaling on these scores. The observed values of $\mathbf{CRR}$ and estimated ($\widehat{\boldsymbol{CRR}}$) one using proposed ML methods are rescaled according to these categories for simplicity and consistency in comparison. Table 4 illustrates the actual **CRR** values for each company categorized with respect to the coding and the estimated **CRR** obtained by four ML methods with and without feature selection method. If the predicted value and the actual value remain in the same range, it is assigned as "TRUE", otherwise as "FALSE". By dividing the number of accurately estimated observations by the total number of observations, the accuracy rate is determined.

Table 4. *The prediction of intervention stages*

Company	CRR Level	$\widehat{CRR}_{RF}$		$\widehat{CRR}_{NN}$		$\widehat{CRR}_{GBM}$		$\widehat{CRR}_{XGBoost}$	
		Full	Boruta	Full	Boruta	Full	Boruta	Full	Boruta
1	IV	V	V	V	V	V	V	V	V
2	V	V	V	V	V	V	V	V	V
3	V	V	V	V	V	V	V	V	V
4	V	V	V	V	V	V	V	V	V
5	V	V	V	V	IV	III	V	V	V
6	V	V	V	V	V	V	V	V	V
7	IV	IV	III	V	IV	III	V	IV	III
8	V	V	V	V	V	V	V	V	V
9	V	V	V	V	V	V	V	V	V
10	V	V	V	III	V	V	V	V	V
11	IV	III	III	II	III	III	IV	III	IV
12	IV	IV	IV	V	III	III	IV	IV	V
13	V	V	V	IV	III	V	V	V	V
14	V	V	V	V	V	V	V	V	V
15	V	V	V	V	V	V	V	V	V
16	V	V	V	V	V	V	V	V	V
17	IV	V	V	II	V	IV	V	IV	V
18	III	IV	IV	II	I	V	III	III	IV
19	V	V	V	V	V	V	V	V	V
20	V	V	V	V	V	V	V	V	V
21	V	V	V	V	V	V	V	V	V
22	IV	IV	IV	V	V	V	IV	V	IV
23	V	V	V	V	V	V	V	V	V
24	V	V	V	V	V	V	V	V	V
25	V	V	V	IV	V	V	V	V	V
26	V	III	II	III	II	II	II	II	II
27	V	V	V	V	V	V	V	V	V
28	IV	IV	IV	V	IV	V	IV	IV	III
29	IV	V	V	III	IV	IV	V	IV	V
30	V	V	V	V	V	V	V	V	V
31	V	V	V	III	III	V	IV	V	V
32	V	V	III	V	IV	II	IV	V	V
33	III	II	II	I	I	I	I	II	II
34	V	V	V	V	V	V	V	V	V
FALSE		7	9	15	12	11	8	5	9
TRUE		27	25	19	22	23	26	29	25
PERCENTAGE		0.79	0.74	0.56	0.65	0.68	0.76	0.85	0.74

Table 4 also summarizes the performance on prediction illustrated in the last three rows. XGBoost method that has the lowest test RMSE also has the best accuracy in the administrative measures stages with 85%. NN and GBM are found to be more successful in estimating with fewer features. However, RF and XGBoost have higher accuracy rate for Full data set. NN with an RMSE value of more than 0.5, higher than other methods for both Full and Boruta data sets, has accuracy behind other methods in precautionary administrative measures analysis.

6. CONCLUDING COMMENTS

An indicator that can guide decision makers to take as an early warning sign for an insurance company's solvency is contributory and important. The implementation of ML algorithms on financial ratios to establish criteria as an early warning indicator is shown to be meaningful and practical as the main outcome of this paper. It can be concluded that the implementation of ML methods on financial ratios enables us to identify the risk of insolvency based on the financial history of the company. Even though drawbacks in the sample size on the applied data sets, the best fitting ML method yields a satisfactory performance to predict the company's future solvency state as an early warning indicator. This method can be used to keep tabs on the insurance industry and serve as a guide for any future action that needs to be taken. We anticipate that it will help regulatory and supervisory authorities carry out risk-focused supervision. As we teach the algorithm more knowledge, the predictive power grows. Furthermore, feature selection estimates applied in data sets exhibit good performance.

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CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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