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Evaluation of Financial Risk Prediction Method Using EDAS Method

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Abstract. In recent years, financial risks A variety of early identification Classification techniques are used. Finance in risk assessment, given A suitable classifier for the dataset (or group of classifiers) how Knowing what to choose is an important challenge. Performance measurement and Finance of classifiers depending on environment Note that risk prediction performance may vary Previous research has shown that better classifiers for problems Selection is very much in data mining. As a variety of factors are involved it is one of the most difficult tasks. Different options on multiple criteria to evaluate, a multi-criteria decision is made Using (MCDM) procedures Significant. Simplified MCDM Financial risk using the approach Significantly associated with prediction This is to sort the classifiers The primary objective of the work is Significant classification algorithms Analysis is also of this method MCTM is another leader in performance. In this study, MCDM is the EDAS approach Financial risk with Bayes Net and Naive Bayes The first two is for datasets Ranks into classifiers.

Keywords:market risk, F-Measure, Area under ROC, MCDM method

1. Introduction

For better decision making in the modern scenario It is very important to find out How to gain useful insights. These new insight opportunities to obtain and minimize risks, it also helps in managing expenses. “Big Data Analysis” of large volumes of data Basically study, identify and refer to methods for achieving results [1]. In the financial sector, big data technologies make it more crucial to investigate insightful data for data-driven decision-making and to benefit from reducing risks in the financial market. Many financial data analyses employed time series modeling techniques to anticipate stock values [2]. Risk is the exposure to unpredictable results, which are often negative ones. They are uncertainties connected to any type of finance. Consider operational risk as it relates to the health insurance sector. [3]. The danger that a business will not be able to make its debt payments is sometimes thought of as financial risk. Prediction models, which are viewed as early warning systems of approaching difficulties in the examined organizations, are used to evaluate the state of company financial health and remove prospective financial hazards. Based on chosen financial indicators, other firm features, or the environment in which they operate, their role is to assess the company's financial health [4]. There is a risk spillover effect, which describes how the failure of one market or financial institution can immediately affect other markets or institutions. As a result, many experts both domestically and internationally have concentrated on the systemic vulnerabilities of financial markets [5]. It has become crucial to figure out how to efficiently avoid, reduce, or even completely eradicate the detrimental impacts brought on by systemic risks in the financial markets for the country's economy to operate and grow. [6]. Numerous industrial and financial organizations incurred significant losses and even went bankrupt during the most recent global financial crisis. The relevance of financial risk prediction (FRP) is crucial in such a financial climate. There is usually a lot of discussion about how to increase crisis awareness and early warning capacity. One of the key instruments is the application of the FRP model. As a result, researchers constantly focus on ways to increase the predictive power of FRP models. [7].

2. Financial Risk

Due to its significance, predicting financial risk has been a hot issue for many years. Predicting insolvency or default is one of the most crucial challenges in financial risk management. The categorization of bankruptcy is a classic unbalanced classification issue since the number of defaults or bankruptcies is much higher than the number of non-defaults or bankruptcies. [8]. Financial threats include credit risk, business risk, investment risk, and operational risk. They are uncertainties connected to any type of finance. Business intelligence, which also refers to the study of financial data, may assist organizations in making better decisions by enabling them to identify potential financial risks early on and take the necessary precautions to reduce defaults. In financial risk analysis, supervised and unsupervised learning approaches are both crucial. [9]. High priority for every organization One of the types of risk involved is financial risk. Market changes pose risks to the economy, and they are variously Affected by causes. market risk, Credit risk, liquidity risk, operational Risk and legal risk are financial Some for different types of risk Examples. Market risk is a financial instrument Risk due to changes in price. [10]. Changes in interest rates and stock prices are the main causes of directional risk. Undirected risk, however, can change over time. Credit risk occurs when individuals breach their responsibilities to another party. [11].

The term "financial crisis" refers to a country or Some financial indicators in the region are fast Indicates a worsening event. This Examples of phenomena include currency Crises, credit crises and banking Crises are included, and they are frequent emerge together. Because of this, affected economy demonetization, finance Others like recession, political volatility It also experiences negative effects. [12]. The study of financial crisis contagion has become a popular issue in academia due to the frequent occurrence of financial risk and the significant effects brought on by the transmission of financial risk. [13]. The 2008 financial crisis brought to light the weaknesses of lending environment risk management procedures and micro level risk assessment (PD estimation). Regulators, lenders, and other corporate investors need timely information on the likelihood of corporate default in lending and derivative portfolios. [14]. Corporate subpopulations (e.g., SMEs, private companies, listed Organizations, sector-specific models) individual Feature Oriented Default (PD) Probability of creation of models, in macro environment Calibrated according to changes, Of course, for corporate risk management Effective "Internal Review Boards" (IRB) Availability of data for banks to establish and Being on time is essential. [15]. Widespread use of financial services, finance Models that attempt to minimize risks for creation, for credit risk management It has attracted the attention of academics. debt, Market and operational risks There are three main types of banking risks [16]. One of the most important business problems that banks and other financial institutions deal with is whether or not to extend credit to a qualified potential client. Additionally, it poses a substantial danger. Because of the global financial crisis, credit risk evaluation is now more important than ever. Financial institutions must do a thorough credit evaluation [17]. When major events occur, the structure of the capital markets may shift for a variety of reasons, particularly those related to macroeconomic order. A crisis has the greatest influence on the financial markets of any one occurrence [18].

3. EDAS MCDM Method

Researchers' drive to develop novel MCDM techniques is becoming increasingly competitive. Since the beginning, trends in the development of MCDM techniques have demonstrated a great deal of interest among academics in this field in creating solid frameworks for handling difficult decisions. Their focus was on understanding the decision system's requirements, then adding variables and parameters and integrating those variables logically to create a particular tool [19]. An MCDM approach that is extremely effective in decision situations with competing criteria is the EDAS technique. The best option is according to the EDAS technique by which the distance from the average response (AV) is determined. From the average positive distance (PDA) and Negative Distance from Mean (NDA) Two measurements should be calculated to determine by How desirable are the alternatives (NDA) [20]. Another tip for evaluating alternatives The point system is EDAS. It is a traditional method. Optimum option to choose, this time from the average response Distance must be taken into account. Calculations with findings Agree, they are substantial and are simplified. We have some competition When there are criteria, be specific Possible alternatives for purposes This strategy will be very helpful for selection [21]. Additionally, an MCDM will attempt to solve the challenge When options are predetermined Benchmarking, alternatives for rating and ranking is proper. For optimal and average solutions Traditional for evaluating alternatives Gray Correlation Analysis (GRA) in Methods and of distance from the mean (EDAS), Basically includes assessment. [22]. In real-world problems, usually two Types of uncertainties include: Environmental, economic or technological Random bound with data about Uncertainty and subjective estimates and with the characteristics of decision makers The associated ambiguity is uncertainty. How is the suggested randomization process? To prove that it works, we are a Consider a straightforward numerical example. Pick up and use EDAS Step by step recommended method We solve it by using Additionally, Applicability of the recommended technique to prove character, let’s use the example of a review performance of bank [23]. These findings from the randomized EDAS approach Many others using example Methods are compared, and When the weights of the criteria are changed How are the results consistent? A sensitivity analysis to show that is done. Bank branches in this study Recommended method of assessment Although It can be used to solve problems applied, science, management and real world in engineering [24].

In this paper, several key classifications Mechanisms and performance measures Selected and their classification Performance was evaluated. Financial risk Some notable ones related to prediction Classification algorithms in this work were discovered and used. Classification Algorithms for Fraud Detection are widely used for activities. In terms of accuracy in spotting cases of undetected fraud, linear logistic regression was shown to be among the top three classifiers. When it comes to detecting credit card fraud, Bayesian neural network classification is extremely effective and efficient. The best classification accuracy and processing speed are provided by Naive Bayes. Support vector machines provide excellent insight and better outcomes for the categorization of hidden data. Across many applications, random forest performs better than other methods. RBF networks are quite accurate in detecting.

Overall accuracy, TP Rate, TN Rate, F-Measure, Area under ROC are the important performance measures for the financial risk prediction. Overall accuracy: A frequently used criterion to assess categorization ability is accuracy. It is the proportion of events that were correctly categorized.TP Rate: How successfully a classifier can identify anomalous records is gauged by its TP rate. It also goes by the name "sensitivity measure." Bankruptcies, fraud, and incorrect accounts are examples of atypical situations in the context of financial risk identification**.** TN Rate:A classifier's TN rate gauges how effectively it can identify typical records. Measure of specificity is another name for it. The regular situations are accurately classed as True Negative rates.Area Under ROC:ROC is the ability of a classifier to predict Precisely positive events (Receiver Operating Characteristic) by area under the curve (AUC). which is the TP ratio and Tradeoff between FP rate Explains. Because of this, very skewed data of false positives in sets Quantitatively significant change also in AUC at the rate of FP used No significant impact. The classifier performs better in large regions.F-Measure: In comparison to precision recall, F-Measure is advised since it reveals true positives.

TABLE 1. Evaluation of Classifier Performances

	Overall accuracy	TP Rate	TN Rate	F-Measure	Area Under ROC
BayesNet	0.7443	0.499	0.8494	0.5375	0.7788
Naïve Bayes	0.7509	0.4917	0.8642	0.5478	0.7754
LibSVM	0.7	0	1	0	0.5
Logistic Regression	0.7548	0.4877	0.8642	0.5328	0.7485
Random Forest	0.7345	0.4352	0.8547	0.4965	0.73254
RBF Network	0.7357	0.4245	0.8675	0.4857	0.7546
Simple CART	0.7542	0.4157	0.8754	0.4865	0.7148

Values for the Evaluation of Classifier Performances data set are displayed in Table 1. As alternate parameters, eight significant classification algorithms were chosen: BayesNet, Naive Bayes, LibSVM, Logistic Regression, RBF Network, Random Forest, and Simple CART. Here, the key performance indicators for predicting financial risk are assumed to be overall accuracy, TP Rate, TN Rate, F-Measure, and Area under ROC.

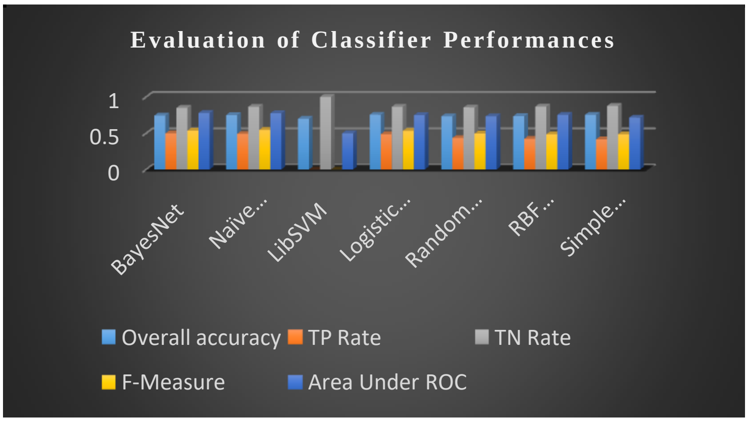

FIGURE 1. Evaluation of Classifier Performances

Figure 1 illustrates the graphical representation of data set value of Evaluation of Classifier Performances.

TABLE 2. Positive Distance from Average (PDA)

	Overall accuracy	TP Rate	TN Rate	F-Measure	Area Under ROC
BayesNet	0.006899	0.2684291	0	0.2189	0.08931
Naïve Bayes	0.015828	0.2498729	0	0.24226	0.08455
LibSVM	0	0	0.13353	0	0
Logistic Regression	0.021104	0.2397051	0	0.20824	0.04693
Random Forest	0	0.1062532	0	0.12592	0.02461
RBF Network	0	0.0790544	0	0.10143	0.05546
Simple CART	0.020292	0.0566853	0	0.10325	0

Table 2 displays the Positive Distance from Average data values (PDA).

TABLE 3. Negative Distance from Average (NDA)

	Overall accuracy	TP Rate	TN Rate	F-Measure	Area Under ROC
BayesNet	0	0	0.03718	0	0
Naïve Bayes	0	0	0.0204	0	0
LibSVM	0.05303	1	0	1	0.30065
Logistic Regression	0	0	0.0204	0	0
Random Forest	0.00636	0	0.03117	0	0
RBF Network	0.00473	0	0.01666	0	0
Simple CART	0	0	0.00771	0	0.00021

Table 3 shows the data values of Negative Distance from Average (NDA). Eight important classification algorithms were selected Namely BayesNet, Naïve Bayes, LibSVM, Logistic Regression, RBF Network, Random Forest, and Simple CART as alternate parameters. Here Overall accuracy, TP Rate, TN Rate, F-Measure, Area under ROC are taken as the important performance measures for the financial risk prediction.

TABLE 4. Weight

	Overall accuracy	TP Rate	TN Rate	F-Measure	Area Under ROC
BayesNet	0.25	0.25	0.25	0.25	0.25
Naïve Bayes	0.25	0.25	0.25	0.25	0.25
LibSVM	0.25	0.25	0.25	0.25	0.25
Logistic Regression	0.25	0.25	0.25	0.25	0.25
Random Forest	0.25	0.25	0.25	0.25	0.25
RBF Network	0.25	0.25	0.25	0.25	0.25
Simple CART	0.25	0.25	0.25	0.25	0.25

Table 4 shows the weight in all weightages distributed the same value.

TABLE 5. Weighted PDA

	Overall accuracy	TP Rate	TN Rate	F-Measure	Area Under ROC	SPi
BayesNet	0.001725	0.0671	0	0.0547	0.0223	0.1459
Naïve Bayes	0.003957	0.0625	0	0.0606	0.0211	0.1481
LibSVM	0	0	0.0334	0	0	0.0334
Logistic Regression	0.005276	0.0599	0	0.0521	0.0117	0.129
Random Forest	0	0.0266	0	0.0315	0.0062	0.0642
RBF Network	0	0.0198	0	0.0254	0.0139	0.059
Simple CART	0.005073	0.0142	0	0.0258	0	0.0451

Table 5 shows the data values of Weighted Positive Distance from Average and sum of Weighted Positive Distance from Average

TABLE 6. Weighted NDA

	Overall accuracy	TP Rate	TN Rate	F-Measure	Area Under ROC	SNi
BayesNet	0	0	0.0093	0	0	0.0093
Naïve Bayes	0	0	0.0051	0	0	0.0051
LibSVM	0.013258	0.25	0	0.25	0.0752	0.5884
Logistic Regression	0	0	0.0051	0	0	0.0051
Random Forest	0.00159	0	0.0078	0	0	0.0094
RBF Network	0.001184	0	0.0042	0	0	0.0053
Simple CART	0	0	0.0019	0	5E-05	0.002

Table 5 displays the data values of the weighted NDA and the total of the weighted NDA.

TABLE 7. NSPi and NSNi value

	NSPi	NSNi
BayesNet	0.9849	0.984204
Naïve Bayes	1	0.991331
LibSVM	0.2254	0
Logistic Regression	0.8708	0.991331
Random Forest	0.4334	0.984055
RBF Network	0.3982	0.990909
Simple CART	0.3042	0.996637

Table 7 shows values of NSPi and NSNi values calculated from table 5 and 6 respectively.

TABLE 8. ASi and Rank

	ASi	Rank
BayesNet	0.9845	2
Naïve Bayes	0.9957	1
LibSVM	0.1127	7
Logistic Regression	0.9311	3
Random Forest	0.7087	4
RBF Network	0.6946	5
Simple CART	0.6504	6

This table 8 shows that from the result, Naïve Bayes is having the highest Asi value and LibSVM is having the lowest value.

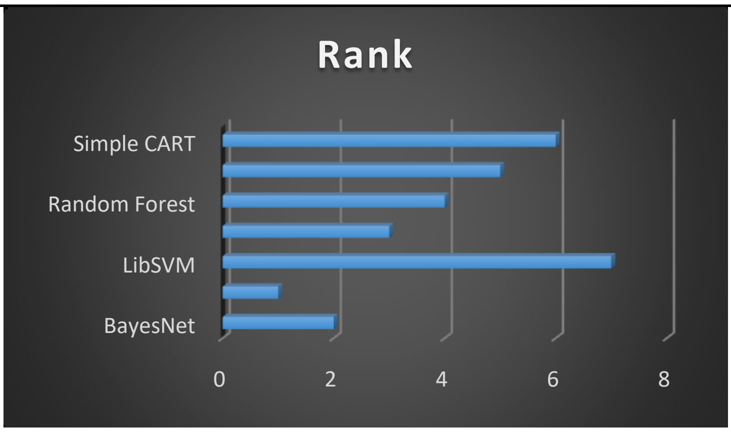

FIGURE 2. Ranking Classifiers by EDAS method

The ranking of classifiers using the EDAS approach is shown graphically in Figure 1. While LibSVM is ranked seventh, Naive Bayes is ranked first.

4. Conclusion

Financial risk is a risk associated with debt Shareholders who invest in the company. A company's cash flow is its debt If insufficient to pay, Risk of losing money. When a business employs debt financing, in the event that it goes bankrupt, its creditors are paid back before its shareholders. Financial risk is frequently seen as the possibility that a business would stop making its debt payments. Prediction models, which are viewed as early warning systems of approaching difficulties in the examined organizations, are used to evaluate the state of company financial health and remove prospective financial hazards. In this study, on financial risk Diversity in datasets Multiple alternatives to criteria (Classifiers) A to assess an abbreviated MCDM approach is used. Here, many Significant classification methods and Selection of performance metrics and their classification Assessed for skills. Financial risk Some notable ones related to prediction Classification algorithms in this work were discovered and used. Classification algorithms are used for detection activities. Results of this paper shows LibSVM seventh Placed, whereas Naive Bayes ranks first.

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