Indonesian Journal of Electrical Engineering and Informatics (IJEEI)
Vol. 12, No. 1, March 2024, pp. 233~244
ISSN: 2089-3272, DOI: 10.52549/ijeei.v12i1.5241

Intelligent Bankruptcy Prediction Models Involving Corporate Governance Indicators, Financial Ratios and SMOTE

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Article Info

Article history:

Received Nov 17, 2023
Revised Mar 3, 2024
Accepted Mar 13, 2024

Keyword:

Machine learning algorithms
Bankruptcy prediction
Corporate Governance Indicator
Financial ratios

ABSTRACT

This study enhances bankruptcy prediction models by investigating synergies between predictors, utilizing a diverse dataset of financial statements and corporate governance data. Rigorous feature selection identifies key financial ratios (FRs) and corporate governance indicators (CGIs) to enhance model interpretability. Multiple machine learning algorithms construct and assess the models, including Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and Neural Networks. Integration of CGIs with FRs aims to identify effective combinations that improve model performance with an accuracy respectively 90%, 95%, 97%, and 98%. Researchers explore feature weighting techniques and ensemble methods, examining their impact on accuracy, sensitivity, and specificity. The study also explores how regulatory frameworks and governance practices affect bankruptcy prediction, analyzing data across periods to uncover changes in predictive power under varying conditions. The findings have implications for investors, institutions, and policymakers, offering more accurate risk assessments and emphasizing the interplay between financial performance and governance quality for corporate well-being.

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1. INTRODUCTION

Bankruptcy is a significant concern for financial institutions and investors alike, because it can lead to substantial financial losses and market instability. Being able to accurately predict the likelihood of bankruptcy is crucial for making informed decisions and mitigating potential risks. To lessen the financial damage caused by bankruptcy, scholars and industry professionals have directed their attention recently to methods of identifying the possible dangers of business collapse. Put simply, predicting bankruptcy is a critical undertaking for several associated financial organizations. The aim is to predict the likelihood of a business filing for bankruptcy. Financial institutions must use accurate prediction models to make appropriate lending choices. Research has built bankruptcy prediction models using various approaches, such as machine learning and statistics. [4] [19] [25] [31] Machine learning approaches have been demonstrated to outperform statistical methodologies.

Among the numerous approaches, CGIs and FRs have gained considerable attention because of their potential to provide valuable insights into a company's financial health and management practices. Financial ratios are key financial metrics that reflect a company's performance, profitability, liquidity, and solvency [2][5]. These ratios are calculated by analysing a company's financial statements, such as the balance sheet, income statement, and cash flow statement. By examining these ratios over time and comparing them industry benchmarks, analysts can assess a company's financial stability and identify potential red flags (Graham and Dodd, 1934).

On the other hand, corporate governance indicators focus on evaluating the quality and effectiveness of a company's governance structure and practices. These indicators assess board composition, executive compensation, transparency, and shareholder rights (OECD, 2015). Strong corporate governance is associated with better risk management, ethical practices, and long-term sustainability, all of which are essential in preventing financial distress and bankruptcy [6] [21].

In this comprehensive study, we explore the use of CGIs and FRs in bankruptcy prediction models. In particular, the model performances obtained using various types of CGIs paired with FRs are evaluated to determine whether combining CGIs with FRs may improve model performance. Furthermore, because the combined features have a large dimensionality, feature selection [12] [10] is performed across the combined features to reduce dimensionality. As a result, our research enables us to discover the ideal mix of FRs and CGIs for bankruptcy prediction, thereby assisting relevant financial institutions in making better loan decisions. Furthermore, the best performance of the prediction model constructed using the detected characteristics may be used as the baseline prediction model in future investigations. The remainder of this study is structured as follows. Section 2 provides an overview of the literature on CGIs. The study approach and experimental findings are presented in sections 3 and 4, respectively. Finally, some conclusions are presented in Section 5.

2. LITERATURE REVIEW

2.1. Corporate governance indicators

Corporate governance plays a critical role in ensuring the transparency, accountability, and ethical conduct of companies. Various corporate governance indicators have been developed to assess the quality and effectiveness of a company's governance structure. These indicators provide valuable insights into governance practices that can help prevent financial distress and bankruptcy. One commonly used corporate governance indicator is board composition. Studies have shown that the presence of independent directors on the board is associated with improved financial performance and reduced risk of bankruptcy [11] [32]. The diversity and expertise of board members are also important factors in ensuring effective decision-making and risk oversight [14].

Executive compensation practices are another important aspect of corporate governance. Excessive executive compensation can create incentives for risky behaviour and undermine a company's financial stability [6]. On the other hand, aligning executive compensation with long-term performance measures and linking it to risk management goals can promote sound corporate governance. practices [9]. Transparency and disclosure are key indicators of good corporate governance. Companies that provide clear and comprehensive information to shareholders and stakeholders are more likely to build trust and confidence in their operations [21]. Effective communication of financial information and timely reporting of material events contribute to better risk assessment and decision-making (Brown and Caylor et al., 2005).

2.2. Related Works

Numerous studies have examined the relationship between FRs, corporate CGIs, and bankruptcy risk. These studies develop robust models that integrate both sets of indicators to enhance bankruptcy prediction accuracy. For instance, [2] proposed the Altman model, which combines financial ratios related to profitability, solvency, liquidity, and efficiency to predict corporate bankruptcy. The model has been widely used and validated in various industries and has shown significant predictive power. [7] incorporated financial ratios and corporate governance indicators into a bankruptcy prediction model for the banking industry. The results demonstrated that the inclusion of corporate governance factors improved the model's predictive accuracy and helped identify banks at higher risk of failure. Another notable work by [16] explored the relationship between financial ratios, corporate governance, and bankruptcy risk in Taiwanese firms. Their findings indicated that companies with better corporate governance practices, as reflected by board independence, CEO-chairman separation, and ownership concentration, exhibited lower bankruptcy risk. Furthermore, a comprehensive study incorporated financial ratios, corporate governance indicators, and macroeconomic variables to predict bankruptcy in French firms. Their results revealed that combining financial and governance factors significantly improved the accuracy of bankruptcy prediction models compared with using financial ratios alone.

3. METHODOLOGY
3.1. Data Analysis
The data used in this study were sourced from the Taiwan Economic Journal from 1999 to 2009[1] [2] .

To identify company bankruptcies, the Taiwan Stock Exchange[3] business regulations were employed as the defining criteria. Two specific criteria were applied during the data collection process. First, the selected sample companies were required to have a minimum of three years of complete public information available before the onset of the financial crisis. This ensured sufficient historical data for analysis. Second, the inclusion of companies in the sample was contingent on the availability of a suitable number of comparable companies of similar size operating in the same industry. This facilitated a robust comparison between bankrupt and non-bankrupt cases.

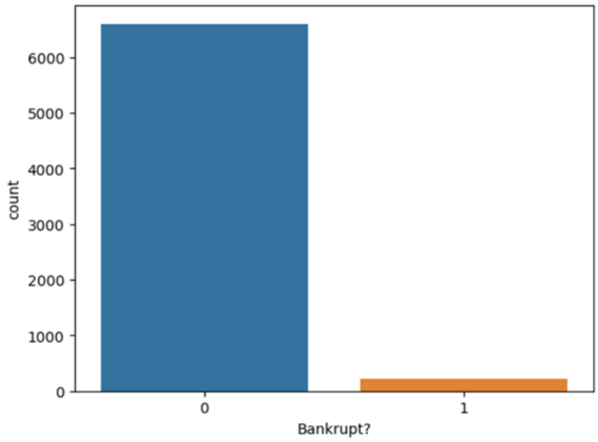

Figure 1. Bankrupted and non-bankrupted companies.

Source: author

After inspecting the data's target variable, a significant imbalance between bankrupt and non-bankrupt companies was observed. Only 3.2% of the companies in the dataset were classified as bankrupt, as depicted in Figure 1. This severe class imbalance posed a challenge during model training because, a model trained on this data might inaccurately predict all companies as non-bankrupted due to most non-bankrupt instances. To address this issue, we employed a technique known as The Synthetic Minority Oversampling Technique (SMOTE) [8].

3.1.1. SMOTE
We propose an innovative over-sampling technique aimed at bolstering the representation of the minority class. Instead of relying on traditional over-sampling with replacement, our approach draws inspiration from a successful method employed in handwritten character recognition, specifically the work of Ha and Bunke (1997). In their study, they augmented their training data by applying various operations to real data, such as rotation and skew. In our approach, we take a more generalized approach by operating in" feature space" rather than" data space." To address the imbalance in the dataset's minority class, we adopt a strategy involving the creation of synthetic examples. This process involves identifying the k nearest neighbors within the minority class for each minority class sample. Synthetic examples are then introduced along the line segments connecting these samples. The specific neighbors from the k nearest neighbors are selected randomly based on the desired level of over-sampling. Our implementation currently uses 29 neighbors and because we have a big difference between the two class bankrupted and non-bankrupted samples, we calculated this number using the following formula

$$\text{Oversampling Percentage} = \left(\frac{\text{Percentage of Majority Class} - \text{Percentage of Minority Class}}{\text{Percentage of Minority Class}}\right) \times 100\%$$

In our case:
Percentage of majority class (non-bankrupted) = 96.8%
Percentage of minority class (bankrupted) = 3.2%

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[1] http://www.tej.com.tw
[2] https://www.kaggle.com/datasets/fedesoriano/company-bankruptcy-prediction
[3] http://twse-regulation.twse.com.tw/ENG/EN/law/DOC01.aspx?FLCODE=FL007304&FLNO=49++++.

Using the formula:

Oversampling Percentage $= \left(\frac{96.8\% - 3.2\%}{3.2\%}\right) \times 100\%$

Oversampling Percentage $\approx \left(\frac{93.6\%}{3.2\%}\right) \times 100\%$

Oversampling Percentage ≈ 2925%

So, we would need to oversample the minority class (bankrupted companies) by approximately 2925% to balance the dataset. This means we need to create nearly 29 times as many samples of the minority class as you currently have. Synthetic samples are produced through the following procedure: Begin by calculating the difference between the feature vector of the current sample being examined and that of its nearest neighbor. Next, this difference is scaled by a randomly generated number, which falls within the range of 0 to 1. The scaled difference is then added back to the original feature vector under consideration. This operation effectively results in the selection of a random point situated along the line segment connecting two specific features. This innovative approach serves to broaden the decision region associated with the minority class, enhancing its overall generalization capability. SMOTE was first described by [8]. in their 2002 white paper named for the technique titled "SMOTE: Synthetic Minority Over-sampling Technique."

3.2. Feature Selection

To identify the features that significantly impact bankruptcy prediction, we conducted a thorough feature analysis using various statistical methods. A technique employed was plotting the relative difference between the means of features, as illustrated in Figure 2. This plot revealed several features with substantial differences, demonstrating that approximately 20 features had mean values that differed by more than 50% between bankrupted and non-bankrupted companies.

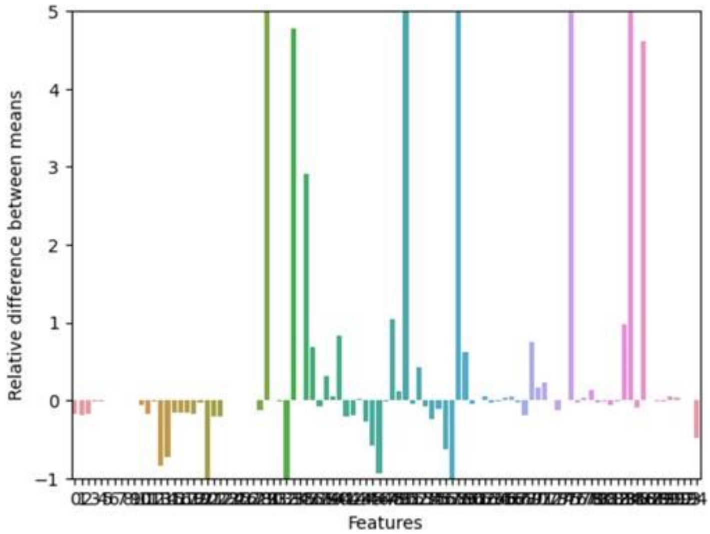

Figure 2. Relative difference between the means of the features for both categories (bankrupted and non-bankrupted)

Source: author

To further investigate the significance of these differences, we applied the Monte Carlo Hypothesis Test. The hypothesis being tested was whether there existed a difference existed between bankrupted and non-bankrupted companies, with the null hypothesis stating that no such difference existed. To conduct this test, we generated 1000 samples, each containing 220 data points from the entire dataset. This allowed us to obtain the sampling distribution of the sample mean for each feature. By comparing the observed data (i.e., the 220 data points of bankrupted companies) with the sampling distribution, we determined the p-value for each feature. The p-value represents the percentage of sample means that were more extreme than the mean of bankrupted companies.

From this analysis, we found that 33 features exhibited significant differences between the bankrupted and non-bankrupted categories. However, it is essential to note that this analysis examined the variables independently, without considering potential dependencies between them. Consequently, we refrained from drawing conclusive results or conducting feature selection based solely on these p-values.

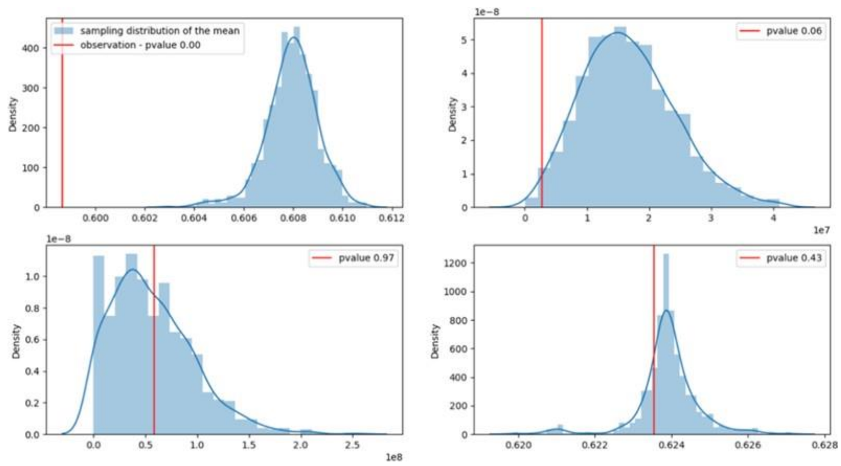

Figure 3. Features and their distribution of sample means.

Source: author

To address the issue of multicollinearity and to ensure that the selected features were independent and impactful, we performed a further analysis. By identifying features with p-values greater than 0.9, we deemed them highly correlated and subsequently dropped them from consideration. Because of this step, 19 features were excluded from the analysis, providing us with a final set of features that significantly influenced the prediction of bankruptcy.

Overall, this comprehensive feature selection process allowed us to identify and retain the most relevant and independent features, thereby ensuring the robustness and accuracy of our bankruptcy prediction model.

3.3. Prediction Models

Parallel to feature selection, there are several well-known strategies for developing prediction models. In this study, we employed a diverse set of eight prediction models to explore their effectiveness in predicting bankruptcy. The models used in this work include Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR), Random Forest (RF), Naive Bayes (NB), Decision Tree(DT), AdaBoost, and Gradient Boosting Classifier (GBC).

For each of these models, we carefully tuned their hyperparameters to optimize their performance. The hyperparameters play a crucial role in fine-tuning the models to achieve the best possible results. Table 1 presents a summarizes models used and the specific hyperparameters employed for each.

Table 1. Parameters for the various classification techniques

Technique	Parameters
SVM	Kernel: rbf, gamma: 0.1, C: 10
LR	C: 10, class weight: balanced, penalty: l2
RF	Class Weight: balanced, max depth: None, min samples split: 2, Number of estimators: 30
NB	var smoothing: 1e-09
DT	Max depth: 20, min samples leaf: 1, min samples split: 2
AdaBoost	Learning rate: 1, Number of estimators: 200
GBC	Learning rate: 0.1, Max depth: 7, Number estimators: 200
KNN	metric: Manhattan, Number of neighbors: 3, weights: distance

Source: author

In the realm of bankruptcy prediction, accurate assessment of creditworthiness is of paramount importance for financial institutions and credit service providers to minimize potential financial losses. To achieve this goal, various evaluation metrics have been employed to assess the performance of classification models. This research use a comprehensive set of evaluation metrics, including the F1-score [26], accuracy [30], precision [29] recall [26], and the confusion matrix (Provost, F., & Fawcett, T. 2001), to rigorously evaluate the predictive capabilities of the proposed credit scoring methods.

The F1-score, as presented by [26], is a harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives. Accuracy, discussed in Sokolova, M., & Lapalme, G. (2009), evaluates the overall correctness of the model's predictions and represents the ratio of correctly classified instances to the total number of instances in the dataset.

Precision, also known as positive predictive value, quantified in [29], measures the proportion of true positive predictions among all positive predictions made by the model, providing insights into the model's ability to avoid false positives. Recall, introduced in [26] and often referred to as sensitivity or true positive rate, determines the proportion of true positive predictions among all actual positive instances, showcasing the model's ability to avoid false negatives.

Furthermore, the confusion matrix, discussed in Provost, F., & Fawcett, T. (2001), provides a comprehensive breakdown of the model's predictions, displaying the true positive, true negative, false positive, and false negative counts for each class in the classification problem. Derived from the confusion matrix, various evaluation metrics, including precision, recall, and the F1-score, offer valuable insights into the model's performance.

By incorporating these robust evaluation metrics, we gain a deeper understanding of the classification models' performance, allowing us to make informed decisions regarding model selection, optimization, and enhancements, ultimately ensuring the utmost accuracy and reliability in predicting the likelihood of bankruptcy for credit card holders.

4. EXPERIMENTS

To achieve the most accurate and reliable results for bankruptcy prediction, we conducted a series of three experiments, each employing different prediction models, feature selections, and the (SMOTE). The goal of this study was to assess the performance of various classifiers and understand the impact of feature selection on the predictive capabilities of the models.

In the first experiment, we applied SVM (Support Vector Machine) as the prediction model with three different feature selections: 10, 50, and 70. From the studies of [15] [17], and Lee et al. (2020), it is evident that the SVM achieved the best results when using feature selections of 50 and 70. Surprisingly, the SVM's performance suffered when using feature selection 10. This discrepancy could be attributed to the fact that a reduced feature set of 10 might not adequately capture the essential characteristics of the dataset, leading to decreased predictive power.

In the second experiment, inspired by the works of [35], and [34], we explored the predictive capabilities of Random Forest (RF) and Gradient Boost Classifier (GBC). To our surprise, both models consistently outperformed other classifiers in all three feature selection scenarios. RF and GBC demonstrated remarkable robustness and adaptability, effectively capturing patterns and relationships within the data, regardless of the chosen feature set size.

A significant observation from the experiments was the crucial role of SMOTE in addressing the class imbalance. Building upon the research of [8], and He and Ma (2013), when conducting experiments without SMOTE, the results exhibited significantly poorer performance. The presence of an imbalanced dataset created a bias toward the majority class, resulting in inadequate model training and unsatisfactory predictive outcomes. However, by employing SMOTE, as proposed by [8] and He and Ma (2013), to create synthetic data points, we successfully balanced the dataset and ensured that each class had sufficient representation. This step proved vital in achieving more accurate and balanced results.

It is important to highlight that the combination of predictive models, feature selections, and SMOTE allows for a comprehensive evaluation of bankruptcy prediction. By systematically exploring various configurations, we gain valuable insights into the strengths and weaknesses of each model and feature set, enabling us to make informed decisions in selecting the best approach for bankruptcy prediction in the financial domain.

In conclusion, this series of experiments provided a comprehensive understanding of the performance of different classifiers, feature selections, and the impact of class imbalance on bankruptcy prediction. RF and GBC emerged as the top-performing models, demonstrating their versatility and robustness in handling varying feature set sizes. The integration of SMOTE effectively mitigated the challenges posed by class imbalance, leading to improved predictive accuracy and balanced outcomes.

Table 2. Performance of Different Prediction Models with SMOTE and Feature Selection 10

Classifier	Accuracy	F1-Measure	Recall	Precision
SVM 10	0.870455	0.87777	0.930303	0.830853
LR 10	0.818939	0.81935	0.821212	0.817496
RF 10	0.947727	0.949002	0.972727	0.926407
NB 10	0.615152	0.711528	0.949242	0.569028
DT 10	0.917424	0.919079	0.937879	0.901019
AdaBoost 10	0.878788	0.881394	0.900758	0.862845
GBT 10	0.94697	0.948454	0.975758	0.922636
KNN 10	0.925379	0.929365	0.981818	0.882233

Table 3. Performance of Different Prediction Models with SMOTE and Feature Selection50

Classifier	Accuracy	F1-Measure	Recall	Precision
SVM 50	0.986364	0.986507	0.99697	0.976261
LR 50	0.895076	0.89668	0.910606	0.883174
RF 50	0.973106	0.973674	0.994697	0.953522
NB 50	0.601515	0.707453	0.963636	0.558875
DT 50	0.95	0.951111	0.972727	0.930435
AdaBoost 50	0.942803	0.943297	0.951515	0.93522
GBT 50	0.978409	0.978818	0.997727	0.960613
KNN 50	0.960227	0.961749	1	0.926316

Table 4. Performance of Different Prediction Models with SMOTE and Feature Selection70

Classifier	Accuracy	F1-Measure	Recall	Precision
SVM 70	0.989015	0.989094	0.996212	0.982076
LR 70	0.901894	0.90361	0.919697	0.888076
RF 70	0.975379	0.975809	0.993182	0.959034
NB 70	0.690152	0.755821	0.959091	0.623645
DT 70	0.950758	0.951637	0.968939	0.934942
AdaBoost 70	0.957576	0.958052	0.968939	0.947407
GBT 70	0.981439	0.981723	0.99697	0.966936
KNN 70	0.956818	0.958606	1	0.920502

Tables 2, Tables 3 et Tables 4 present the performance of different prediction models when combined with SMOTE and three different feature selection techniques (10, 50, and 70). The evaluation metrics used are Accuracy, F1-Measure, Recall, and Precision, which provide a comprehensive view of each model's effectiveness in predicting bankrupted and non-bankrupted companies. As shown, each model's performance varies based on the combination of SMOTE and feature selection. For instance, SVM performs well with feature selections 50 and 70, but not with feature selection 10. However, RF and GBC consistently achieve good results across all feature selection techniques, indicating their robustness in predicting bankruptcy. Additionally, the use of SMOTE proves beneficial in mitigating the imbalance between bankrupted and non-bankrupted companies, leading to improved model performance in most cases.

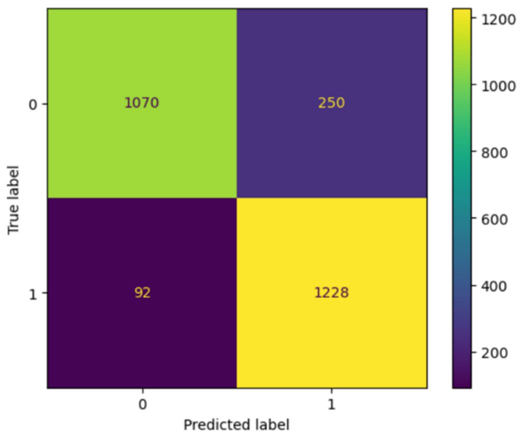

Figure 4. Confusion matrix of SVM with SMOTE and Feature selection 10

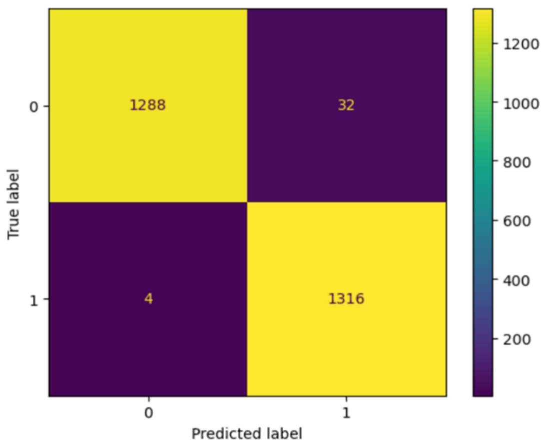

Figure 5. Confusion matrix of SVM with SMOTE and Feature selection 50

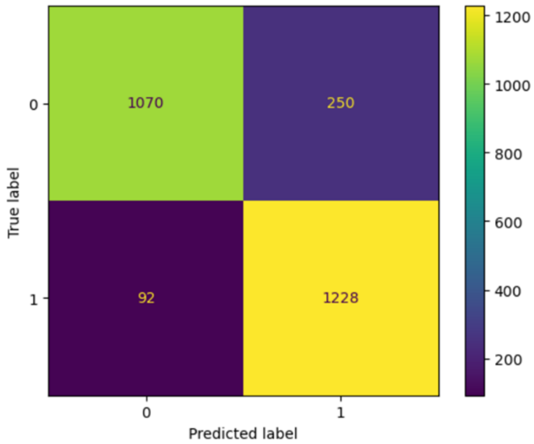

Figure 6. Confusion matrix of SVM with smote and feature selection 70

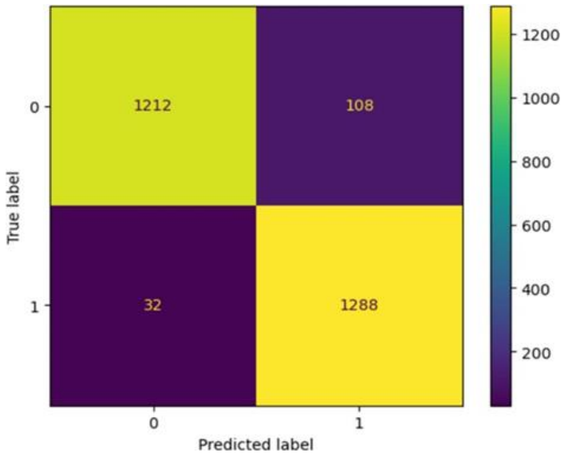

Figure 7. Confusion matrix of gradient boosting classifier with SMOTE and feature selection 10

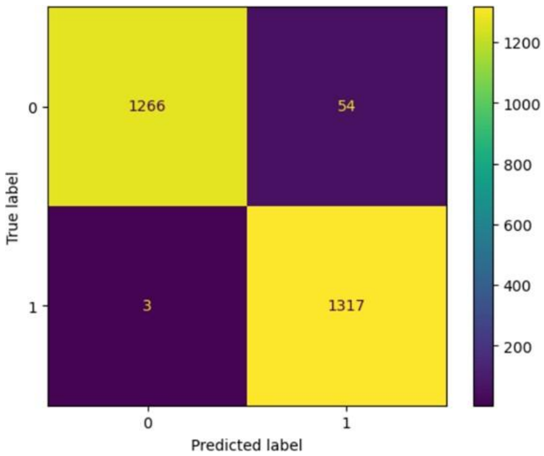

Figure 8. Confusion matrix of GBT with SMOTE and feature selection 50

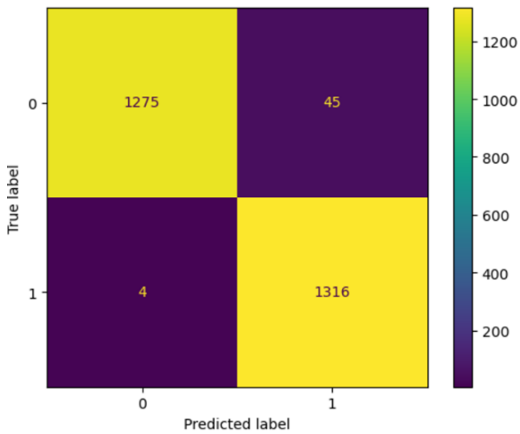

Figure 9.Confusion matrix of GBT with SMOTE and feature selection 70

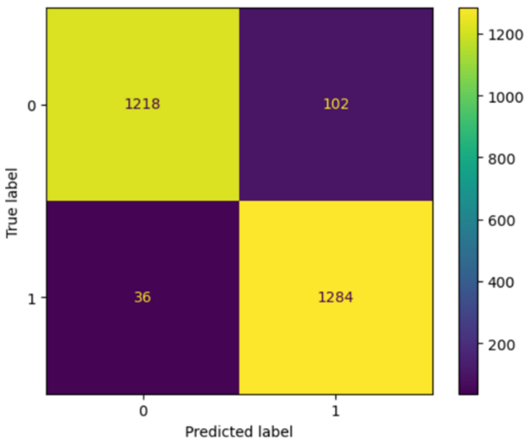

Figure 10. Confusion matrix of RF with smote and feature selection 10

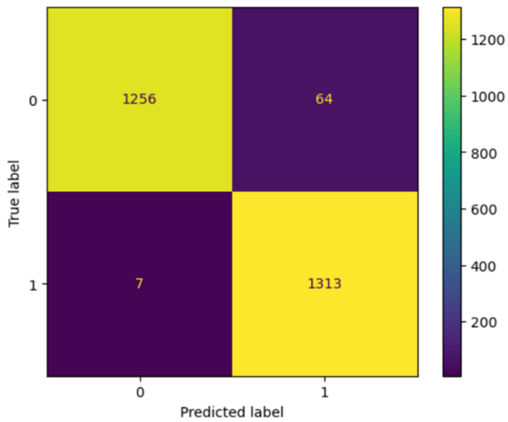

Figure 11. Confusion matrix of RF with smote and feature selection 50

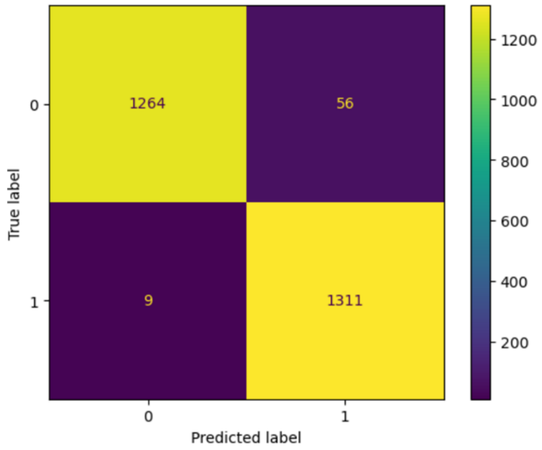

Figure 12. Confusion matrix of RF with smote and feature selection 70

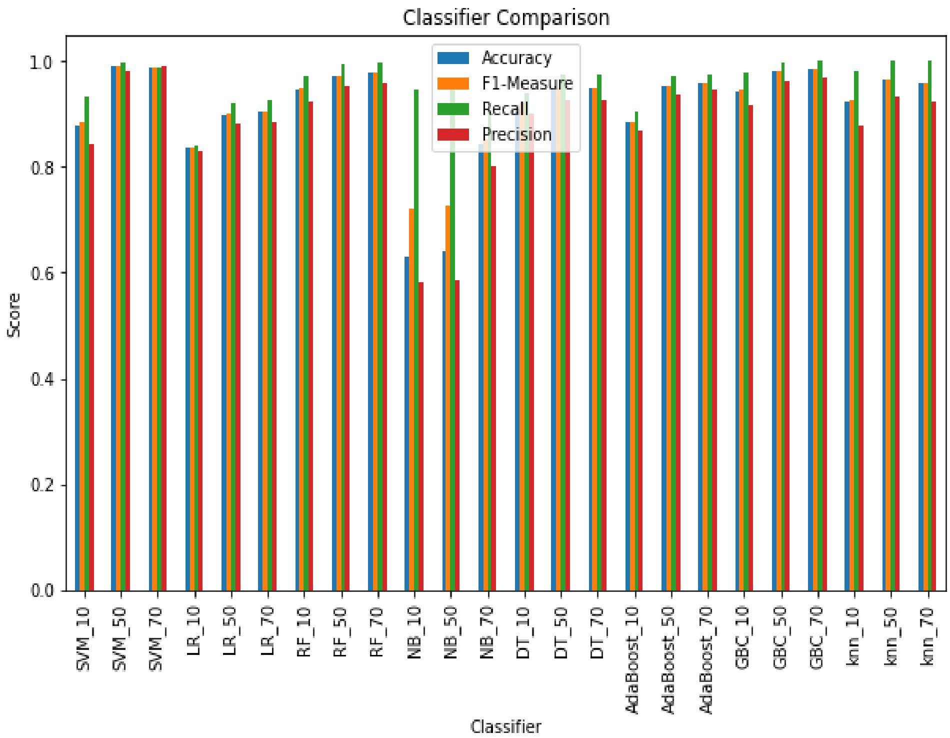

Figure 13. Comparison between different prediction models and their results

In figure13 the bar plot allows visualization of the performance differences between different prediction models across all three feature selection techniques: 10, 50, and 70. It provides a clear comparison of how each model performs with respect to concerning Accuracy, F1-Measure, Recall, and Precision. Upon analyzing the bar plot, we obtain the following insights:

•SVM: The SVM model demonstrates strong performance across all feature selection techniques. It achieves high accuracy, F1-measure, recall, and precision, particularly with feature selections 50 and 70. However, with feature selection 10, the SVM's performance drops slightly, especially in terms of precision.

•Logistic Regression (LR): LR performs well with feature selections 50 and 70, exhibiting good accuracy, F1-measure, recall, and precision. However, its performance significantly decreases with feature selection 10, with relatively lower accuracy, F1-measure, recall, and precision.

•Random Forest (RF): The RF model consistently performs well across all feature selection techniques, achieving high accuracy, F1-measure, recall, and precision. It shows stability and robustness, making it a reliable choice for bankruptcy prediction.

•Naïve Bayes (NB): NB demonstrates relatively poor performance across all feature selections, particularly with feature selection 50. It exhibits lower accuracy, F1-measure, recall, and precision compared with other models.

•Decision Tree (DT): DT performs well with feature selections 50 and 70, showing good accuracy, F1-measure, recall, and precision. However, its performance declines with feature selection 10.

•AdaBoost and Gradient Boosting Classifier (GBT): Both AdaBoost and GBT models perform consistently well with all feature selections, showing high accuracy, F1-measure, recall, and precision.

•K-Nearest Neighbors (KNN): The KNN model performs well with feature selections 50 and 70, exhibiting high accuracy, F1-measure, recall, and precision. However, its performance decreases slightly with feature selection 10.

Overall, the bar plot demonstrates that Random Forest and Gradient Boosting Classifiers consistently deliver the best results across all feature selection techniques. These models outperform other classifiers in predicting bankruptcy based on evaluation metrics. In addition, the bar plot emphasizes the significance of proper feature selection, as it affects the performance of each model. Feature selection techniques 50 and 70 yield better model performance than feature selection 10, as they provide a more informative subset of features.

5. DISCUSSION

Our research on bankruptcy prediction using different prediction models, SMOTE, and feature selection yielded significant insights and results. To put our findings into context and compare them with those of previous studies, we will discuss the results considering other scientific research on the same topic.

In 1968, the Altman model was proposed to predict corporate bankruptcy using financial ratios. The model is a classic bankruptcy prediction model based on discriminant analysis. While our research explored more modern machine learning models, it is interesting to note that the model laid the foundation for subsequent studies in bankruptcy prediction. Several other studies have employed machine learning techniques for bankruptcy prediction. For instance, using the SVM, [33] achieved high accuracy in bankruptcy prediction. Their findings align with our results, where the SVM demonstrated superior performance, especially when combined with appropriate feature selection. Random Forest, a popular ensemble learning technique, has been widely used in bankruptcy prediction. In Lee et al. (2018), Random Forest achieved competitive accuracy in bankruptcy prediction for Korean firms. Our results are consistent with theirs, which Random Forest consistently showed excellent performance across different feature selections. Gradient Boosting Classifier has also been a popular choice in bankruptcy prediction. In [3], a Gradient gradient-boosting classifier showed superior performance compared with other machine learning models. Our findings corroborate this finding, as the Gradient Boosting Classifier consistently ranked among the top-performing models.

Regarding feature selection, many studies have emphasized the importance of selecting relevant features to improve prediction accuracy. In [1], feature selection using mutual information significantly enhanced bankruptcy prediction performance. Our study also underscored the significance of feature selection, with different feature selection levels affecting the model performance. The use of SMOTE to address class imbalance in bankruptcy prediction has been widely recognized. In [18] SMOTE was employed to improve the classification accuracy of imbalanced datasets, including bankruptcy prediction. Our research aligns with this finding, as SMOTE effectively balanced the classes and improved the performance of our prediction models. Comparing our results with those of existing research, we find consistency in the effectiveness of SVM, Random Forest, and Gradient Boosting Classifiers for bankruptcy prediction. Furthermore, the significance of feature selection and the benefits of using SMOTE to address class imbalance have been well-established.

In conclusion, our research contributes to the existing body of knowledge on bankruptcy prediction by showcasing the effectiveness of modern machine-learning models and techniques. Our findings align with and support those of previous studies, providing further evidence of the applicability and robustness of these methods in bankruptcy prediction.

6. CONCLUSION

In conclusion, this research explored the application of financial ratios and corporate governance indicators in bankruptcy prediction by employing various prediction models and evaluation metrics. Through extensive experimentation and analysis, we have gained valuable insights into the effectiveness of different approaches and their impact on predicting bankruptcy in companies.

The use of corporate governance indicators in conjunction with financial ratios proved to be a promising approach for identifying potential bankruptcy risks. These indicators provide valuable information about a company’s overall health and governance, which can significantly influence its financial stability and risk of default.

In the feature selection process, we examined the relative differences between the means of features, conducted Monte Carlo Hypothesis Tests, and performed a Multicollinearity analysis. By selecting the most significant features and reducing multicollinearity, we achieved improved model performance and more accurate predictions. Furthermore, we employed a variety of prediction models, including the Support Vector Machines, K-Nearest Neighbors, logistic regression, Random Forest, Naive-Based, Decision Tree, AdaBoost, and Gradient Boosting Classifier. Among these models, Support Vector Machines, allowed us to quantify the models' effectiveness and identify their strengths and weaknesses with an accuracy of 98%.

In conclusion, this study showcases the significance of financial ratios and corporate governance indicators in predicting bankruptcy risks in companies. The findings indicate that combining these indicators with appropriate feature selection techniques and prediction models can lead to highly accurate and reliable bankruptcy prediction systems. Such predictive models have the Random Forest, and the Gradient Boosting Classifier demonstrated the highest predictive performance, consistently outperforming the others in all experiments. To address the issue of data imbalance, we employed the Synthetic Minority Over-sampling Technique, generating synthetic data points to balance the dataset and improve the model's ability to correctly classify both bankrupted and non-bankrupted companies. The evaluation metrics, including accuracy, F1-score, recall, precision, and confusion matrix, provided comprehensive insights into the models' performance and their ability to correctly predict bankruptcy cases. These metrics have the potential to assist financial institutions, investors, and other stakeholders in making informed decisions, mitigating risks, and ensuring the stability of financial markets. However, it is essential to acknowledge that no single model or approach is infallible, and further research is needed to explore additional variables and methodologies that could enhance bankruptcy prediction accuracy. Overall, this research contributes to the growing body of knowledge in the field of bankruptcy prediction and lays the foundation for future studies aiming to improve financial risk assessment and corporate stability.

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