2025, 9 (1), 20-36

Uluslararası Ekonomi, İşletme ve Politika Dergisi

International Journal of Economics, Business and Politics

https://dergipark.org.tr/tr/pub/ueip

Predicting Financial Distress in The Textile Industry: A Comparative Analysis of Meta Models and Single Classifiers

Tekstil Endüstrisinde Finansal Sıkıntının Tahmini: Meta Modellerin ve Tek Sınıflandırıcıların Karşılaştırmalı Analizi

Ahmet Akusta [a] **Musa Gün** [b*]

[a] Lect.Dr., Rectorate, Konya Technical University, Konya/Türkiye, aakusta@ktun.edu.tr, ORCID: 0000-0002-5160-3210

[b] Assoc.Prof.Dr., The Faculty of Economics and Administrative Sciences, Recep Tayyip Erdogan University, Rize/Türkiye, musa.gun@erdogan.edu.tr, ORCID: 0000-0002-5020-9342

ARTICLE INFO

Article Type
Research Article

Keywords
Financial Distress Prediction
Machine Learning
Feature Engineering
Financial Markets

Received: Dec, 10, 2025
Accepted: Mar, 22, 2025

ABSTRACT

This study evaluates the effectiveness of meta-models in predicting financial distress in the Turkish textile industry. Using economic data from 2013 to 2023, the research applies a meta-model that integrates Lasso, Ridge, Random Forest, Gradient Boosting Machines (GBM), and Support Vector Machines (SVM) as base models, with XGBoost serving as the meta learner. The results show that the meta-model outperforms a standalone XGBoost classifier, especially in minimizing false negatives, which is critical for the early detection of financial distress. The meta-model achieved superior recall and F1 scores, offering a more reliable tool for predicting financial instability in volatile sectors like textiles. However, the study also acknowledges limitations such as model selection bias, the complexity of hyperparameter tuning, and reduced interpretability due to the ensemble nature of the approach. The findings highlight the potential of meta-modeling for industry-specific financial risk prediction while suggesting future improvements in model transparency and generalizability.

MAKALE BİLGİSİ

Makale Türü
Araştırma Makalesi

Anahtar Kelimeler
Finansal Sıkıntı Tahmini
Makine Öğrenmesi
Özellik Mühendisliği
Finansal Piyasalar

Geliş Tarihi : 10 Aralık 2024
Kabul Tarihi: 22 Mart 2025

ÖZ

Bu çalışma, Türk tekstil sektöründeki finansal sıkıntıları tahmin etmede meta modellerin etkinliğini değerlendirmektedir. Araştırma, 2013'ten 2023'e kadar olan finansal verileri kullanarak Kement, Ridge, Rastgele Orman, Gradyan Arttırma Makineleri (GBM) ve Destek Vektör Makinelerini (DVM) temel modeller olarak entegre eden ve XGBoost'un meta öğrenici olarak hizmet ettiği bir meta model uygulamaktadır. Sonuçlar, meta modelin, özellikle finansal sıkıntının erken tespiti için kritik olan yanlış negatifleri en aza indirmede bağımsız bir XGBoost sınıflandırıcıdan daha iyi performans gösterdiğini göstermektedir. Meta model, tekstil gibi değişken sektörlerde finansal istikrarsızlığı tahmin etmek için daha güvenilir bir araç sunarak üstün hatırlama ve F1 puanları elde etmiştir. Bununla birlikte, çalışma aynı zamanda model seçimi yanlılığı, hiperparametre ayarının karmaşıklığı ve yaklaşımın topluluk doğası nedeniyle yorumlanabilirliğin azalması gibi sınırlamaları da kabul etmektedir. Bulgular, meta modellemenin sektöre özgü finansal risk tahmini için potansiyelini vurgularken, model şeffaflığı ve genelleştirilebilirliğinde gelecekte yapılabilecek iyileştirmelere dair önerilerde bulunmaktadır.

1. Introduction

Corporate financial distress is becoming a critical focus of financial management due to its substantial impact on the individual concerned firms, financial intermediaries, and the economy at large. Firms' financial distress, generally described as a failure of a firm to meet financial obligations as they come due can result in serious problems of disruption of operations, loss of customers and suppliers, and lastly bankruptcy. Consequently, corporate financial distress prediction has become more important. Managers need this kind of approach to anticipate corporate financial distress and hence can pro-actively intervene to prevent the degradation of a firm's financial position, while also

* *Corresponding Author / Sorumlu Yazar*

Cite as/Atıf: Akusta, A. and Gün, M. (2025). Predicting Financial Distress in The Textile Industry: A Comparative Analysis of Meta Models and Single Classifiers. *International Journal of Economics, Business and Politics*, 9(1), 20-36. https://doi.org/10.29216/ueip.1599431

assisting financial institutions in identifying early-stage high-impact defaults so that efficient commercial credit assignment is optimized (Cao et al., 2011). Moreover, the ramifications of financial distress go far beyond a single firm to the economy at large. When firms are in financial distress, this typically snowballs into broader operational challenges and broader economic instability (Islam et al., 2023).

One of the main reasons that financial distress prediction is critical is due in part to its preservation of stakeholder interests. The early detection of financial distress holds the key because it fulfills stakeholders by informing their decisions. Identifying early warning signs of financial distress is crucial for all stakeholders, enabling them to respond appropriately to potential failures (Ashraf et al., 2019). Regardless of firm size, financial distress is a big danger to firms and is therefore a prominent issue for research within corporate finance (Khoja et al., 2019). Stakeholders can use different financial ratios and predictive models to evaluate the possibility of distress, and some of them can immediately start mitigating actions to decrease further severe financial disasters.

Historical financial ratios and statistical models are the mainstays of many traditional approaches for predicting financial distress. Altman's Z-Score and Ohlson's O-Score have been widely used to evaluate the degree of distress as a function of historical financial statements (Campbell et al., 2008). These models employ financial ratios (profitability, liquidity & leverage) for evaluating the financial health of a firm based on historical data. However, while these models have proven valuable, recent advancements in machine learning have introduced more sophisticated techniques that enhance the accuracy of distress predictions by processing large datasets and identifying complex patterns. As an example, a financial distress prediction model that used sparse algorithms and Support Vector Machines (SVM) has been constructed to withstand dataset imbalance problems providing accuracy elevation due to prediction quality in unbalanced datasets (Zeng et al., 2020). Similarly, deep learning algorithms have been proven to considerably increase the predictive ability of financial distress models by abstracting deep trends in the data as well (Elhoseny et al., 2022).

In this paper, we use a meta-model learning method to predict financial distress in Turkey's textile industry, a key sector sensitive to economic fluctuations. The textile industry was chosen due to its significant role in Turkey's economy and global markets. In 2023, Turkey's textile exports reached $9.5 billion, with 19,794 firms employing 397,000 people. Globally, the sector was valued at over $1.8 trillion in 2023 and is projected to grow 7.4% annually, surpassing $3 trillion by 2030. This study provides valuable insights into the financial stability of this vital and growing industry (TC Ticaret Bakanlığı, 2025).

There are lots of papers regarding financial distress prediction across different industries and regions using various testing methods. For instance, a cost-sensitive stacking ensemble learning model is proposed on making more agile identification rates of financially distressed firms in China market with key features like asset-liability ratios and industry prosperity indices (Wang and Chi, 2024). Likewise, another stacking ensemble model produced superior results as opposed to classical approaches for financial distress classification by feeding it with both stock information and non-financials (Chen et al., 2024).

Besides stacking models, other ensemble strategies such as Random Forest and Gradient Boosting Machines (GBM) are often used in financial distress prediction. Machine learning approaches like Random Forest and XGBoost (over traditional statistical results) are particularly superior at distinguishing between distressed and non-distressed firms with high precision and recall rates (Ramzan, 2023). Moreover, a model using non-stationary datasets validated by classification models can effectively predict financial distress across different economic environments (Chaves, Debiaso, & Garcia, 2023).

While research on financial distress prediction models has advanced, industry-specific research that considers specifics in different sectors is still required. For example, the utility of the Random Forest model to forecast financial distress in a conventional bank was illustrated, notably the Total Asset Turnover ratio as one of the key influential factors (Lestari, 2023).

This study aims to contribute to the current literature by exploring a meta-model learning for predicting financial distress in the Turkish textile sector. This paper, through comparing meta-models against classical single classifiers such as XGBoost, seeks to reveal the best method for predicting financial distress for this purpose. In the ensemble method, this study also aims to improve prediction accuracy with different machine learning models (Lasso Regression, Ridge Regression, Random Forest GBM, and SVM). It also investigates whether advanced predictive modeling approaches have potential in the Turkish textile industry and how industry-specific factors affect the prediction of financial distress.

2. Literature Review

The latest developments in financial distress prediction have identified methodology improvements and the use of original data and ensembles for predictiveness as key areas of innovation. This review summarizes the major studies on ensemble learning and meta-models in predicting corporate financial distress.

Many studies have recently contributed with different new insights into financial data uncertainty and applied state-of-the-art data science/machine learning techniques. Abdullayev et al. (2025) presented an IAFDP-RWNVD approach with financial data uncertainty being treated by relative weighted neutrosophic valued distances. Various other studies have used multi-source data integration and sophisticated feature selection techniques to enhance the prediction accuracy.

Wang and Chi (2024), tackling the data imbalance issue, put forward cost-sensitive stacking ensemble learning which for example targets important variables such as asset-liability ratios in predicting accuracy for Chinese companies. Chaves et al. (2023) are another implementer of this since they built strategies to cope with data stream characteristics; namely non-stationary and imbalanced, which is a challenge with concept drafts as well. These studies also emphasize the importance of sophisticated models (stacked models) for treating imbalance datasets which is one of the objectives performed in this study.

Similarly, Yu et al. (2024) developed a classification framework for dealing with missing and imbalanced data, that can increase the prediction accuracy. Using a stacked model to deal with different data environments in this research has increased robustness in predicting financial distress in the textile industry.

Different studies have been compared to analyze financial distress prediction between machine learning methodologies and traditional models. Ramzan (2023) and Ha et al. (2023) showed that machine learning models, i.e. Random Forest& XGBoost algorithms deliver a lot of lead to the traditional statistical models in terms of prediction accuracy. For example, Sehgal et al. (2021) contrasted neural networks with support-vector machines and logit models and found that in the Indian corporate sector machine learning performed far better in terms of predictive performance. This result significantly infers the study to meta-models that amalgamate some of machine learning algorithms in order of high accuracy predictions.

Ensemble models (specifically stacking) have shown superior performance on many problems when compared to traditional algorithms (Hadi et al., 2022; Chen et al., 2024). Additional factors such as financial management and textual data have been observed to dramatically increase the performance of ensemble models (Tang et al., 2020). Based on these findings, our research employs meta-models to fuse multiple classifiers into a comprehensive and effective financial distress prediction model. One also could look at the intersection of multiple textual data and/or genetic algorithms using neural networks, as a way to improve ensemble model performance (Zhang et al., 2022). Working together, these series of studies concur with the field of research emphasizing ensemble methods, especially stacked models combining different classifiers to improve predictive outputs as in this current research.

Furthermore, previous studies specifically focusing on the Turkish textile sector provide valuable insights into how financial distress models can be adapted to industry-specific contexts. For instance, Ezin (2022) conducted a ratio analysis on the Turkish textile manufacturing sector, leveraging data from the Central Bank of the Republic of Turkey and BIST listings from 2009 to 2021, to investigate liquidity, financial structure, operational efficiency, and profitability. Similarly, Akkaya et al. (2008) explored capital structure, asset utilization, and profitability in the ISE leather-textile industry using regression techniques, demonstrating the sector's importance within Turkish manufacturing. Another key contribution by Altaş and Giray (2005) employed factor analysis and logistic regression to develop a financial failure model specific to the Turkish textile industry, highlighting both its significance and its vulnerability to economic crises. These studies underscore the necessity of examining the textile sector in Turkey, which remains a critical component of the country's economy and serves as a strong motivator for adopting advanced ensemble learning methods in financial distress prediction.

Many have tried, different ways of integrating non-traditional data sources such as sentiment analysis and textual info into financial distress prediction models. Zhang et al. (2022) proposed a fine-grained sentiment analysis to develop early warning signals of financial distress, while Zhao et al. (2022) integrated sentiment tone features for better accuracy. Wang et al. (2018) introduced a random subspace method that integrates sentiment and textual data to enhance the performance of the model. Including these non-financial indicators resonates with our research's goal to leverage ensemble learning models, especially stacked models, that can integrate and process diverse data types effectively.

Deep learning models are also popular for financial distress prediction. For instance, several studies have established neural networks for financial distress prediction in Chinese-listed companies. Kong et al. (2023) and El-Bannany et al. (2020) have made the comparison of deep learning techniques including MLP, LSTM, and CNN in terms that outperformed particularly for high dimensional datasets. Zhong and Wang (2022) indicate AI methods help in making early warning systems to predict financial distress more effectively. Inspired by this we expand on this study to incorporate deep learning models into meta-model frameworks that can better capture high-level patterns in financial data.

While these developments have occurred, problems like data imbalance and model interpretability remain unsolved. Chaves, Debiaso, and García (2023) and Sun et al. (2021) addressed dynamic models that handle imbalanced datasets, while Liu et al. (2019) integrated network-based features with a GA-based gradient boosting method for enhanced accuracy. As we argued model interpretability, Zhang et al. (2022) were among the few proposing an explainable AI approach that uses Shapley additive explanations and partial dependence plots to improve financial distress prediction model transparency. Tran et al. (2022) similarly employed SHAP values to interpret Vietnamese financial distress prediction, emphasizing an ongoing trend in the research field for more interpretable models whilst seeking to balance how much accuracy should be sacrificed. The paper enumerates the efforts stated above via optimizing stacked models to deliver reliable predictions and suitable insights for decision-makers.

3. Methodology

3.1. Data Collection

This study uses data from the Eikon financial database and a dataset of Turkish textile companies spanning the years 2013 to 2023. Our dataset consists of 13 textile companies over time, with each company year is treated as a single observation, resulting in a total of 143 observations. The variables in the dataset are given in Table 1.

Table 1: Variables

Ratio	Category	Literature References
Net Profit Margin (%)	Profitability Ratios	(Prapanca and Kumalasari, 2023), (Wisnu and Astuti, 2023), (Silviyani et al., 2024), (Nurtati and Yuni, 2023), (Vebrizha et al., 2024), (Eduard, and Adeline, 2023), (Apasya et al., 2024)
Current Ratio, Quick Ratio	Liquidity Ratios	(Wisnu and Astuti, 2023), (Apasya et al., 2023), (Arifuddin et al., 2023), (Putri and Hendeyana, 2022), (Lumbantobing, 2020), (Agung Saputra, 2019)
Total Debt to Total Assets (%)	Leverage Ratios	(Apasya et al., 2023), (Vebrizha et al., 2024), (Arifuddin et al., 2023), (Widiastuti and Ali Ikhsan, 2022), (Elmi Dini and Umi, 2023), (Fatimah et al., 2019)
Asset Turnover	Activity/Efficiency Ratios	(Vebrizha et al., 2024), (Nurtati and Yuni, 2023), (Suryani and Desy, 2022), (Arini et al., 2021), (Prapanca and Kumalasari, 2023)
Beta, WACC Equity Risk Premium (%)	Market/Valuation Ratios	(Goetz, 2020), (Atika, and Siti Handayani, 2013), (Heymans and Brewer, 2023), (Korteweg, 2007), (Jorge Ceron, 2012)
ZScore	Solvency/Distress Prediction Ratios	(Silviyani et al., 2024), (Mavengere and Gumede, 2024), (Mufidah and Handayani, 2024), (Pravin and Dhabaliya, 2023), (Say, 2024), (Sharma et al., 2023)

Several data preparation steps are required before the data can be used for model training and analysis, which ensures its quality and consistency.

3.2. Data Preprocessing

This dataset contains missing values for some company-year observations. It is managed with mean imputation for missing values and selected mean imputation over alternatives such as median and mode imputation since it performs better at maintaining data properties (Maheswari et al., 2020).

Table 2: Descriptive Statistics

Metric	Count	Mean	Std. Dev.	Min	25%	50%	75%	Max
ZScore	16	2.28	0.89	0.62	1.71	2.00	2.74	4.02
Beta	16	0.81	0.36	0.22	0.53	0.79	1.02	1.39
Asset Turnover	16	0.63	0.16	0.37	0.53	0.64	0.76	0.94
Net Profit Margin (%)	16	2.69	9.03	-20.90	-1.98	4.00	8.25	15.20
Tot Debt/Tot Assets (%)	16	24.96	10.23	11.70	16.60	20.20	34.60	41.60
Current Ratio	16	1.29	0.20	1.04	1.16	1.29	1.37	1.79
Quick Ratio	16	0.71	0.17	0.46	0.62	0.70	0.80	1.08
WACC Equity Risk Premium (%)	16	7.54	2.15	4.20	6.53	7.20	8.00	12.10

We apply Z-score normalization to scale the independent variables and make them comparable across different scales. Z-scores, numerical measures from a dataset's mean and standard deviation are popularly employed as a performance metric by ranking developers based on their scores (Santhanakrishnan and Senthooran, 2022). Z-standardization allows us to normalize the values and put them on one scale so they are understandable and comparable in the same sense (Mukhametzyanov, 2023).

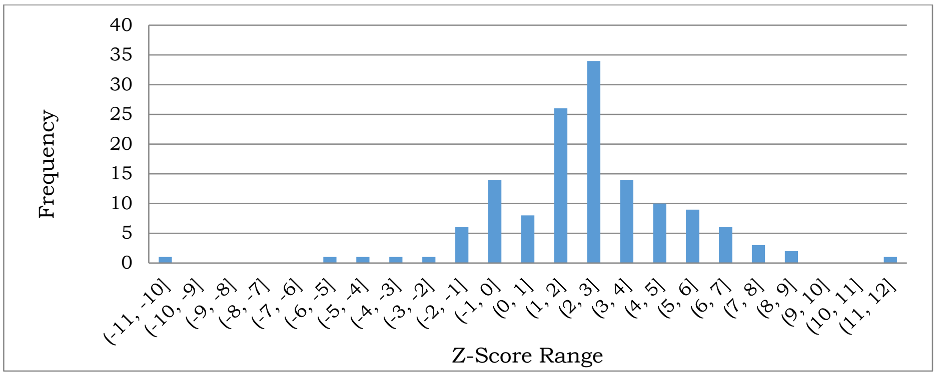
As shown in Table 2, financial metrics vary widely, particularly Net Profit Margin (%) and Total Debt/Total Assets (%), with standard deviations of 9.03 and 10.23, respectively. This high variability underscores the importance of normalization to mitigate the impact of extreme values and skewness. Additionally, the WACC Equity Risk Premium (%) ranges from 4.20% to 12.10%, indicating varying levels of risk across firms, which further supports the need for consistent data scaling.

The Altman Z-Score approach is a well-known framework for forecasting financial difficulties in companies in different industries so it evaluates the probability of bankruptcy. Developed by Edward I. Altman, the model crunches a variety of discriminant analyses to relegate companies into zones or risk tiers according to their Z-Scores and was adapted here to assist in decisions on the health of a firm (Ahuja and Singhal, 2014). According to Altman (1968), companies whose Z-scores are lower than 1.81 are considered poor beasts or bankrupt (very risky class) with a higher probability of declaring bankruptcy. Altman Z-Score dependent variable (binary classification) is defined as "*Distressed*". Specifically, instances (observations) with a Z-Score of less or equal to 1.8 are labeled Distressed (0), and all others i.e. greater than 1.8 as Not Distressed (1). This binary classification allows classification algorithms to predict financial distress effectively.

3.3. Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) is a conceptual knowledge of the dataset that helps to predict corporate financial distress. In this section, we give visualizations of the distribution of financial health for companies in the study and how this has evolved.

Figure 1: Distribution of Z-score



We use Altman Z-scores as the reliant metric for this analysis which is one of the most popular indicators of financial distress globally. In Figure 1, there is a very large amount of variation from negative to highly positive scores. The distribution of most companies has moderate Z-scores, and yet the tail is longer on the high end so many firms are doing merely a wash of their financial stability. This distribution depicts the wide spectrum of financial performance trends of the industry throughout the reporting period.

Figure 2: Z-scores by Company

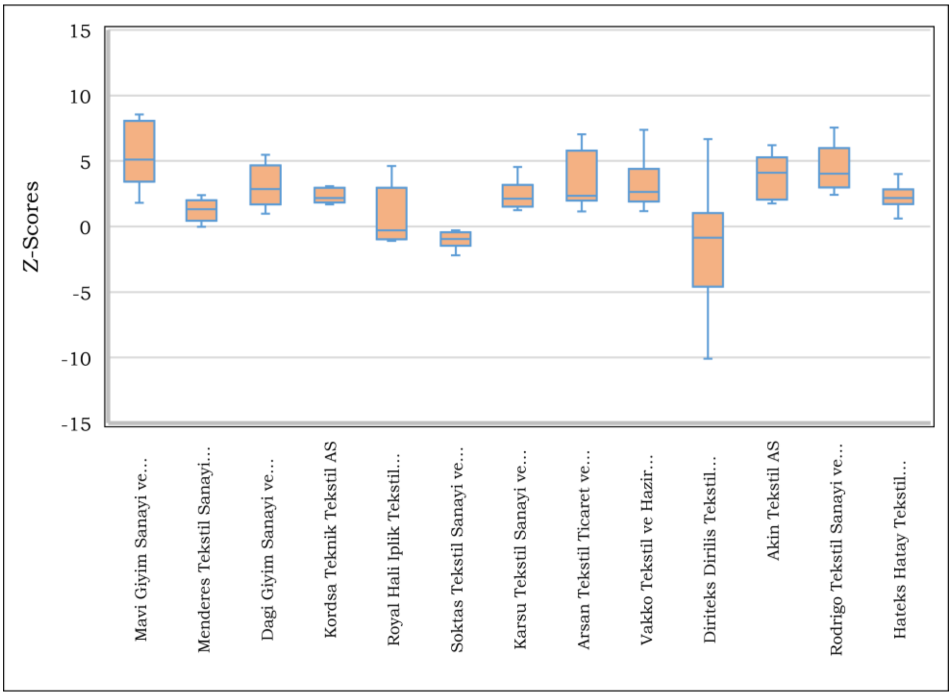


Figure 2 further disaggregates the distribution to Show that companies differ in terms of their financial distress. There are some companies that certainly always have better Z-scores consistently, indicating stable and solid financial health standing. In contrast, others display a broader range of Z-scores, suggesting periods of both stability and distress. Some companies also show many outliers, indicating that some firms had extreme events that caused them large swings in their Z-scores.

Figure 3: Number of Distressed vs. Not Distressed Companies

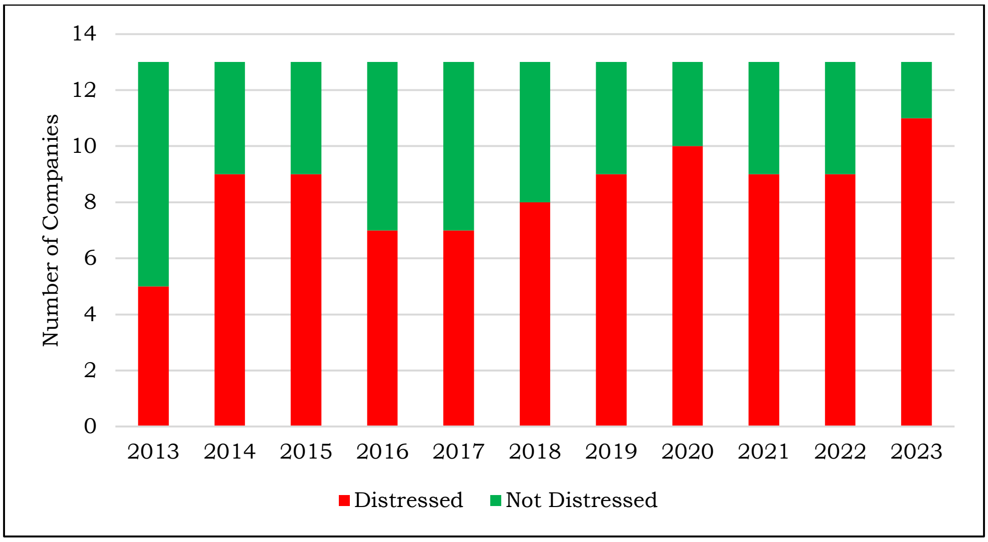
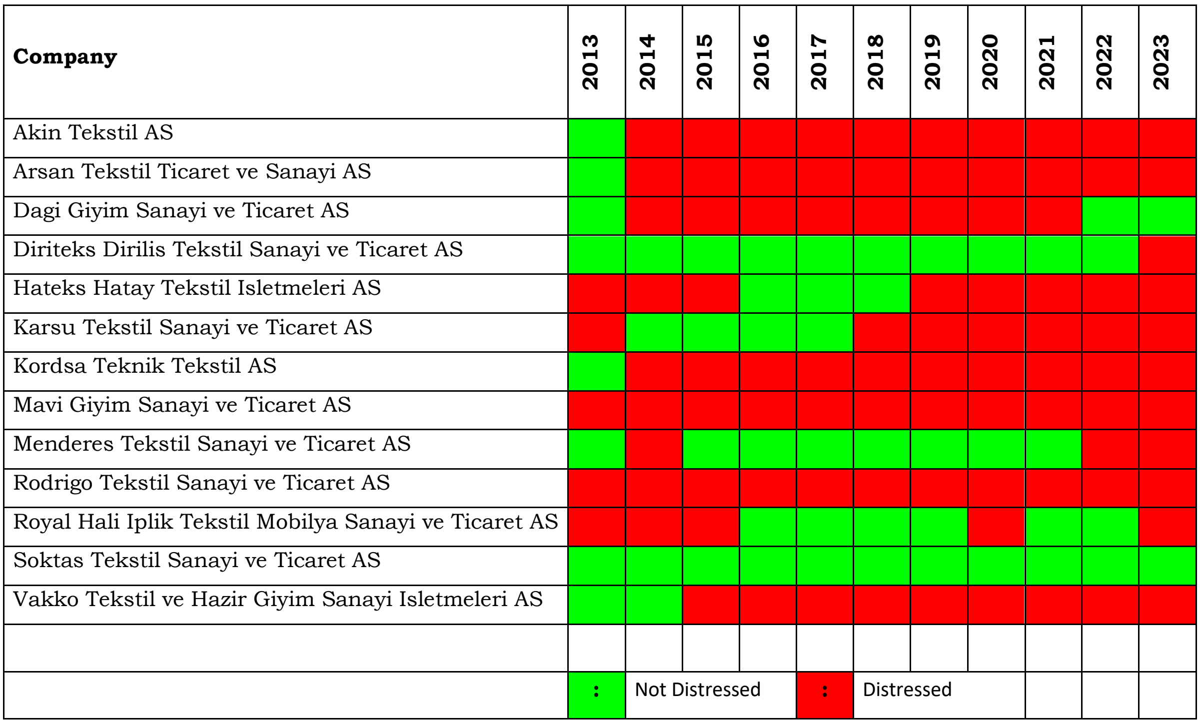


Figure 3 provides a clear cut to the number of distressed versus not distressed companies over the years and it gives an idea of where the industry is at its financial health trends. The chart shows some ups and downs over the number of bankrupt companies, certain years have more firms in trouble than others.

Figure 4: Company Financial Distress Status Over the Years



The plots of time-dependent financial distress status for all the companies are presented in Figure 4. This one-dimensional visualization provides a pixel-perfect, company-specific representation — where every cell suggests whether the company was in distress (Z-score < 1.8) or not distressed (Z-score ≥ 1.8) for a given year. The heatmap illustrates an evolution from financial health and distress of all companies in our study period, where some keep relatively stable for years profitable or lossmaking others oscillate between distress and stability.

This time-series view is important when trying to classify firms as chronically distressed versus temporarily financially disordered.

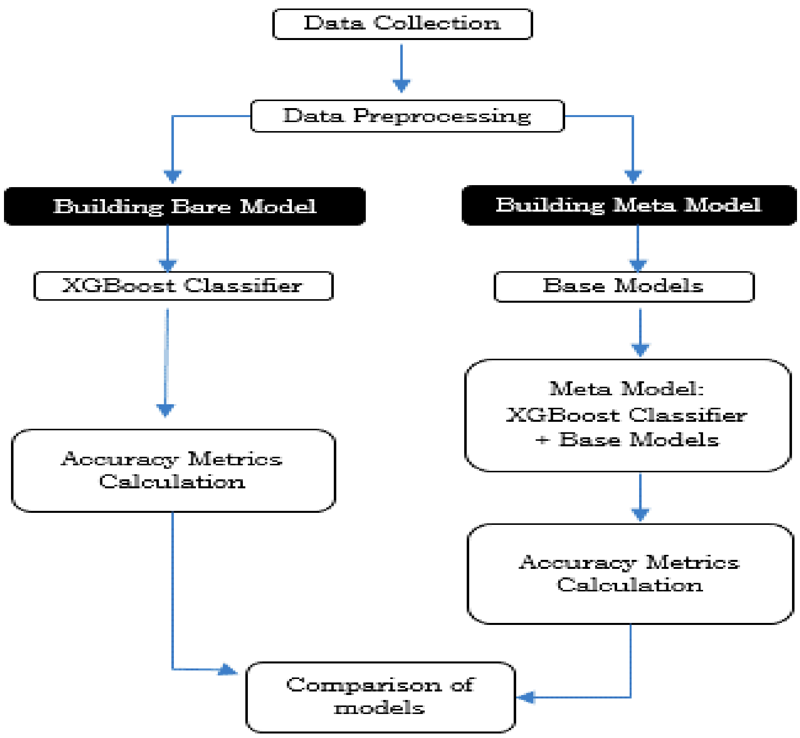
3.4 Train-Test Split Train-Test Split

The dataset is divided into 2 groups: 70% of the data is reserved for the training, comprising 100 observations, while the remaining 30%, consisting of 43 observations, is allocated for the test set. The split is conducted randomly, ensuring that the training set is representative of the overall dataset, including a balanced proportion of distressed and non-distressed companies.

3.5. Model Development

The method of building and testing two different predictive models: the bare model and the meta-model are depicted in Figure 5.

Figure 5: Model Development Workflow



Data collection and preprocessing followed by the workflow split which led to two branches one for a bare XGBoost model developing and the other building a meta-model relying on base classifiers. The first pathway involves the development of a bare model employing an XGBoost Classifier, which subsequently, calls for accuracy evaluation metrics. The second pathway on the other hand deals with building a meta-model where the models are developed first whole it is followed by an XGBoost Classifier approach to act as a meta-learner in immediate base estimators. A valid comparison of the bare and meta-models' performance in terms of predictive qualities is taken by computing these accuracy metrics of both and then arranging them systematic. The goal of our comparison study is to establish the efficacy of the meta-model method vs the bare model in terms of prediction accuracy and robustness.

The selection of base models, including Lasso Regression, Ridge Regression, Random Forest Classifier, Gradient Boosting Machine (GBM), and Support Vector Machine (SVM), is well-justified based on their strengths and suitability for handling diverse data characteristics. Lasso Regression is particularly effective for high-dimensional data with multicollinearity, offering both regularization and interpretability (Kan et al., 2019). Ridge Regression further mitigates multicollinearity issues while preventing overfitting (Chen & Jiang, 2017). Random Forest Classifier enhances predictive accuracy and captures complex, nonlinear relationships due to its ensemble learning structure (Rodriguez-Galiano et al., 2014). Gradient Boosting Machine (GBM) excels at feature discovery and handling intricate datasets (Xia et al., 2021). Support Vector Machine (SVM) is well-suited for classification tasks with complex decision boundaries (Chen, 2011). The XGBoost classifier was chosen as the meta-learner due to its high scalability, efficiency, and ability to integrate outputs from diverse models effectively (Sprangers et al., 2021). Moreover, evaluation metrics such as accuracy, precision, recall, and F1-score were deliberately selected to provide a comprehensive performance assessment, ensuring both correctness and robustness. This multifaceted evaluation approach ensures balanced insights into classification effectiveness, especially when managing class imbalances or varying misclassification costs.

A metamodel, or a combination of models, defines how specific model inputs are mapped to those corresponding outputs. These are frequently generated by sampling a direct model and training a machine learning algorithm to predict certain outputs while the input values change (Lejeune, 2020).

Meta-learning or, learning to learn, studies the systematic observations of different kinds of performance machines across multiple tasks and employs the lessons learned to help with the learning of the new tasks. This workflow leads to improved machine learning pipelines and neural architecture design as well as data-driven algorithms in the place of classical hand-engineered heuristics (Vanschoren, 2019). They are most helpful in few-shot learning settings wherein these frameworks can lower the meta-model space to learn and in general show improvement on what we've unseen before (Ye et al., 2021). Besides that, meta-learning helps non-expert users with learning algorithms that are likely to perform well for a specific dataset, greatly decreasing the need for extensive human model building and data analysis (Shahoud et al., 2021).

Combined the outputs per base models and produced yet another dataset, which is now known as the meta-feature dataset. It is used as input for the meta-model in this case is the XGBoost classifier.

Table 3: Models

Model	**Parametreler**
Lasso Regression	alpha=1.0, max_iter=1000, tol=0.0001
Ridge Regression	alpha=1.0, solver='auto', max_iter=1000
Random Forest	n_estimators=100, max_depth=None, random_state=42
Gradient Boosting Machine (GBM)	n_estimators=100, learning_rate=0.1, max_depth=3
Support Vector Machine (SVM)	C=1.0, kernel='rbf', gamma='scale'
XGBoost (Meta Model)	n_estimators=100, learning_rate=0.1, max_depth=3, eval_metric='logloss'

XGBoost meta-model was fitted on the meta-feature data frame with the original Distressed training labels. Hyperparameters were tuned for both model complexity and performance, to make sure that the meta-model was synthesizing the inputs effectively from all base models.

The trained meta-model produced final binary predictions for each observation, classifying firms as distressed or not distressed by the aggregated insights of the base models. Similarly, we trained the XGBoost model on the original Distressed labels from the training set. The model (once tuned with its hyperparameters for tradeoff between complexity and correctness) classified the firms accordingly as either Distressed or Not Distressed by doing some pattern matching on the dataset.

3.6. Model Results

The comparison between the Bare XGBoost classifier and the Meta Model (Base Models + XGBoost) illustrates that the Meta Model performs better across most metrics as shown in Table 4. Meta Model has a significantly better accuracy of 86.0% than the Bare XGBoost (83.72%), which means that it is overall more correct in classifying. The Meta Model also excels in a recall, with 93.0%, suggesting it is better at identifying distressed companies than the Bare XGBoost, which has a recall of 80.77%. The F1 score is stronger (90.0% vs. 85.71%), meaning the balance between precision and recall might be better in the Meta Model. However, the Bare XGBoost performs better in precision (91.3% vs. 85.0%), which is more reliable when predicting a company as distressed.

Table 4: Model Results

Model	Bare XGBoost Classifier	Meta Model (Base Models + XGBoost Classifier)
Accuracy (%)	83.72	86.0
Precision (%)	91.3	85.0
Recall (%)	80.77	93.0
F1 Score (%)	85.71	90.0

The primary goal is to predict corporate financial distress accurately; minimizing false negatives is likely more critical. Missing a distressed company could have severe financial and operational repercussions. For that, the Meta-Model wins again with better recall and F1 score (90.00%). The meta-model does not increase the classification performance of a model, but the reduction in precision which stems from it is compensated by a larger recall and thus there is an overall improvement in a precision-recall trade-off. This means that the meta-model is therefore more reasonable and practical for financial distress prediction, where the cost of missing a distressed company (false negative) is much higher than the cost of a false alarm (false positive).

4. Discussion

In this study, we provide the basic XGBoost classifier and directly compare it to a meta-model for forecasting economic distress in businesses. Meta-model is far better than XGBoost in reducing false negatives -- an important aim when predicting financial distress. Previous literature suggests ensemble learning approaches, especially with meta-models show better performance than a single predictor like XGBoost. Studies in line with Chen et al. (2024) have developed the efficiency of classifier combination, which is consistent with our comparison in that the meta-model outperforms XGBoost across the board for important metrics in this study. Higher recall and F1 scores of the meta-model reflect better performance in catching distressed companies, which is important for the detection of financial distress.

Financial distress prediction criteria were studied in this research, with the primary objective of reducing false negatives in that failing to predict an impending declared bankruptcy can result in a loss of opportunity for early intervention and bankruptcy. The meta-model's recall of 93% makes it much better suited for this goal than XGBoost, which achieved a recall of 80.77%. The meta-model shows this feature its value in this important area, as it can identify distressed companies better.

While the slightly lower precision of the meta-model (85%) compared to XGBoost (91.3%) highlights the trade-off between precision and recall, recall is typically prioritized in the context of financial distress prediction. In volatile industries, false positives outweigh the overfit of a meta-model and thus, we prefer the meta-model for its high recall. Recall is highest with the meta-model so that is especially important in sectors such as textiles being ridden with financial volatility state.

The performance metrics observed in this study—accuracy (86%), precision (85%), recall (93%), and F1 score (90%)—are consistent with results reported in the literature. For example, recent works like Engin and Durer (2023) had analogous results when applying XGBoost for financial distress prediction on Borsa Istanbul data which confirms the credibility of machine learning models in this kind of analytics. These comparable results thus also lend further support to predictive distress modeling, and machine learning particularly when financial ratios can be considered as independent variables.

Despite the strong performance of the meta-model, it should be noted that there are several limitations. The model using only historical financial data from one industry can run the risk of not being able to generalize the results. This meta-model approach should be further investigated in other industries and geographies to judge the wider applicability of the model. For instance, Arini (2021) explored global retail companies using the Grover model, achieving a lower accuracy of 76.67%. The application of meta-models to different sectors could serve as a validation of their generalized utility.

Even if the meta-model is expressive at predicting accurately, interpretability is hard. Most meta-models are not easily interpretable, as is usual with complex models. One way to solve this problem, Zhang et al. (2022) propose employing explainable AI methods for supporting transparency. In subsequent studies, researchers can incorporate explainable AI techniques like Shapley additive explanations to increase accessibility to decision-makers while maintaining the power of these advanced models.

From a practical standpoint, stakeholders such as financial analysts, investors, and policymakers can leverage the meta-model's predictions to make proactive decisions. For instance, investors can use early distress signals to adjust their portfolios and mitigate risk exposure, while financial institutions can tighten credit policies for at-risk firms. Policymakers may implement sector-specific support strategies based on predictive insights to stabilize vulnerable industries. Additionally, integrating explainable AI methods can further empower stakeholders by providing transparent reasoning behind distress predictions, fostering trust and enabling more informed decision-making.

This study applied several key methodological strategies to enhance robustness and mitigate the risk of overfitting. Stratified sampling was used to ensure a balanced representation of distressed and non-distressed companies, preventing bias in model evaluation. Missing values were imputed, and independent variables were standardized to avoid the overfitting risk.

Additionally, the meta-model combines predictions from multiple base models—Lasso, Ridge, Random Forest, Gradient Boosting, and Support Vector Machine—each capturing distinct patterns in the data. By leveraging the strengths of these base models, the meta-model improves the generalizability of the final prediction. Meta-models borrow the techniques provided by base models such as Lasso and Ridge regression to decrease overfitting, enable and then generalize the solution for unseen input ranges.

The model is further evaluated on an independent test set to determine that its performance can still hold up beyond just the training data using metrics such as accuracy, precision, recall, and F1 scores.

5. Conclusion

In this study, we used a meta-model strategy to predict financial distress in the Turkish textile sector. It outperforms XGBoost for early detection of financial distress, especially in reducing false negatives and understanding its potential as well. This result is important for financial distress prediction because the non-observation of distressed firms will certainly cost them bankruptcy. The results are very indicative that meta-models may be employed as a useful tool in the classification of financial distress in volatile sectors, such as textiles.

This research sheds light on how machine learning models, especially meta-models can help improve the performance of financial distress predictions. The study results show that meta-models are superior in reducing false negative performance; identifying insights is invaluable for enhancing the predictive accuracy of financial distress models. These findings are relevant to the overall debate on financial distress prediction, discussing the benefits of meta-modeling techniques for better risk-management practices elaboration in dynamic sectors.

The study contributes to the literature by showing meta-models can predict financial distress and this specificity can be exploited in an industry-specific context. The first of which is to illustrate the power of employing a meta-model to amalgamate the attributes of several base models for financial distress prediction. Better performance (recall and F1 score) with the meta-model than all other baselines shows that this method adds significant value over existing approaches. This research also brings discussion of the importance of sector-specific models and explains that within textiles financial ratios can inform distress (possibly to be applied across other sectors).

This study has however several limitations as well. The historical financial data of a single industry used in this study may limit the generalization of the results. The method must be further developed for other sectors and regions to confirm its appropriateness. Moreover, incorporating additional indicators (non-financial like macroeconomic variables or sentiment analysis) could further improve the predictive power and relevance of the model in changing economic environments.

Future research should explore how the integration of sector-specific models with macroeconomic and market sentiment indicators can enhance predictive accuracy across diverse industries. Additionally, expanding the model to account for global economic trends and cross-industry comparisons could offer deeper insights into financial distress patterns. Addressing these aspects will not only validate the model's adaptability but also contribute to the broader research on financial distress prediction, potentially leading to more comprehensive and resilient risk management strategies.

Statement of Support and Acknowledgments: No external support was received in the preparation of this research.
Declaration of Researchers' Contribution Rate: Both authors contributed equally to this study. Ahmet Akusta and Musa Gün shared responsibility and contributions equally, with each author contributing 50% throughout all stages of the research. These contributions include the research design, data collection, analysis, writing, and revision processes.
Conflict Declaration: As the authors of the research, we do not declare any conflict of interest.
Research and Publication Ethics Statement: All rules specified in the Higher Education Institutions Scientific Research and Publication Ethics Directive have been complied with. None of the actions specified under the heading "Actions Contrary to Scientific Research and Publication Ethics" of the directive have been carried out. During the writing process of this study, citations were made in accordance with ethical rules, and a bibliography was created. The work has been checked for plagiarism check.
Ethics Committee Permission: The study does not require ethics committee permission

References

Abdullayev, I., Osadchy, E., Shcherbakova, N., & Kosorukova, I. (2025). An innovative approach to financial distress prediction using relative weighted neutrosophic valued distances. *International Journal of Neutrosophic Science*, 370–381. https://doi.org/10.54216/IJNS.250133

Agung Saputra, J. (2019). The effect of liquidity ratio, leverage ratio, and activity ratio in predicting financial distress. *Management and Economic Journal*, 3(5), 581-592.

Ahuja, B. R., & Singhal, N. (2014). Assessing the financial soundness of companies with special reference to the Indian textile sector: An application of the Altman Z score model. *Indian Journal of Finance*, 8(4), 38–48. https://doi.org/10.17010/ijf/2014/v8i4/71922

Akkaya, G. C. (2008). Sermaye yapısı, varlık verimliliği ve karlılık: imkb'de faaliyet gösteren deri-tekstil sektörü işletmeleri üzerine bir uygulama. *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, (30), 1-13.

Altaş, D., & Giray, S. (2005). Mali başarısızlığın çok değişkenli istatistiksel yöntemlerle belirlenmesi: Tekstil sektörü örneği. *Sosyal Bilimler Dergisi,* (2), 13-28.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589–609. https://doi.org/10.2307/2978933

Apasya, T., Machmuddah, Z., & Sumaryati, A. (2023). The effect of financial ratios on financial distress conditions is moderated by profitability ratios. *Jurnal Penelitian Ekonomi dan Bisnis*, 8(2), 67-79. https://doi.org/10.33633/jpeb.v8i2.7961

Arifuddin, A., Erwin, H., Ika Sari, M., & Annisa Yulianti, F. (2023). How liquidity, profitability, and leverage ratios influence financial distress: A study on Indonesian mining firms. *Jurnal Perspektif Pembiayaan dan Pembangunan Daerah,* 11(3), 243-252. https://doi.org/10.22437/ppd.v11i3.27470

Arini, I. N. (2021). Analisis akurasi model-model prediksi financial distress. *Jurnal Ilmu Manajemen*, *9*(3), 1196-1204. https://doi.org/10.26740/jim.v9n3.p1196-1204

Arini, S. A., Samrotun, Y. C., & Masitoh, E. (2021). Determinant of financial ratio analysis to financial distress. *Jambura Science of Management*, 3(1), 26-35. https://doi.org/10.37479/jsm.v3i1.6962

Ashraf, S., Félix, E. G. S., & Serrasqueiro, Z. (2019). Do traditional financial distress prediction models predict the early warning signs of financial distress? *Journal of Risk and Financial Management*, 12(2), 55. https://doi.org/10.3390/jrfm12020055

Atika, Darminto, & Siti Handayani, R. (2013). Pengaruh Beberapa Rasio Keuangan terhadap Prediksi Kondisi Financial Distress. *Jurnal Administrasi Bisnis*, 1(2), 1-11.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance*, 63(6), 2899–2939. https://doi.org/10.1111/j.1540-6261.2008.01416.x

Cao, Y., Guang-yu, W., & Wang, F. (2011). Predicting financial distress of Chinese listed companies using rough set theory and support vector machine. *Asia-Pacific Journal of Operational Research*, 28(01), 95–109. https://doi.org/10.1142/s0217595911003077

Chaves, R. M., Rossi, A. L. D., & Garcia, L. P. F. (2023). A financial distress prediction using a non-stationary dataset. *Anais do XX Encontro Nacional de Inteligência Artificial e Computacional (ENIAC 2023),* 300-314. https://doi.org/10.5753/eniac.2023.234013

Chaves, R., Debiaso, A. L., & García, L. E. (2023). Financial distress prediction in an imbalanced data stream environment. *Lecture Notes in Computer Science*, 168–179. https://doi.org/10.1007/978-3-031-40725-3_15

Chen, J., & Jiang, Y. (2017). Optimal margin distribution ridge regression. *Journal of Computer Research and Development, 54*(8), 1744–1750. https://doi.org/10.7544/issn1000-1239.2017.20170349

Chen, L. (2011). Social post-evaluation of World Bank projects in Yanhe Basin based on ridge regression and support vector machines. In *2011 3rd International Workshop on Intelligent Systems and Applications (ISA 2011)*. IEEE. https://doi.org/10.1109/ISA.2011.5873358

Chen, X., Wu, C., Zhang, Z., & Liu, J. (2024). Multi-class financial distress prediction based on stacking ensemble method. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.3020

Eduard, A., Binsar, N., & Adeline, N. (2023). Ratio analysis to financial distress with profitability as a moderation variable. *Jurnal Reviu Akuntansi dan Keuangan,* 13(2), 412-440. https://doi.org/10.22219/jrak.v13i2.24506

El-Bannany, M., Sreedharan, M., & Khedr, A. M. (2020). A robust deep learning model for financial distress prediction. *International Journal of Advanced Computer Science and Applications*, 11(2). https://doi.org/10.14569/IJACSA.2020.0110222

Elhoseny, M., Metawa, N., Sztanó, G., & El-Hasnony, I. M. (2022). Deep learning-based model for financial distress prediction. *Annals of Operations Research*. https://doi.org/10.1007/s10479-022-04766-5

Elmi Dini, T., & Umi, M. (2023). Financial distress perusahaan sektor pariwisata: Pengaruh profitabilitas, likuiditas dan leverage. *Prosiding Seminar Nasional Forum Manajemen Indonesia*, 1, 257-73. https://doi.org/10.47747/snfmi.v1i.1506.

Engin, U., & Durer, S. (2023). Financial Distress Prediction from Time Series Data Using Xgboost: Bist100 of Borsa Istanbul. Doğuş Üniversitesi Dergisi, 24(2), 589-604. https://doi.org/10.31671/doujournal.1238432

Ezin, Y. (2022). Tekstil sektörünün oran analizi ve topsis yöntemi ile değerlendirilmesi. *Kafkas Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi,* *13*(25), 213-243. https://doi.org/10.36543/kauiibfd.2022.010

Fatimah, F., Akhmad, T., & Aryo, P. (2019). The influence of liquidity, leverage and profitability ratio on financial distress. *Owner, 3*(1), 103. https://doi.org/10.33395/owner.v3i1.102

Goetz, S. (2020). Is financial distress value relevant? – Implications for multiple-based valuation. *Journal of Business Valuation and Economic Loss Analysis*, *15*(1), 20190015. https://doi.org/10.1515/jbvela-2019-0015

Ha, H. H., Dang, N. H., & Tran, M. D. (2023). Financial distress forecasting with a machine learning approach. *Corporate Governance and Organizational Behavior Review*, 7(3), 90-104. https://doi.org/10.22495/cgobrv7i3p8

Hadi, M. F., Liang, D.-R., Priyambodo, T. K., & Sn, A. (2022). Financial distress prediction with stacking ensemble learning. *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, *16*(3), 281. https://doi.org/10.22146/ijccs.76575

Heymans, A., & Brewer, W. (2023). Measuring the relationship between intraday returns, volatility spillovers, and market beta during financial distress. In P. W. Buys & M. Oberholzer (Ed.), *Business Research,* 77-98. Springer Nature Singapore. https://doi.org/10.1007/978-981-19-9479-1_5

Islam, M. N., Li, S., & Wheatley, C. M. (2023). Accounting comparability and financial distress. *Review of Accounting and Finance*, 22(3), 353–373. https://doi.org/10.1108/raf-07-2022-0207

Jorge Ceron, M. (2012). Going distress on the WACC. *Social Science Research Network*. https://doi.org/10.2139/SSRN.2464431

Kan, H. J., Kharrazi, H., Chang, Y., Bodycombe, D., Lemke, K., & Weiner, J. P. (2019). Exploring the use of machine learning for risk adjustment: A comparison of standard and penalized linear regression models in predicting health care costs in older adults. *PLOS ONE, 14*(3), e0213258. https://doi.org/10.1371/journal.pone.0213258

Khoja, L., Chipulu, M., & Jayasekera, R. (2019). Analysis of financial distress cross countries: Using macroeconomic, industrial indicators and accounting data. *International Review of Financial Analysis*, 66, 101379. https://doi.org/10.1016/j.irfa.2019.101379

Kong, L., Zhu, Z., Xu, L., Wu, T., & Xu, X. (2023). Neural network-based financial distress prediction for listed companies in china. *Proceedings of the 2023 4th International Conference on Big Data Economy and Information Management*, 199-203. https://doi.org/10.1145/3659211.3659245

Korteweg, A. G. (2007). The costs of financial distress across industries. *Social Science Research Network*. https://doi.org/10.2139/SSRN.945425

Lejeune, E. (2020). Mechanical MNIST: A benchmark dataset for mechanical metamodels. *Extreme Mechanics Letters*, 36. https://doi.org/10.1016/j.eml.2020.100659

Lestari, F. (2023). Prediksi finansial distress pada salah satu bank konvensional menggunakan machine learning. *Indonesian Journal of Applied Mathematics*, 3(1), 21. https://doi.org/10.35472/indojam.v3i1.1284

Liu, J., Wu, C., & Li, Y. (2019). Improving financial distress prediction using financial network-based information and GA-based gradient boosting method. *Computational Economics*, 53(2), 851–872. https://doi.org/10.1007/S10614-017-9768-3

Lumbantobing, R. (2020). The effect of financial ratios on the possibility of financial distress in selected manufacturing companies which listed in indonesia stock exchange. *Proceedings of the 6th Annual International Conference on Management Research (AICMaR 2019)*. Jakarta, Indonesia. https://doi.org/10.2991/aebmr.k.200331.014

Maheswari, K., Packia Amutha Priya, P., Ramkumar, S., & Arun, M. (2020). Missing data handling by mean imputation method and statistical analysis of classification algorithm. *EAI/Springer Innovations in Communication and Computing*, 137–149. https://doi.org/10.1007/978-3-030-19562-5_14

Mavengere, K., & Gumede, P. (2024). Financial distress prediction competence of the Altman Z score and Zmijewski model: Evidence from selected Zimbabwe stock exchange firms. *Journal of Business, Economics and Finance,* 11(1), https://doi.org/10.17261/pressacademia.2024.1892

Mufidah, K., & Handayani, A. (2024). Prediksi financial distress pada sektor perbankan dengan menggunakan metode Altman Z-Score, Grover, Springate dan Zmijewski. *Jurnal Ekonomi Manajemen Sistem Informasi (JEMSI),* 5(6), 540-553. https://doi.org/10.38035/jemsi.v5i6.2479

Mukhametzyanov, I. Z. (2023). MS-transformation of Z-score. *International Series in Operations Research and Management Science*, 348, 151–166. https://doi.org/10.1007/978-3-031-33837-3_8

Nurtati, & Yuni, S. (2023). The effect of financial ratio on financial distress (Empirical study on sub industry of hotels, resorts and cruise lines listed on the Indonesia Stock Exchange). *Galore International Journal of Applied Sciences and Humanities,* 6(4), 30-44. https://doi.org/10.52403/gijash.20221006

Prapanca, D., & Kumalasari, H. M. (2023). Strategic formulations and financial distress: İnsights from sales growth and profitability ratios. *JBMP (Jurnal Bisnis, Manajemen dan Perbankan)*, *9*(2), 210-225. https://doi.org/10.21070/jbmp.v9i2.1814

Pravin, P., & Dhabaliya, D. A. (2023). Analysis of financial distress using Altman's Z-score model in selected Indian pharmaceutical companies. *Journal of Advanced Research in Economics and Administrative Sciences*. *4*(4), 1-13. https://doi.org/10.47631/jareas.v4i4.626

Putri, R. A., & Hendayana, Y. (2022). Pengaruh rasio profitabilitas, rasio solvabilitas, dan rasio likuiditas terhadap financial distress. *Fair Value: Jurnal Ilmiah Akuntansi dan Keuangan*, *4*(12), 5646-5653. https://doi.org/10.32670/fairvalue.v4i12.2091

Ramzan, S. (2023). Comparison of financial distress prediction models using financial variables. *2023 International Conference on Electrical, Computer and Energy Technologies*, 1-7. https://doi.org/10.1109/ICECET58911.2023.10389294

Rodriguez-Galiano, V., Mendes, M. P., Garcia-Soldado, M. J., Chica-Olmo, M., & Ribeiro, L. (2014). Predictive modeling of groundwater nitrate pollution using Random Forest and multisource variables related to intrinsic and specific vulnerability: A case study in an agricultural setting (Southern Spain). *Science of the Total Environment, 476–477*, 189–206. https://doi.org/10.1016/j.scitotenv.2014.01.001

Santhanakrishnan, K., & Senthooran, V. (2022). A parallel distributed cluster computing model for Z-score computation in respect of Sri Lankan university admissions. *ICARC 2022 - 2nd International Conference on Advanced Research in Computing*, 344–348. https://doi.org/10.1109/ICARC54489.2022.9754093

Say, S. (2024). Determining Financial Distress with The Help Of The Altman Z-Score Model. *Toplum Ekonomi Ve Yönetim Dergisi*, 5(2), 327-341. https://doi.org/10.58702/teyd.1416150

Sehgal, S., Mishra, R. K., Deisting, F., & Vashisht, R. (2021). On the determinants and prediction of corporate financial distress in India. *Managerial Finance*, 47(10), 1428–1447. https://doi.org/10.1108/MF-06-2020-0332

Shahoud, S., Winter, M., Khalloof, H., Duepmeier, C., & Hagenmeyer, V. (2021). An extended meta learning approach for automating model selection in big data environments using microservice and container virtualizationz technologies. *Internet of Things (Netherlands)*, 16. https://doi.org/10.1016/j.iot.2021.100432

Sharma, B., Srikanth P, & Jeevananda, S. (2023). Financial distress and value premium using altman revised z-score model. *Vision: The Journal of Business Perspective*, *0*(0). https://doi.org/10.1177/09722629231198604

Silviyani, Y. A., Risthi, A., & Afandi, A. (2024). Prediksi financial distress model almant z-score, kinerja keuangan dan pengaruhnya terhadap nilai perusahaan. *AKADEMIK: Jurnal Mahasiswa Ekonomi & Bisnis*, *4*(2), 692-704. https://doi.org/10.37481/jmeb.v4i2.789

Sprangers, O., Schelter, S., & De Rijke, M. (2021). Probabilistic gradient boosting machines for large-scale probabilistic regression. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1510–1520). ACM. https://doi.org/10.1145/3447548.3467278

Sun, J., Liu, X., Ai, W., & Tian, Q. (2021). Dynamic financial distress prediction based on class-imbalanced data batches. *International Journal of Financial Engineering*, 08, 2150026. https://doi.org/10.1142/S2424786321500262

Suryani, S., & Desy, M. (2022). Memprediksi financial distress melalui faktor internal pada perusahaan jasa sub sektor property dan real estate. *Jurnal Ilmiah Akuntansi Kesatuan*. https://doi.org/10.37641/jiakes.v10i3.1441

T.C. Ticaret Bakanlığı. (t.y.). *Sektörler*. Kolay İhracat. Retrieved January 11, 2025, from https://www.kolayihracat.gov.tr/sektorler/

Tang, X., Li, S., Tan, M., & Shi, W. (2020). Incorporating textual and management factors into financial distress prediction: A comparative study of machine learning methods. *Journal of Forecasting*, 39(5), 769–787. https://doi.org/10.1002/FOR.2661

Tran, K. L., Le, H. A., Nguyen, T. H., & Nguyen, D. T. (2022). Explainable machine learning for financial distress prediction: Evidence from vietnam. Data, 7(11), 160. https://doi.org/10.3390/data7110160

Vanschoren, J. (2019). Meta-Learning. In: Hutter, F., Kotthoff, L., Vanschoren, J. (eds) Automated Machine Learning. *The Springer Series on Challenges in Machine Learning*. Springer, Cham. https://doi.org/10.1007/978-3-030-05318-5_2

Vebrizha, N., Nilwan, A., & Riswan. (2024). The impact of financial ratios on financial distress in the transportation sector. *Asian Journal of Economics and Business Management*, *3*(1), 421-428. https://doi.org/10.53402/ajebm.v3i1.391

Wang, G., Chen, G., & Chu, Y. (2018). A new random subspace method incorporating sentiment and textual information for financial distress prediction. *Electronic Commerce Research and Applications*, 29, 30–49.

Wang, S., & Chi, G. (2024). Cost-sensitive stacking ensemble learning for company financial distress prediction. *Expert Systems with Applications*, 255. https://doi.org/10.1016/j.eswa.2024.124525

Widiastuti, W., & Ali Ikhsan, N. (2022). Pengaruh rasio likuiditas, profitabilitas, dan leverage terhadap financial distress. *Eqien - Jurnal Ekonomi dan Bisnis,* 11(04). https://doi.org/10.34308/eqien.v11i04.1287

Wisnu, F., & Astuti, D. P. (2023). Financial distress: Profitability ratios and liquidity ratios, with financial statement fraud as moderating. Economic Education Analysis Journal, 12(2), 15-26. https://doi.org/10.15294/eeaj.v12i2.67570

Xia, Y., Cheng, K., Cheng, Z., Rao, Y., & Pu, J. (2021). GBMVis: Visual analytics for interpreting gradient boosting machine. In *Lecture Notes in Computer Science (Vol. 12983, pp. 63–72).* Springer. https://doi.org/10.1007/978-3-030-88207-5_7

Ye, H.-J., Li, X.-C., & Zhan, D.-C. (2021). Task cooperation for semi-supervised few-shot learning. *35th AAAI Conference on Artificial Intelligence*, AAAI 2021, 12A, 10682–10690.

Yu, L., Li, M., & Liu, X. (2024). A two-stage case-based reasoning driven classification paradigm for financial distress prediction with missing and imbalanced data. *Expert Systems with Applications, 249, 123745.* https://doi.org/10.1016/j.eswa.2024.123745

Zeng, S., Li, Y., & Yang, W. (2020). A financial distress prediction model based on sparse algorithm and support vector machine. *Mathematical Problems in Engineering*, 2020, 1–11. https://doi.org/10.1155/2020/5625271

Zhang, Z., Wu, C., Qu, S., & Chen, X. (2022). An explainable artificial intelligence approach for financial distress prediction. *Information Processing and Management*, 59(4), 102988. https://doi.org/10.1016/j.ipm.2022.102988

Zhao, S., Xu, K., Wang, Z., Liang, C., Lu, W., & Chen, B. (2022). Financial distress prediction by combining sentiment tone features. *Economic Modelling*, 106, 105709.

Zhong, J., & Wang, Z. (2022). Artificial intelligence techniques for financial distress prediction. AIMS Mathematics, 7(12), 20891–20908. https://doi.org/10.3934/math.20221145