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Research Article

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Predicting Financial Distress with Machine Learning and Explainable Artificial Intelligence: A Study on BIST

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Abstract Predicting financial distress is vital for business survival in dynamic environments. This prediction is realized with the help of models built on financial ratios. Classical models are frequently used to predict financial distress. However, models based on machine learning (ML) algorithms offer new perspectives in this field. This study aims to classify financial distress using ML algorithms. In this study, 39 financial ratios were obtained from the financial statements of 198 enterprises operating in Borsa Istanbul (BIST) between 2015 and 2020. The study was evaluated using three different scenarios. First, all ratios were analyzed using ML algorithms. Second, financial ratios selected via F-regression were used and these ratios were classified using ML algorithms. Third, the stacking ML models were classified into all and selected ratios. All models were tested with a 10-fold cross-validation. According to the experimental results, the CatBoost algorithm obtained the highest average accuracy, with 0.967 in the second scenario. In general, the Boosting-based algorithms showed higher performance than the other algorithms. In addition, the results obtained with the CatBoost algorithm were evaluated by the SHapley Additive exPlanations analysis to explain the importance of financial ratios. SHAP analysis applied to the CatBoost algorithm revealed that the equity-to-asset-ratio (Feature 4) and debt ratio (Feature 3) were the most effective variables in predicting financial distress. The findings underscore the importance of capital structure in assessing financial distress.

Keywords Financial Distress · Financial Ratio · Borsa Istanbul · Machine Learning · Explainable Artificial Intelligence

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INTRODUCTION

In the global economy, insufficient working capital due to the radical changes in a business leads to financial distress and the business's inability to fulfill its obligations with its existing assets (Van Gestel et al., 2006; Wang et al., 2018). Businesses and financial analysts frequently encounter the adverse consequences of financial distress (Gregova et al., 2020). The process of financial distress in businesses is continuous and dynamic; therefore, it can last from a few months to several years. Ultimately, it leads to corporate bankruptcy (Sun et al., 2014). Therefore, considering the current risks and uncertainties that at business may face, predicting financial distress is essential for a long-term situation.

Financial distress prediction methods are an important tool used to measure businesses' solvency, determine the variables that cause distress through financial statements, and distinguish the underlying causes of this distress (Altman et al., 2017). The failure of financial managers to use tools to predict financial distress (Sun et al., 2021) has devastating effects on the business and all stakeholders (Hafiz et al., 2015; Huang et al., 2015). Ultimately, this situation can lead to corporate bankruptcy (Sun et al., 2014), which can result in significant losses not only for the business world but also for the national economy (Huang et al., 2015).

Financial distress prediction is a topic that researchers have addressed for many years. The methods developed in this regard are based on financial ratios derived from financial statements (Laitinen and Laitinen, 2000). Most of the classical prediction methods based on these ratios (Beaver (Beaver, 1966), Altman's Z-score (Altman, 1968), Springate S-score (Springate, 1978), Ohlson O-Score (Ohlson, 1980), and Fulmer H (Fulmer et al., 1984), etc.) used statistical techniques such as regression analysis, multivariate discriminant analysis, and logit to classify businesses as financial normal or distress (Altman, 1968; Ohlson, 1980; Dimitras et al., 1996; Dizgil, 2018). Today, these prediction methods are still used in many industries such as food, textiles, and hospitality (Jawabreh et al., 2017; Medetoğlu and Tutar, 2023; Saha, 2024; Sánchez-Almeyda et al., 2025; Yıldırım and Özekenci, 2025). However, the use of a limited number of financial ratios, nonlinear relationships, and complex interactions between variables in classical forecasting methods limit modeling capacity. Additionally, statistical techniques are often inadequate for making predictions based on historical data and struggling to adapt to dynamic market conditions (Cortes and Vapnik, 1995). There is an increasing need for more innovative and practical approaches to predicting financial distress. Machine Learning (ML) algorithms with universal approach features, big data, and historical data are preferred for predicting future financial distress (Bumin and Ozcalici, 2023).

Related Works

Many ML algorithms based on Random Forests (RF), Artificial Neural Networks (ANN) and Boosting have been widely used to predict financial distress in research applied in different countries. For example, Huang and Yen (2019) used 16 financial ratios from the financial statements of Taiwanese firms between the periods 2010 and 2016. These rates were classified with the Extreme Gradient Boosting (XGBoost) algorithm and reached 90.6% on precision value. Similarly, Qian et al. (2022) evaluated the algorithms with a 10-fold cross-validation method using financial data from 4167 companies listed in China between 2001 and 2019. They obtained high results with the proposed PIMP-XGBoost model. Tran et al. (2022) used 25 financial ratios in Vietnam and achieved the highest classification accuracy with a ratio of 0.9566 in XGBoost. In addition, their study evaluated financial ratios using the SHapley Additive exPlanations (SHAP) method, and the results of ML algorithm were transparently explained. Engin and Durer (2023) used 25 financial ratios and the

XGBoost. They achieved 91.6% accuracy with their proposed model in Borsa Istanbul (BIST). Although they were applied in different years, with varying numbers of rates and countries, Huang and Yen (2019), Qian et al. (2022), Tran et al. (2022), and Engin and Durer (2023) showed successful results in the XGBoost. Zhao et al. (2022) predicted financial distress using 22 financial ratios from data between 2016 and 2020 and achieved a high accuracy of 97.6% with the Categorical Boosting (CatBoost). Similarly, Zhong and Wang (2022) predicted financial distress with ML models using the financial ratios of Chinese manufacturing companies between 2016 and 2021 and obtained the best average accuracy result (96.33%) in CatBoost.

Malakauskas and Lakštutienė (2021) predicted financial distress using data from 12,000 SMEs. They obtained an average accuracy of 62.11% for the RF algorithm. Soydaş and Çam (2024) used the data of 178 enterprises in a study covering the 2015-2019 period of BIST and predicted financial failure with Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), RF and Decision Trees (DT) algorithms. In their proposed study, the RF algorithm partially showed better results than other algorithms. Similarly, Selimefendigil (2023) used SVM, Logistic Regression (LR), RF and K-Nearest Neighbors (KNN) to predict financial distress in BIST and reported that the RF algorithm provided the best precision, accuracy and recall.

Zhang et al. (2022) used 14 financial ratios from businesses' financial statements between 2014 and 2019. Their study proposed GA-MLP ensemble methods. Similarly, Gregova et al. (2020) achieved the best result in predicting the financial distress of businesses in Slovakia using the ANN algorithm. Aydin et al. (2022) used ANN and DT to predict financial distress using 25 financial ratios obtained from 240 BIST businesses operating in different sectors. They classified the nonbankrupt and bankrupt businesses in the model with a higher accuracy (93.10%) using the ANN algorithm. In another study on BIST, Aksoy and Boztosun (2021) used ANN, classification and regression trees (CART), SVM, and K-NN models to predict the financial distress of 86 manufacturing businesses. They obtained the highest prediction using the CART algorithm.

Literature Gap and Statement of Novelty

The current literature shows that financial distress prediction has been carried out using ML algorithms or hybrid models. However, to predict financial distress, many studies have focused on single algorithms (Zhang et al., 2022; Engin and Durer, 2023) or a limited number of financial ratios (Huang and Yen, 2019; Aydin et al., 2022; Tran et al., 2022; Zhang et al., 2022; Zhao et al., 2022; Zhong and Wang, 2022). However, which financial ratio plays a decisive role in the sector is also important. The selection of financial ratios and hyperparameter optimization with ML algorithms to improve the performance of forecasting models becomes more important. In this context, the main motivation of this study is to develop effective forecasting models for financial distress prediction using existing and proposed approaches based on ML algorithms. In addition, it aims to provide to financial managers and analysts with more understandable and applicable results by providing explanations of the ratios that cause financial distress.

Based on this motivation, this study aims to predict financial distress using ML algorithms and identify the financial ratios that affect distress more. A dataset containing 39 financial ratios was created using the financial statements of 198 BIST-traded businesses between 2015 and 2020. According to the technical bankruptcy obligation of the Turkish Commercial Law, the financial status of the business in the dataset was classified as "financial distress" and "financial normal". In this study, 14 different ML algorithms were used and the hyperparameter optimization of these algorithms was performed with the Grid Search method. In this study, financial distress was evaluated using three scenarios. In the first scenario, 39 financial ratios obtained from financial statements were classified using ML algorithms. In the second scenario, feature (financial ratios) selection was applied using the F-regression technique, and the datasets generated

according to the selected 10, 20, and 30 features were classified using ML algorithms. In the third scenario, new models were created by combining high performing algorithms with Stacking technique. These models were tested on the 39-feature dataset and sub-datasets obtained from feature selection. Furthermore, the highest performing models in each scenario were evaluated using the Synthetic Minority Oversampling Technique (SMOTE) method. All models were assessed using a 10-fold cross-validation. Finally, using the best-performing model, financial ratios affecting financial distress were analyzed using the SHAP method.

The Contributions of This Study

- In this study, a comprehensive dataset 198 enterprises were created using 39 financial ratios obtained from the financial statements of BIST in different business lines for the period 2015-2020.
- This study evaluated the financial distress prediction performance of different ML algorithms using 39 financial ratios. In addition, the hyperparameters of the algorithms used were determined using the Grid Search method. In this way, by optimizing the performance of the algorithms, the performance of the algorithms can be improved, and more reliable predictions can be obtained.
- In this study, feature selection was applied with the F-regression method, and sub-datasets containing 10, 20, and 30 financial ratios were created. This scenario can improve the performance of financial distress forecasting models.
- In this study, more than one ML algorithm was combined with the stacking technique to create robust prediction models. Thus, the strengths of the different algorithms were used.
- Using the high-performing model, financial ratios affecting financial distress were analyzed using the SHAP method. In this way, the main ratios that may lead to financial distress have been identified, and enterprises have been able to take measures against these risks.

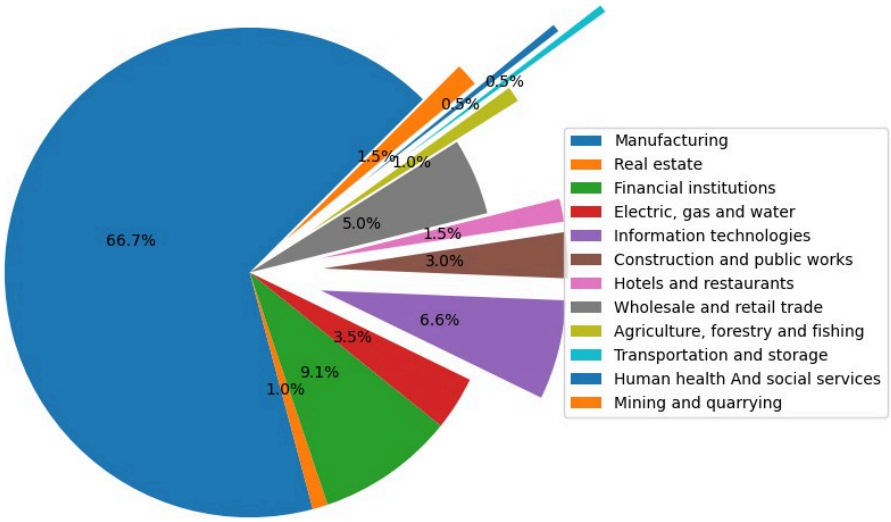
MATERIALS AND METHODS

Data Collection and Preprocessing

The financial statements of the businesses were downloaded from the Public Disclosure Platform (PDP) (https://www.kap.org.tr/tr/). Data were obtained from 198 enterprises traded on the BIST between 2015 and 2020 (6 years). Figure 1 presents the distribution of businesses by sector. Of these businesses, 66.7% were manufacturing businesses, 1% were real estate, 9.1% were financial institutions, 3.5% were electricity, gas, and water, 6.6% were information technologies, 3% were construction and public works, 1.5% were hotels and restaurants, 5.1% were wholesale and retail trade, 1% were agriculture, forestry, and fishing, 0.5% were transportation and storage, 0.5% were human health and social services, and 1.5% were mining and quarrying.

The financial structure and performance dynamics of different sectors differ significantly (Huang and Yen, 2019). Generally, financial distress is predicted using financial condition information for a country, sector or firm-level area (Ghisellini and Ulgiati, 2020; Sankhwar et al., 2020; Elhoseny et al., 2025). Instead of focusing on a specific sector, this study created a comprehensive dataset covering all sectors. This will enable the development of a more generalizable model for predicting financial distress (Huang and Yen, 2019; Sethi et al., 2025).

Figure 1
Distribution of businesses



Financial ratios were obtained from financial statements to determine the safety and profitability of the business's financial status. These ratios are used to improve businesses' investment decisions and investors' future performance (Abdullah and AL-Anber, 2021). Appendix A lists the names and types of selected financial ratios.

In this study, businesses were categorized as financial distress (class: 0) and financial normal (class: 1) based on the technical bankruptcy provisions of 376 of the Turkish Commercial Law (Büyükarıkan and Büyükarıkan, 2018). Technical bankruptcy occurs when businesses go bankrupt, are restructured, are removed from the stock market, their operations are ceased, the equity decreases by at least 2/3, total assets decrease by 10%, or losses are incurred for two consecutive years or more (Yakut and Elmas, 2013; Aydin et al., 2022). Accordingly, there were 1188 data in this study; 965 of these data points were from financial distress (approximately 81%), and 223 of these data points were from financial normal (approximately 19%).

The values obtained from financial ratios can sometimes be extreme and negative, resulting in deviations in the ML algorithms. To eliminate this problem, the values can be normalized (Büyükarıkan and Büyükarıkan, 2018; Huang and Yen, 2019; Qian et al., 2022). Min-max, one of these normalization methods, transforms the data into values between 0 and 1 (Han et al., 2012). Equation 1 was used to calculate the min-max normalization method.

$$V' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Here, V′ is the normalized data, X_i is the input value, $X_{\min}$ is the smallest value in the input set, and $X_{\max}$ is the largest value in the input set.

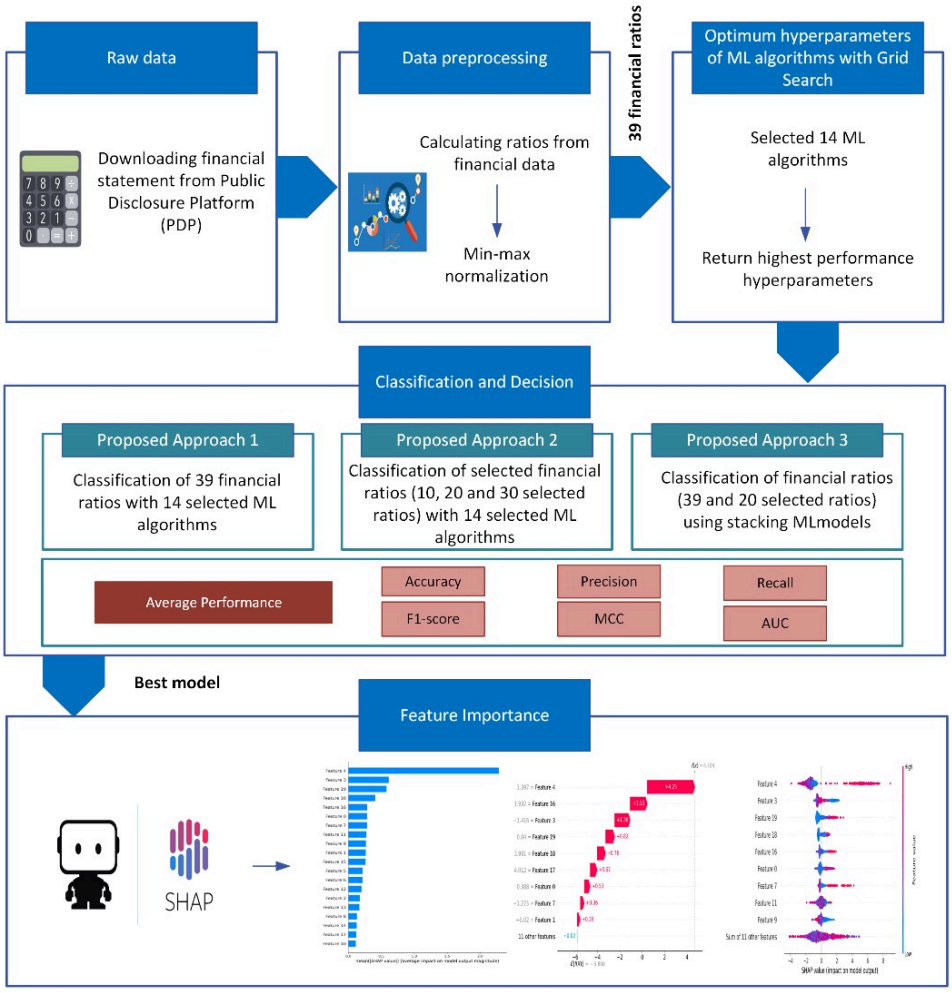
Proposed Methodology

This study proposed several scenarios for predicting financial distress. Figure 2 shows the steps of the proposed methodology. First, 39 financial ratios were obtained from the financial statements of businesses

traded on BIST between 2015 and 2020. These ratios represent the main variables affecting a business' financial performance and distress status. All financial ratios were normalized to the same scale using the min-max normalization method to ensure the reliability of the data analysis, minimizing the impact of extreme values. The businesses' financial distress status was classified into two categories: "financial distress" and "financial normal" in accordance with Turkish Commercial Law. This classification was based on the businesses technical bankruptcy status and was used as the dependent variable.

Figure 2

Proposed financial distress prediction methodology



In this study were used such as LR (Cox, 1958), Quadratic Discriminant Analysis (QDA) (Fisher, 1936), Linear Discriminant Analysis (LDA) (Fisher, 1936), MLP (Rumelhart et al., 1986), SVM (Cortes and Vapnik, 1995), K-NN (Cover and Hart, 1967), RF (Breiman, 2001), DT (Breiman, 2001), Extra Trees (ET) (Geurts et al., 2006), XGBoost (Chen and Guestrin, 2016), Light Gradient Boosting Machine (LightGBM) (Ke et al., 2017), CatBoost (Prokhorenkova et al., 2018), AdaBoost (Freund and Schapire, 1997), and Gradient Boosting (Friedman, 2001). Statistical algorithms such as LR, QDA, and LDA focus on linear relationships within the data. Algorithms, such as MLP and SVM, are more sensitive to complex and nonlinear relationships. Tree-based algorithms, such as RF and DT, explore hierarchical structures among variables in a dataset. Boosting-based algorithms combine weaker learners to create stronger models. This wide range of algorithms provides the opportu-

nity to explore different data characteristics and make more comprehensive performance evaluations. Additionally, the response of each selected algorithm to the dataset includes critical performance factors, and the results vary according to the algorithms structure. Therefore, hyperparameter optimization was performed to obtain the optimum performance of each selected algorithm. Hyperparameter optimization was performed using the Grid Search method, and the necessary parameter settings were made for each algorithm to achieve the best performance. Table 1 lists the hyperparameter ranges and optimal values of the selected algorithms.

Table 1

Parameter settings of multiple ML classifiers

Algorithm	Parameter	Parameter values	Value obtained by the Grid Search
SVM	Kernel	[Linear, RBF, Polynomial]	Linear
	C parameter	[1, 2, 3, 4, 5, 6, 7, 8, 9 ,10, 0.1, 0.01, 0.001, 0.0001]	2
RF	n_estimators	[1, 5, 10, 20, 40, 50, 60, 75, 90, 100]	5
K-NN	n_neighbors	[1-40]	3
	Metric	['Euclidean','Manhattan', 'Minkowski']	'Minkowski'
MLP	Hidden layer sizes	[(10,10,10), (84,84,42), (100,100,100), (150,100), (100,50), (50,20), (120,80,40), (100,50,30), (200), (200,50), (100,100)]	(84,84,42)
	Solver	['lbfgs', 'adam', 'sgd']	sgd
	Alpha	[0.1, 0.01, 0.05, 0.0001,0.00001, 0.000001]	1e-5
LR	C parameter	[1, 2, 3, 4, 5, 6, 7, 8 ,9, 10, 0.1, 0.01, 0.001, 0.0001]	1
DT	max_depth	[4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 20, 30, 40, 50, 70, 90, 120, 150]	10
	Criterion	['Gini', 'Entropy']	Gini
ET	n_estimator	[8,16, 32,50,64,84,100]	100
QDA	reg_param	[0-0.5]	0.5
LDA	n_component	[1-5]	1
	Solver	['lsqr', 'eigen']	lsqr
XGBoost	n_estimators	[1-1000]	100
	learning_rate	[0.001-0.3]	0.3
LightGBM	num_leaves	[5-100]	100
	learning_rate	[0.001-0.3]	0.3
	max_depth	[1-16]	10
CatBoost	n_estimators	[1-1000]	100
	learning_rate	[0.001-0.3]	0.3
	max_depth	[1-16]	10
AdaBoost	n_estimators	[1-1000]	32
Gradient Boosting	n_estimators	[1-1000]	90

Three different scenarios were used in this study. In the first scenario, 39 financial ratios obtained from financial statements were classified using ML algorithms. In the second scenario, the F-regression technique was preferred for selecting important ratios. This technique provides a statistical measure of the linear

relationship between each financial ratio and the target variable. In this study, sub-datasets consisting of 10, 20, and 30 features based on selection were evaluated using ML algorithms. Appendix B lists the names of the financial ratios selected through feature selection. In the third scenario, the stacking technique was used to combine the predictions of multiple ML algorithms to create a more powerful model. The models were tested on both the dataset from the first scenario and the dataset where the highest performance results were obtained from feature selection. However, the LR algorithm, which has a good probability calibration and is widely used in literature, was preferred to evaluate the final outputs of the stacking ML models. The study was evaluated by 10-fold cross-validation and analyzed using the performance measures of accuracy, precision, recall, F1-score, Area Under The Curve (AUC), and Matthews Correlation Coefficient (MCC). Moreover, the best-performing models were trained according to the scenarios applying the SMOTE method after removing the class distribution bias arising from the imbalanced dataset problem. Finally, SHAP analysis, an explanatory method, is used to understand the reasons for the prediction of the best performing model, i.e, to examine the effects of financial ratios on the models.

Performance Metrics

In this study, the accuracy (Equation 2), precision (Equation 3), recall (Equation 4), F1-score (Equation 5), and MCC (Equation 6) metrics were used to evaluate the models' performance. The AUC was calculated using the "roc_auc_score" function of the scikit-learn library. However, the metrics in Equations 2-5 measures are in the range of [0,1], and Equation 6 takes values in the range of [-1,1]. The closer these measures are to 1, the better the algorithm's performance.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1 - score = 2^{*}\frac{Precision^{*}Recall}{Precision + Recall} \tag{5}$$

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{6}$$

A typical confusion matrix is given in Table 2, which explains Equations 2-7. Comparing the true class with the predicted class yields four values: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). While TP and TN represent the number of distress and normal companies that were accurately classified, FP and FN indicate the number of distress and normal companies that were misclassified, respectively.

Table 2 *Confusion matrix*

	Predicted Positive (Financial distress)	Predicted Negative (Financial normal)
Real Positive (Financial distress)	True Positive (TP)	False Negative (FN)
Real Negative (Financial normal)	False Positive (FP)	True Negative (TN)

EXPERIMENTAL RESULTS AND ANALYSIS

Analysis of the Classification Results

In this section, the performance of the proposed scenarios was evaluated based on the classification of all financial ratios obtained from financial statements with ML (Section 3.1.1), the classification of selected ratios with ML (Section 3.1.2), and the classification of all ratios and selected ratios with the stacking ML models (Section 3.1.3).

Scenario 1: Classification of All Financial Ratios Using ML.

Table 3 shows the classification average performance results of the ML algorithms. Boosting algorithms generally achieved higher performance than other algorithms. The CatBoost algorithm had the highest accuracy (0.962), precision (0.937), F1-score (0.939), and MCC (0.879) on average. In this scenario, the XGBoost algorithm obtained the highest recall value.The high recall metric indicates how accurately the classified ratios were classified. In addition, the high F1-score metric indicated the accuracy of the tests performed using the ML algorithms. Moreover, when the algorithms were evaluated according to the MCC metric, CatBoost obtained the highest result. A high MCC value indicated that the classification result was successful. The high AUC value made distinguishing between financial distress and normal classes easy. In this study, the AUC value of the XGBoost algorithm was better than that of other models. The Gradient Boosting, CatBoost, AdaBoost, and LightGBM algorithms closely followed this algorithm.

Table 3

Average results of all financial ratios and ML models

Algorithm	Accuracy	Precision	Recall	F1-score	MCC	AUC
LR	0.901	0.859	0.800	0.823	0.655	0.800
QDA	0.901	0.847	0.821	0.831	0.667	0.821
LDA	0.873	0.839	0.704	0.742	0.525	0.704
MLP	0.913	0.890	0.821	0.850	0.704	0.831
SVM	0.917	0.873	0.849	0.860	0.721	0.849
K-NN	0.928	0.901	0.852	0.873	0.750	0.852
RF	0.878	0.842	0.779	0.845	0.696	0.880
DT	0.939	0.912	0.891	0.900	0.803	0.891
ET	0.955	0.935	0.927	0.930	0.862	0.921
XGBoost	0.961	0.931	**0.949**	0.938	0.878	**0.949**
LightGBM	0.960	0.935	0.941	0.936	0.875	0.941

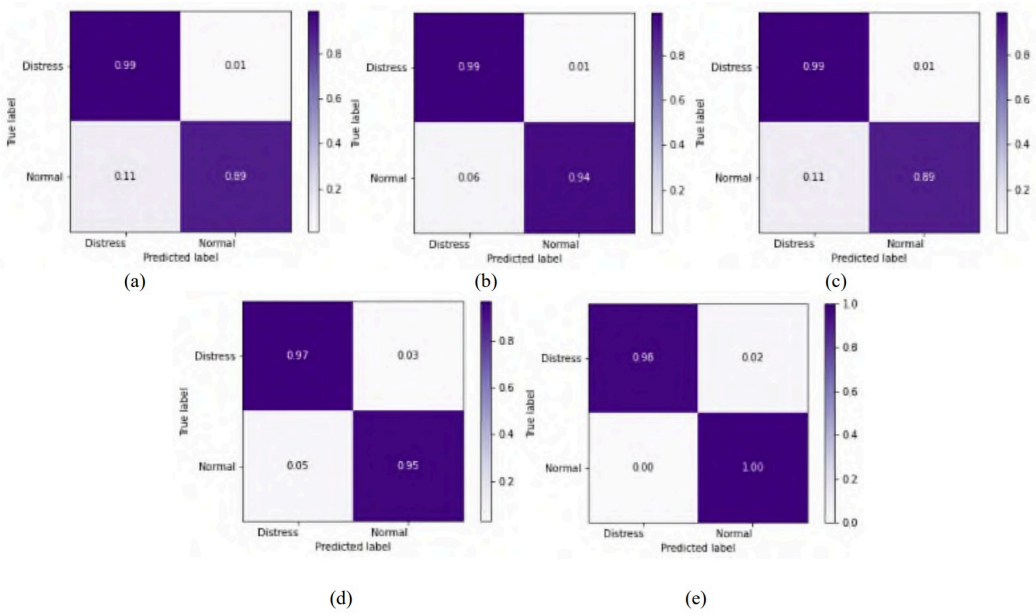
Algorithm	Accuracy	Precision	Recall	F1-score	MCC	AUC
CatBoost	**0.962**	**0.937**	0.943	**0.939**	**0.879**	0.944
AdaBoost	0.957	0.923	0.943	0.932	0.866	0.943
Gradient Boosting	0.957	0.924	0.946	0.933	0.868	0.948

The best results are in bold font

According to the results in Table 3, the confusion matrices of the top 5 ML algorithms with the highest classification accuracy are shown in Figure 3. These results correspond to the folds where the best accuracy values were achieved. The rows in the matrices represent the predicted class, while the columns represent the actual class. In this study, XGBoost (Figure 3a), LightGBM (Figure 3b), CatBoost (Figure 3c), AdaBoost (Figure 3d), and Gradient Boosting (Figure 3e) algorithms predicted almost all classes correctly. While the XGBoost (Figure 3a), LightGBM (Figure 3b), CatBoost (Figure 3c), and AdaBoost (Figure 3d) models were more successful at distinguishing the “financial distress” class, the Gradient Boosting (Figure 3e) model appeared to struggle with recognizing the “financial distress” class. This issue is believed to stem from the "financial distress" class being more numerous than the "financial” normal" class in the dataset.

Figure 3

Confusion matrices of scenario 1 of (a) XGBoost, (b) LightGBM, (c) CatBoost, (d) AdaBoost, (e) Gradient Boosting



Scenario 2: Classification of Selected Financial Ratios Using ML.

Table 4 presents the classification results of the sub-feature sets created using F-regression feature selection with ML algorithms. This scenario obtained the highest performance results with the CatBoost algorithm. The average accuracy values of this algorithm for the 10, 20, and 30 sub-feature sets were 0.958, 0.967, and 0.964, respectively. However, the average F1-score values of these feature sets were 0.932, 0.947, and 0.886, respectively. Similarly, this scenario obtained the highest results from the boosting-based algorithms.

Table 4

Average results of selected ratios and ML

Algorithm	Features count	Accuracy	Precision	Recall	F1-score	MCC	AUC
LR	10	0.901	0.873	0.775	0.810	0.640	0.775
QDA		0.887	0.859	0.741	0.778	0.587	0.741
LDA		0.871	0.852	0.686	0.727	0.511	0.686
MLP		0.913	0.876	0.824	0.846	0.697	0.824
SVM		0.902	0.883	0.776	0.814	0.649	0.776
K-NN		0.926	0.892	0.864	0.875	0.754	0.864
RF		0.899	0.895	0.759	0.800	0.637	0.759
DT		0.941	0.910	0.901	0.902	0.809	0.901
ET		0.953	0.922	0.926	0.923	0.847	0.926
XGBoost		0.955	0.923	0.935	0.927	0.857	0.935
LightGBM		0.954	**0.927**	0.925	0.924	0.851	0.925
CatBoost		**0.958**	**0.927**	**0.941**	**0.932**	**0.867**	**0.941**
AdaBoost		0.949	0.910	0.930	0.918	0.839	0.930
Gradient Boosting		0.952	0.918	0.932	0.922	0.848	0.932
LR	20	0.910	0.887	0.801	0.834	0.682	0.801
QDA		0.875	0.844	0.711	0.749	0.537	0.711
LDA		0.874	0.852	0.697	0.738	0.525	0.697
MLP		0.918	0.889	0.827	0.852	0.713	0.827
SVM		0.908	0.881	0.803	0.833	0.679	0.803
K-NN		0.928	0.896	0.859	0.874	0.753	0.859
RF		0.907	0.912	0.776	0.819	0.673	0.776
DT		0.950	0.921	0.915	0.916	0.835	0.915
ET		0.953	0.929	0.916	0.920	0.844	0.916
XGBoost		0.962	0.932	0.951	0.940	0.883	0.951
LightGBM		0.960	0.934	0.938	0.935	0.871	0.938
CatBoost		**0.967**	**0.944**	**0.954**	**0.947**	**0.897**	**0.954**
AdaBoost		0.951	0.917	0.932	0.922	0.847	0.932
Gradient Boosting		0.962	0.930	0.953	0.940	0.882	0.953
LR	30	0.911	0.883	0.809	0.838	0.687	0.809
QDA		0.896	0.859	0.784	0.811	0.637	0.784
LDA		0.877	0.852	0.707	0.747	0.539	0.707
MLP		0.917	0.898	0.811	0.845	0.703	0.811
SVM		0.918	0.881	0.842	0.859	0.722	0.842
K-NN		0.928	0.895	0.864	0.877	0.757	0.864
RF		0.903	0.903	0.763	0.807	0.650	0.763
DT		0.956	0.927	0.930	0.928	0.857	0.930
ET		0.955	0.928	0.923	0.924	0.923	0.850

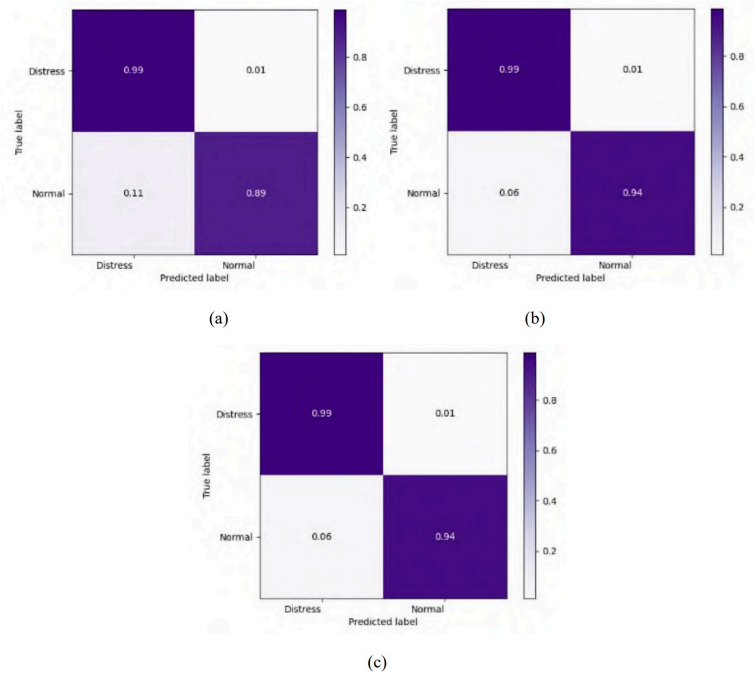
Algorithm	Features count	Accuracy	Precision	Recall	F1-score	MCC	AUC
XGBoost		**0.964**	0.934	**0.956**	**0.943**	**0.888**	**0.956**
LightGBM		0.962	0.937	0.944	0.938	0.880	0.944
CatBoost		**0.964**	**0.938**	0.950	0.942	0.886	0.950
AdaBoost		0.955	0.920	0.936	0.926	0.855	0.936
Gradient Boosting		0.959	0.926	0.946	0.934	0.871	0.946

Best results are in bold font

Figure 4 shows the confusion matrices of the CatBoost and XGBoost algorithms, which demonstrate the highest feature selection performance. When the confusion matrices of both algorithms were compared according to their feature selection, the “financial distress” class was successfully predicted. Comparison of CatBoost and XGBoost showed the performance of the two algorithms on different datasets. Figure 4b and Figure 4c show that the prediction of the “financial normal” class was better in datasets with 20 and 30 features. In this context, features of high importance are critical elements for analyzing financial status.

Figure 4

Confusion matrices of scenario 2 of (a) 10 financial ratios and CatBoost algorithm, (b) 20 financial ratios and CatBoost algorithm, (c) 30 financial ratios and XGBoost algorithm



Scenario 3: Financial Ratio Classification Using Stacking ML.

In this scenario, models were created using boosting-based algorithms and stacking ML models, and these models were tested on datasets containing both 39 and 20 selected features, respectively. This study used the LR algorithm to evaluate the algorithms' prediction of the stacking ML models. Table 5 lists the average performance results of the models created with the Stacking ML models. In the results obtained using all features, the CatBoost-XGBoost model outperformed than the other models. The accuracy, preci-

sion, recall, F1-score, MCC, and AUC metrics of this model were 0.962, 0.909, 0.895, 0.899, 0.878, and 0.937, respectively. The performance results of the CatBoost-XGBoost-LightGBM model were generally better in the results obtained by feature selection. The accuracy, precision, recall, F1-score, MCC, and AUC metrics of this model were 0.965, 0.906, 0.915, 0.908, 0.888, and 0.946, respectively. The results of the metric values of both compared models are very close to each other.

Table 5

Average results of stacking ML models

Stacking ML model	Features count	Accuracy	Precision	Recall	F1-score	MCC	AUC
Model1	39	**0.962**	**0.909**	**0.895**	**0.899**	**0.878**	**0.937**
Model2		0.960	0.908	0.887	0.894	0.872	0.933
Model3		0.959	0.904	0.883	0.889	0.867	0.930
Model4		0.960	0.905	0.891	0.894	0.873	0.934
Model1	20	0.964	**0.906**	0.907	0.903	0.884	0.942
Model2		**0.965**	**0.906**	**0.915**	**0.908**	**0.888**	**0.946**
Model3		0.964	0.903	**0.915**	0.906	0.886	**0.946**
Model4		0.962	0.899	0.911	0.901	0.881	0.943

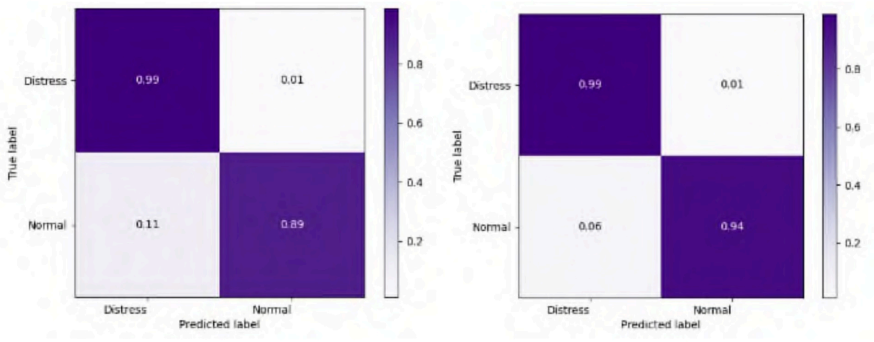
The best results are in bold font

Note: Model1: CatBoost-XGBoost, Model2: CatBoost-XGBoost-LightGBM, Model3: CatBoost-XGBoost-Light-GBM- Gradient Boosting, Model4: CatBoost-XGBoost-LightGBM-Gradient Boosting-AdaBoost

Figure 5 shows the confusion matrices of the models that show the best results in the datasets, according to the stacking ML scenario. As shown in Figures 5a and 5b, the low false negative rates indicated that the models could correctly detect financial distress. Consequently, by analyzing certain features, managers can determine which financial ratios to focus on.

Figure 5

Confusion matrices of the stacking ML, (a) 39 financial ratios and the CatBoost-XGBoost model (Model1), (b) 20 financial ratios and the CatBoost-XGBoost-LightGBM model (Model 2)



(a) (b)

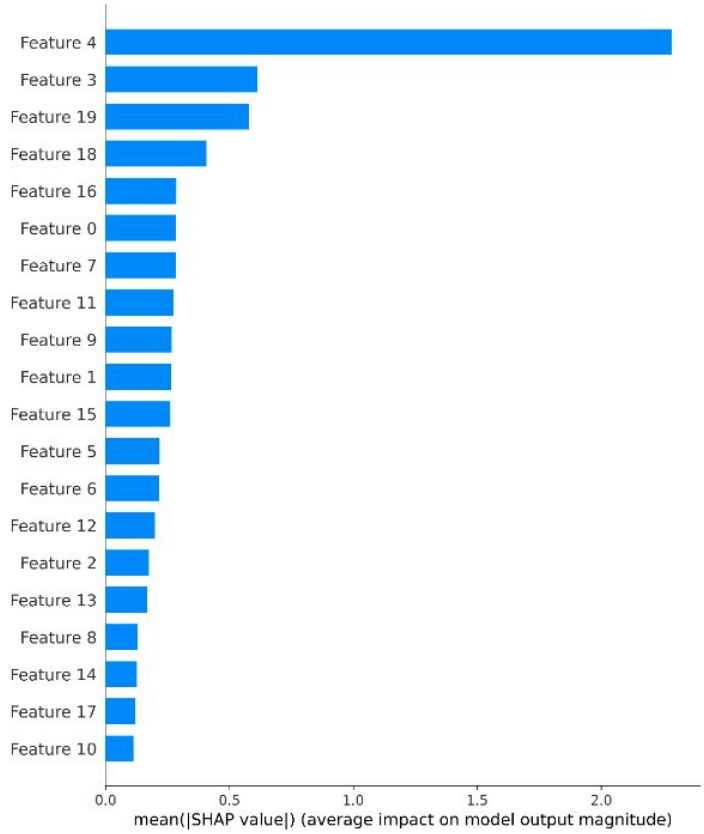
Feature importance for scenario 2

Based on the results of the scenarios, the SHAP technique was applied to explain the importance of financial ratios. The SHAP value is also calculated to determine the contribution of each feature in improving the model's discrimination performance. In addition, it shows not only the degree of effect of the features in each sample but also the positive and negative aspects of the effect (Jiang et al., 2023).

The SHAP technique used in this study identifies the important variables in predicting financial distress and the extent to which financial ratios affect the financial distress achieved. The number of features used here is 20. The SHAP value was calculated for the CatBoost algorithm, which had the best performance. Figure 6 shows the important features according to the SHAP analysis. The first five important features were equity-to-asset ratio (Feature 4), debt ratio (Feature 3), equity-to-long-term liabilities (Feature 19), equity-to-short-term liabilities (Feature 18), and fixed-assets-to-total liabilities (Feature 16), respectively. Accordingly, the solvency ratios were among the most important features. Also, some features, such as Earnings before interest and tax (EBIT) to current liabilities (Feature 10) and current asset to total liabilities (Feature 17), appear to had relatively lower impacts.

Figure 6

Feature importance of CatBoost



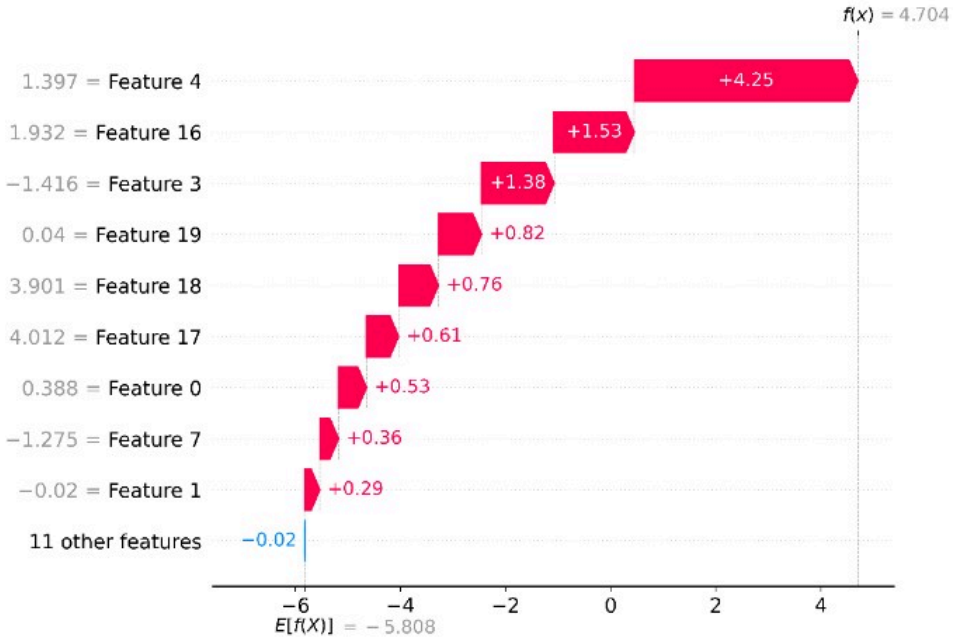
Note: Quick ratio (Feature 0), working capital to net sales (Feature 1), working capital to total assets (Feature 2), debt ratio (Feature 3), equity to asset ratio (Feature 4), active capital turnover (Feature 5), sales to current assets ratio (Feature 6), short term liabilities to assets (Feature 7), return on assets (Feature 8), gross profitability ratio (Feature 9), earnings before interest and tax (EBIT) to current liabilities (Feature 10), inventories to current assets (Feature 11), inventories to total assets (Feature 12), net operating profit margin

(Feature 13), net operating profit to assets (Feature 14), gross profit to long term liabilities (Feature 15), fixed assets to total liabilities (Feature 16), current asset to total liabilities (Feature 17), equity to short term liabilities (Feature 18), equity to long term liabilities (Feature 19).

Figure 7 shows the waterfall plot created for the local interpretation of financial distress. The equity-to-asset ratio (Feature 4) significantly positively predicted financial distress, corresponding to a SHAP value of +4.25. Fixed assets to total liabilities (Feature 16), which corresponds to a SHAP value of +1.53, followed this. In contrast, debt ratio (Feature 3) contributed negatively to the prediction of financial distress.

Figure 7

SHAP waterfall plot of feature contributions

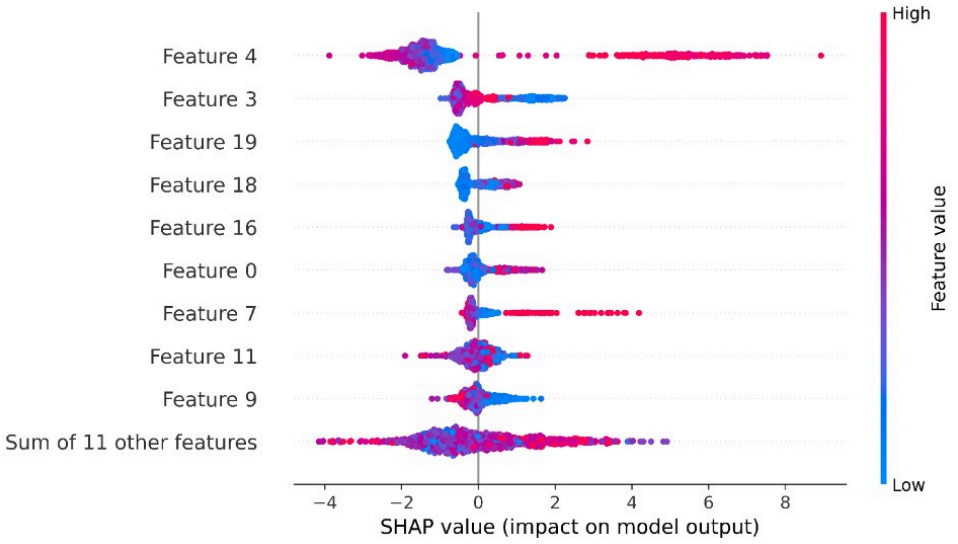


Note: Quick ratio (Feature 0), working capital to net sales (Feature 1), debt ratio (Feature 3), equity to asset ratio (Feature 4), short term liabilities to assets (Feature 7), fixed assets to total liabilities (Feature 16), current asset to total liabilities (Feature 17), equity to short term liabilities (Feature 18), equity to long term liabilities (Feature 19).

Figure 8 illustrates the SHAP values of the top nine and other features. On the y-axis, the values were grouped according to features. For each group, red and blue dots indicate high and low feature values, respectively. In the first five features, the equity-to-asset ratio (Feature 4), equity-to-long-term liabilities (Feature 19), equity-to-short-term liabilities (Feature 18), and fixed assets-to-total liabilities (Feature 16) had a positive effect on the probability of financial distress. The debt ratio (Feature 3) showed a mix of effects. In addition, the debt ratio (Feature 3), which was in the top five features, had negative SHAP values. However, higher values tend to contribute negatively to the predictions, consistent with the general financial principle that a higher debt ratio (Feature 3) decreases a business' financial risk.

Figure 8

SHAP beeswarm plot for CatBoost



Note: Quick ratio (Feature 0), debt ratio (Feature 3), equity to asset ratio (Feature 4), short term liabilities to assets (Feature 7), gross profitability ratio (Feature 9), inventories to current assets (Feature 11), fixed assets to total liabilities (Feature 16), equity to short term liabilities (Feature 18), equity to long term liabilities (Feature 19).

Comparative Assessment of Machine Learning Scenarios

The performance results of the different scenarios are comparatively presented in Figure 9. In the first scenario, 39 financial ratios allowed for a more comprehensive analysis of financial distress. The CatBoost algorithm stood out with an average accuracy of 0.962. Boosting algorithms showed higher performance results in this scenario than other algorithms. In the second scenario, the F-regression technique was reduced the number of financial ratios, and the CatBoost algorithm achieved an average accuracy of 0.967 with the selected 20 financial ratios. Similarly, the boosting-based algorithms obtained better results in than the other algorithms scenario.

The findings demonstrate that boosting algorithms can be used in applications to predict future business success. Moreover, the CatBoost algorithm is a reliable tool for predicting financial distress due to its ability to minimize classification imbalances. In the third scenario, new models were evaluated using the stacking technique. In this scenario, sub-feature datasets containing both 39 and 20 selected ratios were used. According to the experimental results, the performance of the CatBoost-XGBoost-LightGBM model with feature selection was higher than that of the other models. The average accuracy of this model was 0.965. In the original dataset, 965 samples were labeled as financial distress (approximately 81%) and 223 as financial normal (approximately 19%). The performance of the models may be negatively affected due to data imbalance. To overcome this limitation, the SMOTE method was applied in the study, and Table 6 presents the average performance results of the models. The classification performance of the proposed models improved significantly after applying the SMOTE method. A significant increase in the AUC values was observed, reflecting the discriminative power of the models with the class balancing labels. The results show that the SMOTE method effectively improves model generalization performance in imbalanced datasets.

Table 6

Evaluation of the proposed models using the SMOTE method

Scenario	Model	Accuracy	F1-score	MCC	AUC
Scenario 1	CatBoost	0.962	0,939	0,879	0.944
	CatBoost + SMOTE	**0.966**	**0.946**	**0.894**	**0.988**
Scenario 2	CatBoost	**0.967**	**0.947**	**0.897**	0.954
	CatBoost + SMOTE	0.966	0.946	0.894	**0.989**
Scenario 3	CatBoost-XGBoost-LightGBM (Model 2)	0.965	0.908	0.888	0.946
	CatBoost-XGBoost-LightGBM (Model 2) + SMOTE	**0.966**	**0.945**	**0.891**	**0.990**

The best results are in bold font

Discussion

Table 7 shows a comparison of related studies in terms of dataset characteristics, applied methods, number of features, and performance metrics. The most recent research on predicting financial distress has focused on boosting-based algorithms. For example, Huang and Yen (2019) used 16 ratios in their study in Taiwan and found the precision value to be 90.6% with the XGBoost. Qian et al. (2022) obtained an AUC of 0.9291 with the proposed model applied in China between 2001 and 2019. In another study applied in China, Zhao et al. (2022) used 22 financial ratios, and obtained 97.6% accuracy with the CatBoost. Similarly, Zhong and Wang (2022) obtained 96.33% accuracy with CatBoost algorithm. Zhang et al. (2022) achieved 90.75% accuracy using their proposed model. Tran et al. (2022) used 25 financial ratios in their study in Vietnam and achieved an accuracy of 0.9566 using the XGBoost algorithm.

Engin and Durer (2023) used 25 financial ratios in their study on BIST between 2010 and 2020 and obtained 91.6% accuracy with their proposed model. In another study conducted on BIST, Aydin et al. (2022) used 25 financial ratios and obtained approximately 93% accuracy with the ANN. Soydaş and Çam (2024) evaluated the RF algorithm according to different periods, and found that AUC was between 0.894 and 1.000 in the RF algorithm. Similarly, Selimefendigil (2023) obtained an accuracy of 0.95 using the RF algorithm. In another study on BIST, Aksoy and Boztosun (2021) obtained the highest accuracy value of 86.84% using the CART algorithm. In this proposed study, the highest performance was achieved in Scenario 2, with an average accuracy of 0.967 when applied to BIST.

Table 7

A comparative summary of related studies on financial distress prediction

References	Dataset	Number of features	Model	Result
Huang and Yen (2019)	2010-2016, Taiwan	16	XGBoost	P: 90.6%
Qian et al. (2022)	2001-2019, China	44	PIMP-XGBoost	AUC: 0.9291
Tran et al. (2022)	2010-2021, Vietnam	25	XGBoost and SHAP	Acc: 0.9566
Engin and Durer (2023)	2010-2020, BIST (Türkiye)	25	XGBoost	Acc: %91,6
Zhao et al. (2022)	2016–2020, China	22	CatBoost	Acc: 97.6%
Zhong and Wang (2022)	2016-2021, China	26	CatBoost	Acc: 96.33%
Zhang et al. (2022)	2014-2019, China	14	GA-MLP	Acc: 90.75

References	Dataset	Number of features	Model	Result
Aydin et al. (2022)	2009-2014, BIST (Türkiye)	25	ANN	Acc: 93.10%
Soydaş and Çam (2024)	2015-2019, BIST (Türkiye)	24	RF	AUC:0.894-1.000
Selimefendigil (2023)	2012-2021, BIST (Türkiye)	27	RF	Acc: 0.95
Aksoy and Boztosun (2021)	2006-2009, BIST (Türkiye)	25	CART	Acc: 86.84%
This study: Scenario 1	2015-2020, BIST (Türkiye)	39	CatBoost	Acc: 0.962
This study: Scenario 2	2015-2020, BIST (Türkiye)	20	CatBoost and F-regression	Acc: 0.967
This study: Scenario 3	2015-2020, BIST (Türkiye)	20	Model 2: stacking ML	Acc: 0.965

Note: P: precision, Acc: accuracy, AUC: area under the curve

Limitations

- This study's use of data from companies traded only on BIST limits the model' validity at the international level. Not including data from different countries and various economic periods may reduce the general applicability of the proposed models.
- This study was based on business' financial ratios. In other words, macroeconomic and market-based variables, such as interest rates, inflation, and market returns were not considered. The exclusion of these factors may limit the model's validity in real-world conditions. This shortcoming stands out as an important area for improvement in future studies.
- This study did not test the performance of the models against out-of-sample or different time periods that better reflect real-world conditions. This may create uncertainty regarding the generalization performance and time robustness of the models.
- This study focused on evaluating the performance of ML scenarios in forecasting financial distress. Despite their importance in literature, classical methods, such as the Altman Z-Score, the Springate S-score, and the Ohlson O-Score were not included in the study.

CONCLUSION AND THE FUTURE WORK

This study aimed to predict financial distress with ML algorithms and to identify the financial ratios that affect distress more. The study evaluated three scenarios for predicting financial distress. In the first scenario, the dataset was classified using ML algorithms. The CatBoost algorithm obtained the highest performance with an average accuracy of 0.962. Boosting-based algorithms generally showed better performance results than others. In the second scenario, ML algorithms classified a dataset containing 20 financial ratios selected by the F-regression technique. The results obtained an average accuracy of 0.967 for the CatBoost algorithm. In the third scenario, the CatBoost-XGBoost-LightGBM Stacking ML model achieved an average accuracy of 0.965.

In this study, the SHAP technique was applied to the CatBoost algorithm in the second scenario. The proposed financial distress model shows that equity-to-asset ratio (Feature 4) and debt ratio (Feature 3) were relatively dominant factors. Among the first five features, equity-to-asset ratio (Feature 4), equity-to-long-term liabilities (Feature 19), equity-to-short-term liabilities (Feature 18), and fixed assets to total liabilities (Feature 16) had a positive effect, while debt ratio (Feature 3) had a negative effect.

This study is expected to provide more robust ML algorithms for predicting the financial distress of BIST-listed companies in different sectors and provide valuable insights for this sector. In future studies, the models will be evaluated from different country markets over varying time periods to increase the generalizability and robustness of the model.

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Appendix

Appendix 1

Using financial ratio in this study

Ratio name	Financial ratio name	Type
Ratio 1	Current ratio	Liquidity
Ratio 2	Quick ratio	Liquidity
Ratio 3	Working capital to net sales ratio	Liquidity
Ratio 4	Working capital to total assets	Liquidity
Ratio 5	Debt ratio	Solvency
Ratio 6	The equity to asset ratio	Solvency
Ratio 7	Debt to capital ratio	Solvency
Ratio 8	Active capital turnover	Solvency
Ratio 9	Equity turnover rate	Solvency
Ratio 10	Equity multiplier	Solvency
Ratio 11	Sales to current assets ratio	Liquidity
Ratio 12	Fixed asset turnover	Liquidity
Ratio 13	Cost of sales to net sales	Profitability
Ratio 14	Net sales to cost of sales	Profitability
Ratio 15	Short term liabilities to assets	Solvency
Ratio 16	Current assets to active	Solvency
Ratio 17	Fixed assets to equity ratio	Solvency
Ratio 18	Return on equity	Profitability
Ratio 19	Net profit margin	Profitability
Ratio 20	Return on assets	Profitability
Ratio 21	Operating profit margin	Profitability
Ratio 22	Gross profitability ratio	Profitability
Ratio 23	Gross profit to current liabilities	Profitability
Ratio 24	Gross profit margin	Profitability
Ratio 25	Earnings before interest and tax (EBIT) to current liabilities	Liquidity
Ratio 26	EBIT to net sales	Liquidity
Ratio 27	EBIT to assets	Liquidity
Ratio 28	Inventories to current assets	Liquidity
Ratio 29	Inventories to total assets	Liquidity
Ratio 30	Net operating profit to equity	Profitability
Ratio 31	Net operating profit margin	Profitability
Ratio 32	Net operating profit to assets	Profitability
Ratio 33	Gross profit to net operating profit	Solvency
Ratio 34	Gross profit to long term liabilities	Solvency
Ratio 35	Fixed assets to total liabilities	Solvency
Ratio 36	Current assets to total liabilities	Solvency
Ratio 37	Gross profit to fixed assets	Solvency

Ratio name	Financial ratio name	Type
Ratio 38	Equity to short term liabilities	Solvency
Ratio 39	Equity to long term liabilities	Solvency
Ratio 40	Financial distress	Class

Appendix 2

Selected financial ratios

Features Count	Ratio Name (Selected Feature Name)
10	Working capital to total assets (**Feature 0**), Debt ratio (**Feature 1**), Equity to asset ratio (**Feature 2**), Sales to current assets ratio (**Feature 3**), Short term liabilities to assets (**Feature 4**), Return on assets (**Feature 5**), Gross profit to long term liabilities (**Feature 6**), Fixed assets to total liabilities (**Feature 7**), Current asset to total liabilities (**Feature 8**), Equity to short term liabilities (**Feature 9**).
20	Quick ratio (**Feature 0**), Working capital to net sales (**Feature 1**), Working capital to total assets (**Feature 2**), Debt ratio (**Feature 3**), Equity to asset ratio (**Feature 4**), Active capital turnover (**Feature 5**), Sales to current assets ratio (**Feature 6**), Short term liabilities to assets (**Feature 7**), Return on assets (**Feature 8**), Gross profitability ratio (**Feature 9**), Earnings before interest and tax (EBIT) to current liabilities (**Feature 10**), Inventories to current assets (**Feature 11**), Inventories to total assets (**Feature 12**), Net operating profit margin (**Feature 13**), Net operating profit to assets (**Feature 14**), Gross profit to long term liabilities (**Feature 15**), Fixed assets to total liabilities (**Feature 16**), Current asset to total liabilities (**Feature 17**), Equity to short term liabilities (**Feature 18**), Equity to long term liabilities (**Feature 19**).
30	Quick ratio (**Feature 0**), Working capital to net sales (**Feature 1**), Working capital to total assets (**Feature 2**), Debt ratio (**Feature 3**), Equity to asset ratio (**Feature 4**), Debt to capital ratio (**Feature 5**), Active capital turnover (**Feature 6**), Equity multiplier (**Feature 7**), Sales to current assets ratio (**Feature 8**), Fixed asset turnover (**Feature 9**), Short term liabilities to assets (**Feature 10**), Fixed assets to equity ratio (**Feature 11**), Net profit margin (**Feature 12**), Return on assets (**Feature 13**), Operating profit margin (**Feature 14**), Gross profitability ratio (**Feature 15**), EBIT to current liabilities (**Feature 16**), EBIT to net sales (**Feature 17**), EBIT to assets (**Feature 18**), Inventories to current assets (**Feature 19**), Inventories to total assets (**Feature 20**), Net operating profit to equity (**Feature 21**), Net operating profit margin (**Feature 22**), Net operating profit to assets (**Feature 23**), Gross profit to long term liabilities (**Feature 24**), Fixed assets to total liabilities (**Feature 25**), Current assets to total liabilities (**Feature 26**), Gross profit to fixed assets (**Feature 27**), Equity to short term liabilities (**Feature 28**), Equity to long term liabilities (**Feature 29**).