Development of a Machine Learning-based Corporate Management Strategy Prediction Model Reflecting ESG Rating Information

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Abstract

In this study, the model reflected not only financial data but also corporate ESG rating information to predict corporate management strategies. Five Machine learning classifiers such as RF, SVM, XGBoost, LightGBM, and CatBoost were used to develop a model that predicts management strategies using machine learning classification techniques. The research results of this paper are as follows. First, the model that used financial data and ESG rating information together showed better prediction performance than the prediction model that used only financial data. In particular, the best performance was shown when the ESG rating was included, followed by the high performance in the management strategy prediction model in the order of governance, environmental, and social ratings. This means that ESG rating information is important in predicting corporate management strategies. Second, among the five machine learning classifiers, LightGBM performed the best when predicting corporate management strategies, followed by CatBoost, XGBoost, SVM, and RF. These results suggest that the Boost classifier is effective in predicting management strategies. The corporate management strategy prediction model developed in this study can be a useful tool for promoting the sustainable development of a company and is expected to provide important insights to managers and investors. In addition, these models are expected to contribute to improving a company's long-term performance by supporting the establishment of sustainable management strategies.

Keywords: management strategy, machine learning, management strategy prediction, ESG rating

1. Introduction

The purpose of this paper is to develop a model that effectively predicts corporate management strategies. Machine learning technology has the advantage of analyzing large amounts of data to discover patterns and perform predictions. Therefore, this study aims to develop a corporate management strategy prediction model with a high-performance by applying machine learning techniques.

The ESG (Environment, Society, and Governance) rating is emerging as an important indicator for evaluating sustainability and social responsibility of a corporate (Aydoğmuş et al., 2022). ESG factors have a significant impact on investor decision-making and long-term corporate performance, and the interest in them is increasing (Quintiliani, 2022).

The ESG rating has the following correlations with corporate management strategies. First, companies with high ESG ratings pursue sustainable management in terms of the environment, society, and governance (Yu and Xiao, 2022). Active ESG activities have a positive impact on long-term corporate performance and future corporate value. Second, management strategies that take ESG factors into account can reduce risks related to environmental regulations, social responsibility, and governance issues (Behl et al., 2022). This can improve the stability and reputation of the company. Third, since many investors value ESG performance, a high ESG rating can create more investment opportunities (Junius et al., 2020). Fourth, a management strategy that considers ESG helps build trust with customers and improve brand image (Zhang et al., 2020). In other words, through such corelations, companies can integrate ESG factors into their management strategies to achieve long-term growth.

Traditional management strategy analysis mainly relied on financial indicators, but considering ESG factors will allow for more accurate management strategy analysis. Therefore, this paper develops a machine learning-based corporate management strategy prediction model including ESG ratings by utilizing various machine learning classification techniques.

The differences between this paper and previous studies are as follows: First, while previous studies focused on the individual impact of ESG factors, this paper comprehensively integrates them to identify that they are factors that significantly affect management strategies. Second, it precisely models the complex correlation between ESG rating data and management strategy by utilizing the latest machine learning algorithm. Third, presenting a model that predicts a company's management strategy by considering ESG rating is a topic that has not yet been studied domestically or internationally, which has great academic and practical contributions. Fourth, it provides useful information so that executives and investors can make better decisions based on ESG information.

The management strategy prediction model developed in this study can be a useful tool for companies to pursue sustainable development and is expected to provide important insights to managers and investors.

In addition, it is expected that this model will contribute to improving the long-term performance of companies by supporting the establishment of sustainable management strategies.

2. Theoretical Review

2.1 Preceding Researches

The results of examining preceding researches showed that many of the existing studies on corporate management strategies focused on the relationship with management performance. Bowman and Helfat (2001) argued that corporate performance changes according to corporate management strategies. Grant (2002) focused on the scope and content of corporate management strategies. This study analyzed the scope of management strategies, such as which products, markets, and activities a company should participate in, and the content of management strategies, such as how to secure competitive advantage in the market. This paper emphasized the importance of strategic decision-making by managers and explained that management strategies have a significant impact on corporate performance. Yoon Jongrok and Kim Hyeongcheol (2009) conducted a multidimensional analysis of factors affecting the management performance of venture companies. They conducted an empirical analysis using questionnaire data targeting domestic venture companies.

The results of the analysis showed that strategies played a complete or partial mediating role in factors of entrepreneurial capacity, technology, functional capacity and innovativeness among the characteristics of entrepreneurs. Gong Seokjin and Yang Haesul (2014) also studied the impact of management strategy on management performance, and found that offensive and defensive strategies, cost advantage, and differentiation strategies all had a positive effect on financial performance and non-financial performance. In addition, they confirmed that information technology utilization level had a moderating effect on the relationship between management strategy and management performance. Han Gyudong (2019) analyzed the mediating effect of management strategy in the relationship between entrepreneur characteristics and management performance in venture companies. The results of the study showed that the entrepreneur's enterprising spirit had the greatest positive effect on management performance, and that innovativeness and enterprising spirit had a significant effect on technological innovation and marketing differentiation strategies, respectively.

Management strategy had a significant positive effect on management performance, and showed a partial mediating effect in the relationship between entrepreneur characteristics and management performance. Chu Seungyeop et al. (2009) empirically analyzed the impact of the relationship between the management environment, competitive strategy, and internal capabilities of a company on management performance. Environmental uncertainty and differentiation strategy showed a positive relationship, and specific internal capabilities showed a positive effect depending on the type of strategy. In addition, high-performance groups had higher suitability of environment-strategy and capacity-strategy than low-performance groups. Park Dain and Park Chanhee (2018) confirmed that the degree of external cooperation and the degree of utilization of venture management support systems by a company have different effects on competitiveness and performance depending on the life cycle of the company.

The effects on corporate competitiveness were different depending on the introduction stage, early growth stage, high growth stage, maturity stage, and decline stage, and the factors affecting management performance were also different. Koh Sehoon et al. (2013) analyzed the relationship between the management environment, competitive strategy, and management performance of manufacturing SMEs and venture companies. It was confirmed that the industrial environment did not significantly affect the competitive strategy, while the resource and capacity factors affected all strategies except the concentration strategy.

In addition, each competitive strategy contributed to technology, market, and financial performance, and in particular, technology performance was found to affect the market and financial performance.

Meanwhile, the major studies on management strategy, ESG, and CSR are as follows. González-Ramos et al. (2023) analyzed the relationship between knowledge management strategies and corporate social responsibility (CSR) and investigated their impact on innovation capabilities. This paper emphasizes that knowledge management and CSR are important factors in improving a company's innovation capabilities, and suggests that the integration of the two factors can promote innovation performance. Nam Jeongmin and Park Junhyeok (2022) derived the priorities of ESG factors for venture companies using the AHP analysis technique. The results showed that the environment, society, and governance were of importance in that order, and in particular, the CEO's will to practice was important in the environment. In the society sector, basic rights and corruption prevention in the workplace were identified as important factors; and in the governance sector, protection of shareholder rights.

Yoon Seongyong (2023) analyzed the impact of management strategies on companies' ESG activities. It was divided into environment (E), society (S), and governance (G) through the economic justice index to verify the impact of each factor on corporate value. According to the results, the leading management strategy had a positive moderating effect on the relationship between the improvement of governance (G) and corporate value, but had no significant effect on activities in environment (E) and society (S). This suggests that improved governance can control managers' risky decisions and create optimal value.

The study of Yuan et al. (2020) analyzed the relationship between corporate management strategy and corporate social responsibility (CSR). This paper explores how corporate management strategy affects CSR activities and concludes that CSR has a positive impact on corporate reputation and long-term performance.

Previous studies on changes in management strategy according to the digital management environment are as follows: The study of Menz et al. (2021) explored corporate management strategy in the digital era. This paper analyzed the impact of digitalization on corporate strategic decision-making and management methods, and studied the impact of technological innovation on corporate management methods. It also suggested strategic measures for companies to secure competitive advantage in the digital environment.

Avanesova et al. (2021) analyzed the role of strategic management in the system model of corporate organizational development. This paper explored the impact of strategic management on organizational structure and performance for the sustainable development of companies, and emphasized that effective management strategy formulation and implementation were essential for corporate growth.

Akmaeva et al. (2020) analyzed the impact of digitalization on the management strategy and formation of new management models of modern companies. This paper suggested how the development of digital technology could innovatively change the strategic approach and management model of companies and thereby enhance competitiveness.

Gunarathne et al. (2021) analyzed the relationship between institutional pressure, environmental management strategy, and organizational performance due to the advent of the digital age. It emphasized that environmental management strategy contributed to responding to institutional pressure and improving the environmental performance of organizations.

And the major studies on corporate management strategy and human resource management are as follows: Brewster (2017) studied the integration of human resource management and corporate management strategy. It analyzed how human resource management contributed to corporate management strategy through human resource management policy and practice, and suggested a way to improve corporate management performance through harmony between human resource management and management strategy. This study emphasized the strategic importance of human resource management and argued that it could enhance corporate competitiveness.

Joo Sunghan and Jeong Namho (2023) investigated the impact of knowledge management strategies on employees' immersion experience and job retention intention from the perspective of hotel companies. As a result of the study, explicit knowledge management strategies had a significant impact on skills and goal clarity, but tacit knowledge did not. Immersion experience played a mediating role between goal clarity and job retention intention, and it emphasized the importance of balance through appropriate challenge.

2.2 Derivation of Research Issues

The followings are studies on management strategy and future corporate value. Hong Nanhee (2024) analyzed the impact of management strategy on corporate investment real estate holdings and corporate value, and reported that companies with leading strategies had a higher proportion of investment real estate holdings, which had a negative impact on corporate value.

This study provided empirical evidence that management strategy affected managers' decisions regarding investment real estate.

Bowman and Ambrosini (2007) explored how companies created corporate value through various management strategies. They classified corporate management strategies into several categories, and in particular, emphasized that resource allocation and competitive position played an important role in increasing corporate value.

Al-Shaer et al. (2023) investigated the relationship between corporate management value. They found that cost advantage strategy had a positive (+) relationship with strategy, board composition, and corporate

board size, independence, gender diversity, and tenure of executives, but a negative (-) relationship with managerial competence. On the other hand, differentiation strategy was found to have a positive relationship with board size and gender diversity of executives.

These results suggest that companies need to adjust the composition of their boards of directors in line with their management strategies.

Al-Najjar and Anfimiadou (2012) studied the impact of a company's environmental strategy on corporate value. This study emphasized that environmentally friendly strategies could have a positive impact on corporate value and concluded that sustainable management contributed to the creation of long-term corporate value. This suggests that corporate environmental strategy management had a competitive advantage.

Research on corporate management strategies has been actively conducted in various fields, but studies predicting corporate management strategies have not yet been identified. Therefore, research on predicting corporate management strategies through machine learning is expected to contribute to expanding the scope of research in the field of management strategy academically. In practical terms, the results of this study are expected to contribute to maintaining a competitive edge in the market by making strategic decisions ahead of competitors in terms of securing a competitive edge in providing guidelines for companies to identify and respond to potential future risks in advance in terms of risk management. Additionally, the result model presented in this study can help strengthen trust with investors through predictable management strategies.

In particular, predicting management strategies could provide useful information for companies to establish strategies for sustainable growth. Previous studies have verified that ESG activities significantly influenced corporate management strategies (González-Ramos et al., 2023; Yuan et al., 2020).

In particular, it can provide useful information for companies to establish strategies for sustainable growth through management strategy prediction. Previous studies have verified that ESG activities have a significant impact on companies' management strategies (González-Ramos et al., 2023; Yuan et al., 2020).

In this paper, in predicting a company's management strategy, not only financial data related to the management strategy but also ESG rating information of the company are reflected in the model. In other words, this study aims to present the best-performing management strategy prediction model using various recent machine learning classifiers.

3. Research Methods

3.1. Research Design and Data

The financial data of the companies used in this paper were downloaded from Vaule Search of NICE Credit Rating. The sample period is from 2012 to 2023, and financial industries that apply different accounting standards were excluded for data consistency. In addition, only companies with a fiscal year-end in December were used as samples for this study, and capital erosion companies in abnormal situations were excluded from the sample. And companies for which corporate financial data could not be obtained from Vaule Search were also excluded from the sample, and companies for which it was impossible to calculate the management strategy variables, which are the key variables to be predicted in this study, were excluded from the sample as well. Furthermore, companies that did not disclose ESG ratings from the Korea Institute of Corporate Governance and Sustainability(KCGS) were not included in the sample. Through this sample composition process, the final number of company samples used in the empirical analysis of this paper is 9,568. The sample composition process is summarized in <Table 1> below.

<Table 1> Sample Composition

Sample Composition	Number of Sample
Listed companies excluding financial companies from 2012 to 2023	20,577
Excluding companies with a fiscal year-end in December	-332
Capital erosion companies	-57
Excluding companies without corporate financial data	-43
Excluding companies for which management strategies (offensive, defensive) cannot be obtained	-4,765
Companies that did not disclose ESG ratings from the Korea Institute of Corporate Governance and Sustainability	-5,812
Sample 2012~2023	9,568

The corporate management strategy measurement used in this study refers to the method used in Bentley et al. (2013), Choi Gyudam (2016), and Higgins et al. (2015). The corporate management strategy measurement derives the management strategy index by the following six factors.

(1) New product development: Ratio of R&D expenses to sales
(2) Production efficiency: Ratio of number of employees to sales
(3) Growth pattern: Corporate growth rate (Price Book Value Ratio, PBR)
(4) Marketing effort: Ratio of sales expenses to sales
(5) Organizational stability: Standard deviation of total number of employees
(6) Capital intensity: Ratio of facility assets to total assets

The specific process of deriving the management strategy index is as follows: The average value is derived for each of the six measurement factors above that reflect various aspects of corporate management strategy, and they are ranked by year and industry. And then, after classifying it into 5 stages (quintiles), 5 points are given to the highest stage and 1 point to the lowest stage to ensure that the highest score is the leading type and the lowest score is the defensive type. However, in the case of capital intensity, if excessive investment is made in facility assets to achieve efficiency, it is similar to a defensive management strategy, so on the contrary, 1 point is given to the highest level; and 5 points, to the lowest level. If this calculation process is performed for each of the 6 measurement factors, a value between 1 and 5 points is given for each of the 6 measurement factors for each year, and if all the points given for each factor are added up, a comprehensive score between 6 and 30 points is derived. In conclusion, the higher the comprehensive score, the closer it is to a leading management strategy, and conversely; the lower the comprehensive score, the closer it is to a defensive management strategy.

The classification of the management strategy type is classified as a leading (prospector) management strategy if the comprehensive score is 23-30 points; and a defensive (defender) management strategy if the composite score is 6-13 points. The remaining 14-22 points were classified as an analyzer management strategy and were excluded from the sample of this study.

And the ESG ratings used in this study were obtained through the KCGS, and were quantified as 6 for A+ rating, 5 for A rating, 4 for B+ rating, 3 for B rating, 2 for C rating, and 1 for D rating for empirical analysis. The environmental, social, governance ratings, and total ratings were all quantified in the same way. <Table 2> is the definition of the variables used in this study.

<Table 2> Variable Definition

Variable	변수정의
Prospector	Offensive management strategy = 1 if the management strategy index is 23-30, otherwise 0
Defender	Defensive management strategy = 1 if the management strategy index is 6-13, otherwise 0
E	Points are awarded based on the environmental rating of the KCGS. (A+=6, A=5, B+=4, B=3, C=2, D=1)
S	Points are awarded based on the social rating of the KCGS. (A+=6, A=5, B+=4, B=3, C=2, D=1)
G	Points are awarded based on the governance rating of the KCGS. (A+=6, A=5, B+=4, B=3, C=2, D=1)
ESG	Points are awarded based on the total rating of the KCGS. (A+=6, A=5, B+=4, B=3, C=2, D=1)
ROA	Return on total assets = net income / total assets
SIZE	Firm size = natural log value of total assets
LEV	Debt ratio = total debt / total assets
CUR	Current Ratio = Current Liabilities / Current Assets
GRW_Sales	Sales growth rate = (current sales − previous sales) / previous sales
AGE	Company age = natural logarithmic value of (current fiscal year - year of incorporation)
OWN	Largest shareholder's stake = Largest shareholder's stake including the stake of specially-related parties / Total share of shareholders
FORN	Foreign stake = Foreign investor stake / Total share of shareholders
LOSS	Previous loss = 1 if the company reported a loss in its financial statements, otherwise 0

<Table 3> shows the descriptive statistics values for the variables. It was confirmed that the mean value of Prospector, a variable indicating an offensive management strategy, was 0.057, the median was 0.000, and the standard deviation was 0.233. And the mean value of Defender, a variable indicating a defensive management strategy, was 0.042, the median was 0.000, and the standard deviation was 0.201.

The mean value of ESG environmental

2.343, the median was 2.000, and the standard deviation was 1.445. The mean value of ESG social rating was 2.696, the median was 3.000, and the value of ESG governance rating was 2.875, the median was 3.000, and the standard deviation was 1.018. The mean of the ESG total rating was 2.513, the median was 3.000, and the standard deviation was 1.339.

<Table 3> Descriptive statistics

Variable	Number of Sample	Mean	Std	Min	Q1	Median	Q3	Max
Prospector	9,568	0.057	0.233	0.000	0.000	0.000	0.000	1.000
Defender	9,568	0.042	0.201	0.000	0.000	0.000	0.000	1.000
E	9,568	2.343	1.445	0.000	1.000	2.000	3.000	6.000
S	9,568	2.696	1.520	0.000	2.000	3.000	4.000	6.000
G	9,568	2.875	1.018	0.000	2.000	3.000	3.000	6.000
ESG	9,568	2.513	1.339	0.000	2.000	3.000	3.000	6.000
ROA	9,568	0.020	0.090	-0.464	-0.002	0.025	0.058	0.296
SIZE	9,568	26.652	1.453	23.613	25.654	26.455	27.397	30.604
LEV	9,568	0.391	0.204	0.027	0.221	0.391	0.543	0.875
CUR	9,568	2.660	4.216	0.195	0.938	1.464	2.603	32.472
GRW_Sales	9,568	0.060	0.316	-0.701	-0.074	0.026	0.135	2.111
AGE	9,568	3.522	0.582	1.792	3.135	3.689	3.951	4.844
OWN	9,568	0.422	0.165	0.000	0.302	0.425	0.533	1.000
FORN	9,568	0.094	0.127	0.000	0.013	0.043	0.124	1.000
LOSS	9,568	0.246	0.431	0.000	0.000	0.000	0.000	1.000

3.2. Research Model

The corporate management strategy prediction model to be developed in this paper is based on previous studies on management strategy, and extracts financial variables that have a significant impact on management strategy to construct the research model. The specific description of the financial data used in the corporate management performance

rating was prediction model is as follows: First, ROA is a variable that means return on total assets and is often used as a proxy variable for corporate management performance. Corporate management performance is significantly affected by management strategies. Therefore, it was used in the corporate management strategy prediction model. In addition, since the management strategies established differ depending on the size of the company, SIZE, a variable that means corporate size, was also added to the prediction model (D'Amato and Falivena, 2020). The debt ratio and current ratio of a company mean the financial soundness and stability of the company, which can have a significant impact on the establishment and promotion of management strategies, so LEV and CUR were also added to the prediction model (Abraham et al., 2020; Zimon et al., 2021).

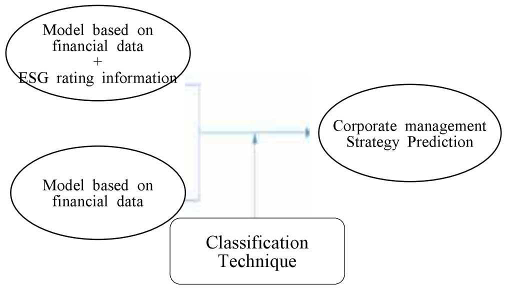
According to the corporate life cycle theory, the corporate management strategy pursued changes according to the growth stage. To reflect this, the variable GRW_Sales, which means the sales growth rate, and the variable AGE, which means the age of the company, were used in the management strategy prediction model (Dewi et al., 2022; Wen et al., 2022).

Meanwhile, since the management strategy of a company is established by the management, the corporate governance structure acts as an important factor (Lubatkin et al., 2005; Cuevas-Rodriguez et al., 2016). Therefore, the variable OWN, which means the largest shareholder's stake, and the variable FORN, which means the foreign investor's stake, which are often used as corporate governance variables, were added to the management strategy prediction model. Finally, since the management strategy pursued may completely change if the company reports a loss, the variable LOSS, which means whether the company reported a loss, was also used in the prediction model.

The prediction model designed with financial variables that significantly affect the management strategy based on previous studies on management strategy is as shown in Equation (1) below. And the prediction model designed by considering not only financial variables that have a significant impact on management strategy
but also ESG rating information is as shown in Equation (2) below.

[Financial Variable-Based Model]
Corporate Management Strategy Prediction (Prospector / Defender
= F(ROA, SIZE, LEV, CUR, GRW_Sales, AGE, OWN, FORN, LOSS) Equation(1)

[Financial Variable-Based Model + ESG Rating]
Corporate Management Strategy Prediction (Prospector / Defender
= F(ROA, SIZE, LEV, CUR, GRW_Sales, AGE, OWN, FORN, LOSS, E, S, G, ESG) Equation(2)



<Figure 1> Research Method

In this study, it is expected that a model with added ESG rating information will have higher prediction performance than a model composed only of financial data related to management strategy when predicting corporate management strategy, and this is proven through various machine learning classifiers.
<Figure 1> is a diagram to make it easy to understand the research methodology of the corporate management strategy prediction model that this paper aims to develop.

3.3. Machine Learning Classification Technique

In this paper, a management strategy prediction model is developed using machine learning classification techniques. In machine learning, classification aims to classify input data into distinct classes (Osisanwo et al., 2017).

Generally, the machine learning model assigns probability scores to each class using the soft-max function in the final output layer (Lopez-Martinez et al., 2018). The class with the highest probability is usually selected in the prediction step (Osisanwo et al., 2017).

To handle classification problems, machine learning uses the cross-entropy loss function to measure the difference between the predicted class probability and the actual class label (Kumari and Srivastava, 2017). The parameters of the model are adjusted to minimize this discrepancy (Wang et al., 2021). In these machine learning classification techniques, evaluation indicators such as Accuracy, precision, Recall, AUC (Area

Under the Curve), and F1 score are used to evaluate the performance of the model (Kumari and Srivastava, 2017).

Accuracy is the proportion of correctly classified samples among all samples, and it measures the frequency with which the model's predictions match the actual class labels, indicating the overall proficiency of the model (Soofi and Awan, 2017). precision is the proportion of actual positive samples among the samples predicted as positive, and is calculated as the proportion of actual positive samples among the predicted positive samples (Narayanan et al., 2016). In other words, precision reflects the ability of the model to correctly identify positive samples. recallis the proportion of actual positive samples correctly predicted as positive, and measures the proportion of actual positive samples correctly identified by the model (Pirscoveanu et al., 2015). In other words, recallevaluates the effectiveness in capturing the positive class.

AUC is the area under the ROC (Receiver Operating Characteristics) curve, which evaluates the overall performance of a classification model (Shafiq et al., 2016). In other words, AUC evaluates a binary classification model by its ability to distinguish between positive and negative classifications using the ROC curve. This curve shows the true positive rate relative to the false positive rate at various classification thresholds (Maxwell et al., 2018). The AUC value ranges from 0 to 1, and the value closer to 1 indicates the classification performance of the model (Shafiq et al., 2016).

The F1 score, which is the harmonic mean of precision and Recall, comprehensively measures the classification ability of the model (Narayanan et al., 2016). The F1 score provides a more balanced evaluation performance for model performance, making it particularly useful when dealing with imbalanced data. The F1 score ranges from 0 to 1, and a higher value indicates better classification performance (Soofi and Awan, 2017).

3.4. Machine Learning Classifier

RF (Random Forest) is an ensemble learning technique that performs predictions using various decision-making trees (Gholizadeh et al., 2020). Each tree learns on a random sample of data, and the final prediction is based on the average of the prediction results of all trees (Khajavi and Rastgoo, 2023). The advantage of RF is that it reduces overfitting and shows high accuracy (Khozeimeh et al., 2022). In addition, RF is robust to noise and can be flexibly applied to various data types (Wongvibulsin et al., 2020). On the other hand, the disadvantage of RF is that it may be expensive in terms of computational cost because it uses many trees, and that it makes model interpretation difficult (Gholizadeh et al., 2020).

SVM (Support Vector Machine) is a supervised learning technique that finds the optimal hyperplane to separate data points in a high-dimensional space (Pisner and Schnyer, 2020). It can solve nonlinear classification problems using kernel tricks (Roy and Chakraborty, 2023). SVM works well on high-dimensional data with clear decision boundaries and performs excellently on small data sets (Kurani et al., 2023). However, SVM is expensive in terms of computational cost, and hyperparameter tuning is complicated for large data sets (Cervantes et al., 2020).

XGBoost (Extreme Gradient Boosting) efficiently implements the gradient boosting algorithm (Qiu et al., 2022). XGBoost improves performance at each step by adding a new model to reduce errors (Asselman et al., 2023). The advantages of XGBoost are its high prediction performance and efficiency (Sagi and Rokach, 2021). And various techniques to prevent overfitting are also included in XGBoost (Zhang et al., 2023). On the other hand, the disadvantage of XGBoost is that it has many hyperparameters, making tuning complex and taking a long time to learn (Asselman et al., 2023).

LightGBM (Light Gradient Boosting Machine) is a gradient boosting framework developed by Microsoft for fast learning on large-scale data sets (Wang et al., 2022). LightGBM uses the Tree Leaf method (Liu et al., 2021). The advantages of LightGBM are learning speed and low memory usage, and it is suitable for large-scale data sets (Rufo et al., 2021). However, the disadvantage of LightGBM is that overfitting may occur due to the complexity of the model, and data preprocessing may be also complicated (Yan et al., 2021).

CatBoost is a gradient boosting algorithm developed by Yandex. It is optimized for categorical data processing and has characteristics that are insensitive to data order (Hancock and Khoshgoftaar, 2020). The advantages of CatBoost are that it has an automatic processing function for categorical data and high prediction performance (Ibrahim et al., 2020). CatBoost also includes various functions to prevent overfitting (Jabeur et al., 2021). On the other hand, the disadvantages of CatBoost are that it can take a long time to learn and may require hyperparameter tuning depending on the situation (Luo et al., 2021).

The characteristics of the classifiers used in this study can be summarized as follows: RF can be applied to various data types and effectively reduce overfitting, but it is expensive in terms of computational cost. SVM performs well in high-dimensional data and is advantageous in small data sets, but it is expensive in terms of computational cost in large data.

XGBoost has high prediction performance and efficiency, but hyperparameter tuning is complicating. LightGBM learns quickly on large data sets and uses less memory, but it can cause overfitting. CatBoost is robust on categorical data and shows high performance, but it may take a long time to learn. Since the performance of each classifier model can vary depending on the characteristics and circumstances of the data, this study uses five machine learning classifier models to compare and analyze their performance in order to predict corporate management strategies and identify which model is the most suitable.

4. Research Analysis Results

This study develops a model that predicts corporate management strategies using machine learning classification techniques. It reveals that models that add ESG rating information have higher prediction performance than models that only consist of financial data related to corporate management strategies when predicting corporate management strategies through various machine learning classifiers. The five machine learning classifiers used in this study are RF, SVM, XGBoost, LightGBM, and CatBoost.

<Table 4> is the research results on the Accuracy performance among the analysis results of corporate management strategy prediction.

First, the results using the RF model are as follows: The management strategy accuracy prediction result by the financial data-based model was 0.7651, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.7814.

In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.7701, and when the governance rating was included, the management strategy accuracy prediction result was 0.7939. Finally, when the ESG total rating was included in the financial data-based model, the management strategy accuracy prediction result was high at 0.8013.

Second, the results using the SVM model are as follows: the management strategy accuracy prediction result by the financial data-based model was 0.7745, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.7978.

And when the social rating among ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.7829, and when the governance rating was included, the management strategy accuracy prediction result was 0.8061. Finally, when the ESG total rating was included in the financial data-based model, the management strategy accuracy result was high at 0.8127.

Third, the results using the XGboost model are as follows: The management strategy accuracy prediction result by the financial data-based model was 0.8013, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.8238.

And when the social rating among ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.8120, and when the governance rating was included, the management strategy accuracy prediction result was 0.8379. Finally, when the ESG total rating was included in the financial data-based model, the management strategy accuracy prediction result was high at 0.8431.

Fourth, the results using the LightGBM model are as follows. The management strategy accuracy prediction result by the financial data-based model was 0.8670, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.8827.

In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.8704, and when the governance rating was included, the management strategy accuracy prediction result was 0.8968. Finally, when the ESG total rating was included in the financial data-based model, the management strategy accuracy prediction result was the highest at 0.9009.

Fifth, the research results using the CatBoost model are presented below. The management strategy accuracy prediction result by the financial data-based model was 0.8329, and when the environmental rating among the ESG rating was included in the financial data-based model, the management strategy accuracy prediction result was 0.8513.

In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy accuracy prediction result was 0.8407, and when the governance rating was included, the management strategy accuracy prediction result was 0.8688.

Finally, when the ESG total rating was included in the financial data-based model, the management strategy accuracy prediction result was high at 0.8827.

<Table 4> Corporate Management Strategy Prediction Results (Accuracy)

Model Type	Classifier	Accuracy	Classifier	Accuracy	Classifier	Accuracy	Classifier	Accuracy	Classifier	Accuracy
financial data-based model		0.7651		0.7745		0.8013		0.8670		0.8329
financial data-based model + E rating		0.7814		0.7978		0.8238		0.8827		0.8513
financial data-based model + S rating	RF	0.7701	SVM	0.7829	XGboost	0.8120	Light GBM	0.8704	Cat Boost	0.8407
financial data-based model + G rating		0.7939		0.8061		0.8379		0.8968		0.8688
financial data-based model + ESG rating		**0.8013**		**0.8127**		**0.8431**		**0.9009**		**0.8827**

<Table 5> presents the research results on precision performance among the results of corporate management strategy prediction. First, the results using the RF model are as follows: The management strategy precision prediction result by the financial data-based model was 0.7542, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy precision prediction result was 0.7738. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy precision prediction result was 0.7701, and when the governance rating was included, the management strategy precision prediction result was 0.7939. Finally, when the ESG total rating was included in the financial data-based model, the management strategy precision prediction result was high at 0.7930.

Second, the results using the SVM model are as follows: The management strategy precision prediction result by the financial data-based model was 0.7832, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy precision prediction result was 0.8032. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy precision prediction result was derived as 0.7901, and when the governance rating was included, the management strategy precision prediction result was derived as 0.8179. Finally, when the ESG total rating was included in the financial data-based model, the management strategy precision prediction result was high at 0.8277.

Third, the results using the XGboost model are as follows: The management strategy precision prediction result by the financial data-based model was 0.8123, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy precision prediction result was 0.8399. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy precision prediction result was derived as 0.8254, and when the governance rating was included, the management strategy precision prediction result was derived as 0.8527. Finally, when the ESG total rating was included in the financial data-based model, the management strategy precision prediction result was high at 0.8681.

Fourth, the results using the LightGBM model are as follows: The management strategy precision prediction result by the financial data-based model was 0.8865, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy precision prediction result was 0.9022. In addition, when the social rating among the ESG ratings was included in the financial data-based model, tthe management strategy precision prediction result was 0.8910, and when the governance rating was included, the management strategy precision prediction result was 0.9137. Finally, when the ESG total rating was included in the financial data-based model, the management strategy precision prediction result was the highest at 0.9278.

Fifth, the results of the research using the CatBoost model are presented below. The management strategy precision prediction result by the financial data-based model was 0.8231, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy precision prediction result was 0.8412. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy precision prediction result was 0.8360, and when the governance rating was included, the management strategy precision prediction result was 0.8536. Finally, when the ESG total rating was included in the financial data-based model, the management strategy precision prediction result was high at 0.8698.

<Table 5> Corporate Management Strategy Prediction Results (Precision)

Model Type	Classifier	Precision	Classifier	Precision	Classifier	Precision	Classifier	Precision	Classifier	Precision
financial data-based model	RF	0.7542	SVM	0.7832	XGboost	0.8123	Light GBM	0.8865	Cat Boost	0.8231
financial data-based model + E rating		0.7738		0.8032		0.8399		0.9022		0.8412
financial data-based model + S rating		0.7612		0.7901		0.8254		0.8910		0.8360
financial data-based model + G rating		0.7825		0.8179		0.8527		0.9137		0.8536
financial data-based model + ESG rating		**0.7930**		**0.8277**		**0.8681**		**0.9278**		**0.8698**

<Table 6> shows the research results on the recallperformance among the results of the prediction of corporate management strategies.

First, the results using the RF model are as follows: The management strategy recall prediction result by the financial data-based model was 0.7705, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy recall prediction result was 0.7924. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy recall prediction result was 0.7811, and when the governance rating was included, the management strategy recall prediction result was 0.8009. Finally, when the ESG total rating was included in the financial data-based model, the result of the prediction of the management strategy recallwas high at 0.8110.

Second, the results using the SVM model are as follows. the management strategy recall prediction result by the financial data-based model was 0.7920, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy recall prediction result was 0.8174. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy recall prediction result was derived as 0.8009, and when the governance rating was included, the management strategy recall prediction result was derived as 0.8288. Finally, when the ESG total rating was included in the financial data-based model, the management strategy recall prediction result was high at 0.8391.

Third, the results using the XGboost model are as follows: The management strategy recall prediction result by the financial data-based model was 0.8233, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy recall prediction result was derived as 0.8469. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy recall prediction result was derived as 0.8340, and when the governance rating was included, the management strategy recall prediction result was derived as 0.8512. Finally, when the ESG total rating was included in the financial data-based model, the management strategy recall prediction result was high at 0.8588.

Fourth, the results using the LightGBM model are as follows: The management strategy recall prediction result by the financial data-based model was 0.8963, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy recall prediction result was 0.9169. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy recall prediction result was 0.9077, and when the governance rating was included, the management strategy recall prediction result was 0.9213. Finally, when the ESG total rating was included in the financial data-based model, the management strategy recall prediction result was the highest at 0.9325.

Fifth, the research results using the CatBoost model are presented below. The result of the management strategy recall prediction by the financial data-based model was 0.8413, and when the environmental rating among the ESG ratings was included in the financial data-based model, the result of the management strategy recall prediction was 0.8624. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the result of the management strategy recall prediction was 0.8507, and when the governance rating was included, the result of the management strategy recall prediction was 0.8790. Finally, when the ESG total rating was included in the financial data-based model, the result of the management strategy recall prediction was high at 0.8806.

<Table 6> Corporate Management Strategy Prediction Results (Recall)

Model Type	Classifier	Recall	Classifier	Recall	Classifier	Recall	Classifier	Recall	Classifier	Recall
financial data-based model		0.7705		0.7920		0.8233		0.8963		0.8413
financial data-based model + E rating		0.7924		0.8174		0.8469		0.9169		0.8624
financial data-based model + S rating	RF	0.7811	SVM	0.8009	XGboost	0.8340	Light GBM	0.9077	Cat Boost	0.8507
financial data-based model + G rating		0.8009		0.8288		0.8512		0.9213		0.8790
financial data-based model + ESG rating		**0.8110**		**0.8391**		**0.8588**		**0.9325**		**0.8806**

<Table 7> presents the research results on AUC performance among the results of corporate management strategy prediction.

First, the results using the RF model are as follows: The management strategy AUC prediction result by the financial data-based model was 0.7603, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.7813. In addition, when the social rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.7708, and when the governance rating was included, the management strategy AUC prediction result was 0.7932. Finally, when the ESG total rating was included in the financial data-based model, the management strategy AUC prediction result was high at 0.8002.

Second, the results using the SVM model are as follows: The management strategy AUC prediction result by the financial data-based model was 0.7821, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.8078. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was derived as 0.7931, and when the governance rating was included, the management strategy AUC prediction result was derived as 0.8121. Finally, when the ESG total rating was included in the financial data-based model, the management strategy AUC prediction result was high at 0.8233.

Third, the results using the XGboost model are as follows: The management strategy AUC prediction result by the financial data-based model was 0.8237, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.8451. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was derived as 0.8310, and when the governance rating was included, the management strategy AUC prediction result was derived as 0.8591. Finally, when the ESG total rating was included in the financial data-based model, the management strategy AUC prediction result was high at 0.8689.

Fourth, the results using the LightGBM model are as follows: The management strategy AUC prediction result by the financial data-based model was 0.8705, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.8901. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.8821, and when the governance rating was included, the management strategy AUC prediction result was 0.9055. Finally, when the ESG total rating was included in the financial data-based model, the management strategy AUC prediction result was the highest at 0.9167.

Fifth, the research results using the CatBoost model are presented below. The management strategy AUC prediction result by the financial data-based model was 0.8312, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.8557. In addition, when the social rating among ESG ratings was included in the financial data-based model, the management strategy AUC prediction result was 0.8408, and when the governance rating was included, the management strategy AUC prediction result was 0.8684. Finally, when the ESG total rating was included in the financial data-based model, the management strategy AUC prediction result was high at 0.8821.

<Table 7> Corporate Management Strategy Prediction Result (AUC)

Model Type	Classifier	AUC	Classifier	AUC	Classifier	AUC	Classifier	AUC	Classifier	AUC
financial data-based model	RF	0.7603	SVM	0.7821	XG boost	0.8237	Light GBM	0.8705	Cat boost	0.8312
financial data-based model + E rating		0.7813		0.8078		0.8451		0.8901		0.8557
financial data-based model + S rating		0.7708		0.7931		0.8310		0.8821		0.8408
financial data-based model + G rating		0.7932		0.8121		0.8591		0.9055		0.8684
financial data-based model + ESG rating		**0.8002**		**0.8233**		**0.8689**		**0.9167**		**0.8821**

<Table 8> shows the research results on the F1 score performance among the results of predicting corporate management strategies.

First, the results using the RF model are as follows: The management strategy F1 score prediction result by the financial data-based model was 0.7637, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.7855. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.7741, and when the governance rating was included, the management strategy F1 score prediction result was 0.7963. Finally, when the ESG total rating was included in the financial data-based model, the management strategy F1 score prediction result was high at 0.8021.

Second, the results using the SVM model are as follows: The management strategy F1 score prediction result by the financial data-based model was 0.7905, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.8128. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.8087, and when the governance rating was included, The management strategy F1 score prediction result was 0.8278. Finally, when the ESG total rating was included in the financial data-based model, the management strategy F1 score prediction result was high at 0.8330.

Third, the results using the XGboost model are as follows: The management strategy F1 score prediction result by the financial data-based model was 0.8209, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.8454. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was derived as 0.8312, and when the governance rating was included, the management strategy F1 score prediction result was derived as 0.8591. Finally, when the ESG total rating was included in the financial data-based model, the management strategy F1 score prediction result was high at 0.8688.

Fourth, the results using the LightGBM model are presented as follows: The management strategy F1 score prediction result by the financial data-based model was 0.8943, and when the environmental rating among ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.9124. And when the social rating among ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was derived as 0.9010, and when the governance rating was included, the management strategy F1 score prediction result was derived as 0.9235. Finally, when the ESG total rating was included in the financial data-based model, the management strategy F1 score prediction result was the highest at 0.9301.

Fifth, the research results using the CatBoost model are presented below. The management strategy F1 score prediction result by the financial data-based model was 0.8348, and when the environmental rating among the ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.8514. In addition, when the social rating among the ESG ratings was included in the financial data-based model, the management strategy F1 score prediction result was 0.8410, and when the governance rating was included, the management strategy F1 score prediction result was 0.8690. Finally, when the ESG total rating was included in the financial data-based model, the management strategy F1 score prediction result was high at 0.8755.

<Table 8> Corporate Management Strategy Prediction Result (F1 score)

Model Type	Classifier	F1 score	Classifier	F1 score	Classifier	F1 score	Classifier	F1 score	Classifier	F1 score
financial data-based model	RF	0.7637	SVM	0.7905	XG boost	0.8209	Light GBM	0.8943	Cat Boost	0.8348
financial data-based model + E rating		0.7855		0.8128		0.8454		0.9124		0.8514
financial data-based model + S rating		0.7741		0.8087		0.8312		0.9010		0.8410
financial data-based model + G rating		0.7963		0.8278		0.8591		0.9235		0.8690
financial data-based model + ESG rating		**0.8021**		**0.8330**		**0.8688**		**0.9301**		**0.8755**

5. Discussion and Conclusion

5.1 Research Summary and Results

In this paper, in predicting corporate management strategies, not only financial data related to management strategies but also ESG rating information of the company were reflected in the model. In this study, machine learning classifiers RF, SVM, XGBoost, LightGBM, and CatBoost were used to develop a model that predicts corporate management strategies by utilizing machine learning classification techniques.

The results of the study are summarized as follows: First, the corporate management strategy prediction model that included ESG rating information in financial data showed better prediction performance than the corporate management strategy prediction model composed of only financial data. The best performance was shown when the ESG total rating was included among the ESG ratings, and the high performance was shown in the order of governance rating, environmental rating, and social rating when these information were considered. This means that ESG rating information is an important factor in predicting corporate management strategies.

Second, among the five machine learning classifiers, LightGBM was confirmed to have the best prediction performance in predicting corporate management strategies. Next, it was confirmed that the best performance was shown in the order of CatBoost, XGBoost, SVM, and RF in predicting corporate management strategies. This result means that the Boost series classifier is effective in predicting management strategies.

5.2 Contributions and Expected Effects

The contributions and expected effects of this paper are as follows: Above all, the followings are academic contributions. First, this study expanded the scope of research in the field of management strategies by proposing a new machine learning model that predicts management strategies by integrating ESG ratings and financial data. Second, it strengthened the academic foundation for research in the field of machine learning prediction by proposing an analysis methodology that utilizes various machine learning algorithms.

And the practical contributions of this study are as follows: First, the research results of this paper can be used as a sophisticated and accurate decision-making support tool that considers ESG factors when establishing corporate management strategies. Second, it indirectly suggests that it is important to reflect ESG factors when establishing corporate management strategies, and that it is important to establish and promote strategies that consider corporate sustainability.

Meanwhile, the academic expected effects of this study are as follows: First, it is expected to promote follow-up research on the relationship between ESG and management strategy and contribute to expanding the research base in the field of management strategy prediction.

Second, it is expected that the new data integration method used in this study will be ues in other research fields and utilized to improve model performance.

And the practical expected effects are as follows: First, it is expected that this study can contribute to improving the long-term management efficiency of companies through a strategy prediction method that reflects ESG factors in terms of improving management efficiency. Second, the results of this study are expected to provide investors with ESG-based management strategy information to support better investment decisions.

5.3 Limitations and Future Research Directions

Despite the above academic and practical contributions and expected effects, the limitations of this paper and future research plans are as follows: There are also problems such as the transparency of evaluating ESG ratings and the differences in the calculation method ratings in the methodology of each rating agency, which increases the volatility, and this has been shown to be a limitation in developing a corporate management strategy prediction model in that there is a high correlation between agencies.

If the management strategy model had been designed by reflecting important qualitative information of companies such as management reports, audit reports, and sustainable management reports in addition to ESG ratings, the prediction performance could have been further improved. In future research, I am planning to develop a more sophisticated and detailed management strategy prediction model by collecting various important qualitative information of companies.

Reference

[Previous Studies in Korea]

고세훈, 유왕진, & 이윤보. (2013). 중소벤처기업의 경쟁전략과 경영성과 간의 구조적 관계 에 관한 실증연구. 생산성연구: 국제융합학술지, 27(1), 225-260.

공석진, & 양해술. (2014). 경영전략이 경영성과에 미치는 영향. Journal of Digital Convergence, 12(1), 177-192.

남정민, & 박준혁. (2022). 벤처기업의 ESG 경영전략 도출을 위한 계층분석과정 (AHP) 적용. Entrpreneurship & ESG 연구, 2(1), 1-25.

박다인, & 박찬희. (2018). 벤처기업의 성장단계별 기업 경쟁력 및 기업 성과 창출 전략. 벤처창업연구, 13(6), 177-189.

윤성용. (2023). 경영전략이 ESG 와 기업가치와의 관계에 미치는 영향. 비즈니스융복합연구, 8(4), 33-38.

윤종록, & 김형철. (2009). 벤처기업의 창업가특성과 차

별화전략이 경영성과에 미치는 영향에 관한 연구. 대한경영학회지, 22(6), 3693-3721.

주성한, & 정남호. (2023). 호텔기업의 지식경영전략이 종사원의 몰입과 직무유지의도에 미치는 영향. 인터넷전자상거래연구, 23(3), 205-231.

최규담. (2016). 경영전략과 발생액의 질. 회계저널, 25(3), 261-305.

추승엽, 유정민, & 임성준. (2009). 경영환경, 경쟁전략 및 기업 내부역량 간의 적합성이 성과에 미치는 영향에 관한 연구. 전략경영연구, 12(1), 101-126.

한규동. (2019). 벤처기업 창업가의 특성과 경영전략이 경영성과에 미치는 영향. 벤처창업연구, 14(6), 29-43.

홍난희. (2024). 경영전략과 투자부동산 그리고 기업가치. 대한경영학회지, 37(4), 611-630.

[Previous Studies Abroad]

Abraham, F., Cortina Lorente, J. J., & Schmukler, S. L. (2020). Growth of global corporate debt: Main facts and policy challenges. World Bank Policy Research Working Paper, (9394).

Akmaeva, R., Arykbaev, R., Epifanova, N., & Glinchevskiy, E. (2020). Influence of digitalization upon formation of corporate strategy and new business models of modern organizations. In SHS Web of Conferences (Vol. 89, p. 03003). EDP Sciences.

Al‐Najjar, B., & Anfimiadou, A. (2012). Environmental policies and firm value. business Strategy and the Environment, 21(1), 49-59.

Al‐Shaer, H., Kuzey, C., Uyar, A., & Karaman, A. S. (2023). Corporate strategy, board composition, and firm value. International Journal of Finance & Economics.

Asselman, A., Khaldi, M., & Aammou, S. (2023). Enhancing the prediction of student performance based on the machine learning XGBoost algorithm. Interactive Learning Environments, 31(6), 3360-3379.

Avanesova, N., Tahajuddin, S., Hetman, O., Serhiienko, Y., & Makedon, V. (2021). Strategic management in the system model of the corporate enterprise organizational development. Economics and Finance, 1(2021), 9.

Aydoğmuş, M., Gülay, G., & Ergun, K. (2022). Impact of ESG performance on firm value and profitability. Borsa Istanbul Review, 22, S119-S127.

Behl, A., Kumari, P. R., Makhija, H., & Sharma, D. (2022). Exploring the relationship of ESG score and firm value using cross-lagged panel analyses: Case of the Indian energy sector. Annals of Operations Research, 313(1), 231-256.

Bentley, K. A., Omer, T. C., & Sharp, N. Y. (2013). management strategy, financial reporting irregularities, and audit effort. Contemporary accounting research, 30(2), 780-817.

Bowman, C., & Ambrosini, V. (2007). Firm value creation and levels of strategy. Management Decision, 45(3), 360-371.

Bowman, E. H., & Helfat, C. E. (2001). Does corporate strategy matter?. Strategic management journal, 22(1), 1-23.

Brewster, C. (2017). The integration of human resource management and corporate strategy. Policy and practice in European human resource management, 22-35.

Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges and trends. Neurocomputing, 408, 189-215.

Cuevas-Rodriguez, G., Guerrero-Villegas, J., & Valle-Cabrera, R. (2016). Corporate governance changes, firm strategy and compensation mechanisms in a privatization context. Journal of Organizational Change Management, 29(2), 199-221.

D'Amato, A., & Falivena, C. (2020). Corporate social responsibility and firm value: Do firm size and age matter? Empirical evidence from European listed companies. Corporate Social Responsibility and Environmental Management, 27(2), 909-924.

Dewi, N. W. S. K., Ratnadi, N. M. D., Yadnyana, I. K., & Suaryana, I. G. N. A. (2022). Selection of profit management strategy: Testing at the company life cycle stage. Linguistics and Culture Review, 6(S1), 530-549.

Gholizadeh, M., Jamei, M., Ahmadianfar, I., & Pourrajab, R. (2020). Prediction of nanofluids viscosity using random forest (RF) approach. Chemometrics and Intelligent Laboratory Systems, 201, 104010.

González-Ramos, M. I., Guadamillas, F., & Donate, M. J. (2023). The relationship between knowledge management strategies and corporate social responsibility: Effects on innovation capabilities. Technological Forecasting and Social Change, 188, 122287.

Grant, R. M. (2002). Corporate strategy: managing scope and strategy content. Handbook of strategy and management, 72-97.

Gunarathne, A. N., Lee, K. H., & Hitigala Kaluarachchilage, P. K. (2021). Institutional pressures, environmental management strategy, and organizational performance: The role of environmental management accounting. management Strategy and the Environment, 30(2), 825-839.

Hancock, J. T., & Khoshgoftaar, T. M. (2020). CatBoost for big data: an interdisciplinary review. Journal of big data, 7(1), 94.

Higgins, D., Omer, T. C., & Phillips, J. D. (2015). The influence of a firm's management strategy on its tax aggressiveness. Contemporary Accounting Research, 32(2), 674-702.

Ibrahim, A. A., Ridwan, R. L., Muhammed, M. M., Abdulaziz, R. O., & Saheed, G. A. (2020). Comparison of the CatBoost classifier with other machine learning methods. International Journal of Advanced Computer Science and Applications, 11(11).

Jabeur, S. B., Gharib, C., Mefteh-Wali, S., & Arfi, W. B. (2021). CatBoost model and artificial intelligence techniques for corporate failure prediction. Technological Forecasting and Social Change, 166, 120658.

Junius, D., Adisurjo, A., Rijanto, Y. A., & Adelina, Y. E. (2020). The impact of ESG performance to firm performance and market value. Jurnal Aplikasi Akuntansi, 5(1), 21-41.

Khajavi, H., & Rastgoo, A. (2023). Predicting the carbon dioxide emission caused by road transport using a Random Forest (RF) model combined by Meta-Heuristic Algorithms. Sustainable Cities and Society, 93, 104503.

Khozeimeh, F., Sharifrazi, D., Izadi, N. H., Joloudari, J. H., Shoeibi, A., Alizadehsani, R., ... & Islam, S.

M. S. (2022). RF-CNN-F: random forest with convolutional neural network features for coronary artery disease diagnosis based on cardiac magnetic resonance. Scientific reports, 12(1), 11178.

Kumari, R., & Srivastava, S. K. (2017). Machine learning: A review on binary classification. International

Journal of Computer Applications, 160(7).

Kurani, A., Doshi, P., Vakharia, A., & Shah, M. (2023). A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. Annals of Data Science, 10(1), 183-208.

Liu, J., Gao, Y., & Hu, F. (2021). A fast network intrusion detection system using adaptive synthetic oversampling and LightGBM. Computers & Security, 106, 102289.

Lopez-Martinez, F., Schwarcz, A., Núñez-Valdez, E. R., & Garcia-Diaz, V. (2018). Machine learning classification analysis for a hypertensive population as a function of several risk factors. Expert Systems with Applications, 110, 206-215.

Lubatkin, M. H., Lane, P. J., & Schulze, W. S. (2005). A strategic management model of agency relationships in firm governance. The Blackwell handbook of strategic management, 225-254.

Luo, M., Wang, Y., Xie, Y., Zhou, L., Qiao, J., Qiu, S., & Sun, Y. (2021). Combination of feature selection and catboost for prediction: The first application to the estimation of aboveground biomass. Forests, 12(2), 216.

Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: An applied review. International journal of remote sensing, 39(9), 2784-2817.

Menz, M., Kunisch, S., Birkinshaw, J., Collis, D. J., Foss, N. J., Hoskisson, R. E., & Prescott, J. E. (2021). Corporate Strategy and the Theory of the Firm in the Digital Age. Journal of Management Studies,

58(7), 1695-1720.

Narayanan, B. N., Djaneye-Boundjou, O., & Kebede, T. M. (2016, July). Performance analysis of machine learning and pattern recognition algorithms for malware classification. In 2016 IEEE national aerospace and electronics conference (NAECON) and ohio innovation summit (OIS) (pp. 338-342). IEEE.

Osisanwo, F. Y., Akinsola, J. E. T., Awodele, O., Hinmikaiye, J. O., Olakanmi, O., & Akinjobi, J. (2017). Supervised machine learning algorithms: classification and comparison. International Journal of Computer Trends and Technology (IJCTT), 48(3), 128-138.

Pirscoveanu, R. S., Hansen, S. S., Larsen, T. M., Stevanovic, M., Pedersen, J. M., & Czech, A. (2015, June). Analysis of malware behavior: Type classification using machine learning. In 2015 International conference on cyber situational awareness, data analytics and assessment (CyberSA) (pp. 1-7). IEEE.

Pisner, D. A., & Schnyer, D. M. (2020). Support vector machine. In Machine learning (pp. 101-121). Academic Press.

Qiu, Y., Zhou, J., Khandelwal, M., Yang, H., Yang, P., & Li, C. (2022). Performance evaluation of hybrid WOA-XGBoost, GWO-XGBoost and BO-XGBoost models to predict blast-induced ground vibration. Engineering with Computers, 38(Suppl 5), 4145-4162.

Quintiliani, A. (2022). ESG and firm value. Accounting and Finance Research, 11(4), 37.

Roy, A., & Chakraborty, S. (2023). Support vector machine in structural reliability analysis: A review. Reliability Engineering & System Safety, 233, 109126.

Rufo, D. D., Debelee, T. G., Ibenthal, A., & Negera, W. G. (2021). Diagnosis of diabetes mellitus using gradient boosting machine (LightGBM). Diagnostics, 11(9), 1714.

Sagi, O., & Rokach, L. (2021). Approximating XGBoost with an interpretable decision tree. Information sciences, 572, 522-542.

Shafiq, M., Yu, X., Laghari, A. A., Yao, L., Karn, N. K., & Abdessamia, F. (2016, October). Network traffic classification techniques and comparative analysis using machine learning algorithms. In 2016 2nd IEEE International Conference on Computer and Communications (ICCC) (pp. 2451-2455). IEEE.

Soofi, A. A., & Awan, A. (2017). Classification techniques in machine learning: applications and issues. Journal of Basic & Applied Sciences, 13, 459-465.

Wang, D. N., Li, L., & Zhao, D. (2022). Corporate finance risk prediction based on LightGBM. Information Sciences, 602, 259-268.

Wang, P., Fan, E., & Wang, P. (2021). Comparative analysis of image classification algorithms based on traditional machine learning and deep learning. Pattern recognition letters, 141, 61-67.

Wen, H., Zhong, Q., & Lee, C. C. (2022). Digitalization, competition strategy and corporate innovation: Evidence from Chinese manufacturing listed companies. International Review of Financial Analysis, 82, 102166.

Wongvibulsin, S., Wu, K. C., & Zeger, S. L. (2020). Clinical risk prediction with random forests for survival, longitudinal, and multivariate (RF-SLAM) data analysis. BMC medical research methodology, 20, 1-14.

Yan, J., Xu, Y., Cheng, Q., Jiang, S., Wang, Q., Xiao, Y., ... & Wang, X. (2021). LightGBM: accelerated genomically designed crop breeding through ensemble learning. Genome biology, 22, 1-24.

Yu, X., & Xiao, K. (2022). Does ESG performance affect firm value? Evidence from a new ESG-scoring approach for Chinese enterprises. Sustainability, 14(24), 16940.

Yuan, Y., Lu, L. Y., Tian, G., & Yu, Y. (2020). management strategy and corporate social responsibility. Journal of management ethics, 162, 359-377.

Zhang, F., Qin, X., & Liu, L. (2020). The interaction effect between ESG and green innovation and its impact on firm value from the perspective of information disclosure. Sustainability, 12(5), 1866.

Zhang, J., Ma, X., Zhang, J., Sun, D., Zhou, X., Mi, C., & Wen, H. (2023). Insights into geospatial heterogeneity of landslide susceptibility based on the SHAP-XGBoost model. Journal of environmental management, 332, 117357.

Zimon, G., Nakonieczny, J., Chudy-Laskowska, K., Wójcik-Jurkiewicz, M., & Kochański, K. (2021). An analysis of the financial liquidity management strategy in construction companies operating in the Podkarpackie Province. Risks, 10(1), 5.

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