PREDICTING THE FINANCIAL HEALTH OF SMEs IN VIETNAM: A COMPARISON AND EVALUATION OF RESULTS BETWEEN CLASSICAL MODELS AND MACHINE LEARNING MODELS

Author: Huynh Thanh Hai[1], Vu Thi Hanh Dung, Phan Thi Thuy Duyen, Le Tuong Vy, Le Quang Bao

Mentor: Vo Thi Le Uyen[2]

University of Economics and Law – Vietnam National University, Ho Chi Minh City

ABSTRACT

Financial health is one of the most important factors to evaluate the effectiveness of the business. Forecasting the financial health of small and medium-sized enterprises (SMEs) helps to make market-appropriate business decisions and increases competitiveness in the international market. However, forecasting financial health for SMEs is facing with many major challenges. Some of them include the shortage of information, especially for start-ups or small businesses. The information on SMEs financial activities is often not made public, leading to difficulties in data collection and analysis. In addition, existing classic models of financial health forecasting such as Z-score, X-score, H-score, while commonly used, have some limitations and are not suitable in today's complex business environment. With the rapid development of technology, machine learning models are becoming an important tool in forecasting the financial health of SMEs. The study compared the effectiveness of machine learning models (Logistic, LDA, SVM, Random Forest, XGBoost) and classic models to forecast the financial health of SMEs in Vietnam. The results showed that the best in the machine learning model is XGBoost with a forecast of 94%, and the best classic one is X-Score with a forecast of 85.6%. This suggests that machine learning models can provide better predictive results than traditional classical models. The use of predictive models and machine learning tools such as XGBoost and the SHAP values algorithm is very useful in assessing the financial health of businesses. From the results of the SHAP algorithm, it can be seen that small and medium enterprises should focus on ROA indicators and quick payment ratios to be able to improve or prevent the risk of their business exhaustion.

Keywords: Financial health, SMEs, classic models, SHAP values.

[1] Corresponding author: Huynh Thanh Hai; Tel: +84 909 378832; Email: haiht20413c@st.uel.edu.vn

[2] Mentor: Vo Thi Le Uyen; Tel: +84 911 647272; Email: uyenvtl@uel.edu.vn

PREDICTING THE FINANCIAL HEALTH OF SMEs IN VIETNAM: A COMPARISON AND EVALUATION OF RESULTS BETWEEN CLASSICAL MODELS AND MACHINE LEARNING MODELS

Author: Huynh Thanh Hai, Vu Thi Hanh Dung, Phan Thi Thuy Duyen, Le Tuong Vy, Le Quang Bao

Mentor: Vo Thi Le Uyen

University of Economics and Law – Vietnam National University, Ho Chi Minh City

ABSTRACT

Financial health is one of the most important factors to evaluate the effectiveness of the business. Forecasting the financial health of small and medium-sized enterprises (SMEs) helps to make market-appropriate business decisions and increases competitiveness in the international market. However, forecasting financial health for SMEs is facing with many major challenges. Some of them include the shortage of information, especially for start-ups or small businesses. The information on SMEs financial activities is often not made public, leading to difficulties in data collection and analysis. In addition, existing classic models of financial health forecasting such as Z-score, X-score, H-score, while commonly used, have some limitations and are not suitable in today's complex business environment. With the rapid development of technology, machine learning models are becoming an important tool in forecasting the financial health of SMEs. The study compared the effectiveness of machine learning models (Logistic, LDA, SVM, Random Forest, XGBoost) and classic models to forecast the financial health of SMEs in Vietnam. The results showed that the best in the machine learning model is XGBoost with a forecast of 94%, and the best classic one is X-Score with a forecast of 85.6%. This suggests that machine learning models can provide better predictive results than traditional classical models. The use of predictive models and machine learning tools such as XGBoost and the SHAP values algorithm is very useful in assessing the financial health of businesses. From the results of the SHAP algorithm, it can be seen that small and medium enterprises should focus on ROA indicators and quick payment ratios to be able to improve or prevent the risk of their business exhaustion.

Keywords: Financial health, SMEs, classic models, SHAP values.

1. Introduction

In the current market economy, most of the GDP is generated from enterprises, at the same time, enterprises play an important role in promoting the development of the economy, creating jobs for workers to bring a stable source of income. Therefore, the performance of enterprises is the main factor determining the development of GDP in particular and the whole socio-economic economy in general. However, many businesses nowadays face and directly be affected by the global recession of the economy, the post-Covid 19 epidemic and the Ukraine-Russia war as well as the internal factors of the business itself. Some businesses with good financial performance will survive and some are on the verge of bankruptcy. Thus, the "financial health" of businesses is an issue that we care about. The financial health of a business or company can be seen as its ability to maintain a balance against changing environmental conditions and in relation to all actors in the business. In assessing financial health and predicting the financial problems of businesses, different indexes are used that can serve as inputs for estimating figures or creating different models. The problem of "financial health" of most businesses is often related to depleted operating capital, high inventory rates, tightening bank lending, unpaid debts... Evaluate based on financial indicators through financial statements published by businesses. In addition, use non-financial factors to consider the financial impact of enterprises to provide a model to forecast the ability to maintain operations, the risk of bankruptcy or insolvency of small and medium-sized enterprises (SMEs) in the market... However, there are many studies in the world as well as a few studies in Vietnam interested in the financial health of enterprises, which are almost all done on enterprises with a large capitalization of over VND 100 billion. Currently, there is not much research focused on SMEs, while in Vietnam, SMEs account for the majority of the market share and are a major contributor to the country's socio-economic development.

On the other hand, SMEs are currently facing and suffering from many financial risks, difficulties in using capital appropriately, encountering some challenges in the process of "transforming" to meet market demand, especially being heavily affected by the country's economic situation such as epidemics, crises, inflation,…

Edward I.Altman's (I.Altman, 1968) work on the Z-Score model provided the first foundation for predicting the likelihood of bankruptcy in businesses with input data of 22 financial indicators of businesses in the US stock market. The Z-score model has given 5 variables to forecast bankruptcy X_1: Working capital / Total assets; X_2: Retained profit / Total assets; X_3: Profit before tax and interest / Total assets; X_4: Market value of equity / Total Liabilities X_5: Total liabilities / Total assets. Altman proposed a predictive model with fixed weights based on statistical methods - Multiple Discriminant Analysis (MDA) and the result is a scale of about 3 levels: Safety, risk and bankruptcy. His research was widely used in the following years, resulting in extremely accurate predictions.

The same method with Altman, in 1984, Fulmer (Fulmer, et al., 1984) introduced the H-Score model forecasting the bankruptcy with 9 variables, V_1: Retained earnings / Total assets ;V_2: Revenue / Total assets; V_3: EBIT / Equity; V_4: Cash flow from operating activities / Liabilities; V_5: Liabilities / Total assets; V_6: Current liabilities / Total assets; V_7: Logarithm(Tangible assets); V_8: Working capital / Liabilities; V_9:Logarithm(EBIT / Interest). Also with statistical methods - Multiple Discriminant Analysis. He used his model with businesses with a capital of about $455,000 as a research platform for small and medium enterprises. Add to the model, Fulmer added fixed-asset elements and the ability to pay interest. The results of Fulmer's H-score model are classified as bankruptcy or safety.

However in the 1980s, the financial markets changed. Financial data is no longer accurate with Altman's and Fulmer's models of Multiple Discriminant Analysis. The constraints of this approach on assumptions and Multiple Discriminant Analysis do not allow adding dummy variables. This hinders the determination of qualitative factors affecting the ability of the business to go bankrupt. Ohlson (Ohlson & J, 1980) invented his O-Score model in 1980 with a method of using logistic regression to predict the probability of a business's bankruptcy. He outlined nine research variables, which added two dummy variables of earning after tax less than zero over two years and a dummy variable of total debt greater than total assets. The results obtained from this method are more accurate and simpler than the statistical method - Altman and Fulmer's Multiple Discriminant Analysis.

From classical models in foreign studies, access to modern machine learning methods. The study of Huynh Thi Cam Ha (Ha, Uyen, & Mai, 2017) studied the application of the classification tree model in forecasting financial distress in enterprises in Vietnam listed on Ho Chi Minh Stock Exchange and Hanoi Stock Exchange in the period of 2009 - 2015. The research paper has 6 groups of variables: liquidity group, capital structure group and debt repayment capacity group, profitability index group, operation index group, growth index group, non-financial index group. The study used two machine learning algorithms, C4.5 and AdaBoost to build a decision tree model. The model removed from 25 input variables remaining 10 important variables, the results from the study ranked the importance of financial indicators and gave a threshold for the impact of those indicators leading to financial distress For the C4.5 algorithm, the variable of financial leverage is the most important in affecting distress, whereas AdaBoost algorithm considers the variable representing the growth in equity as important. The results from the decision tree model are surprisingly accurate with up to 99.5% predictability. However, the disadvantage of the model in the research paper is the need for a large amount of input data, the AdaBoost method needs the number of learning times to be repeated many times because the models learn from each other, leading to difficult model running, requiring large memory.

Summary, from overviews of studies predicting bankruptcy of domestic and foreign enterprises, most of the research focuses on large markets and businesses with huge capitalization such as the US. The great contribution of Altman, Fulmer and Ohlson's research has solved the problems of enterprises in quantifying the risk of bankruptcy to help businesses understand the financial situation of their businesses. The models have measured financial indicators collected and aggregated from corporate financial statements over the years but have not yet expanded and agreed on qualitative variables as well as non-financial factors. main: type of enterprise, classification of business lines, number of shares held by shareholders... The influence of non-financial factors also leads to shortcomings in the ability to forecast the financial health of enterprises. This laid the foundation for the development of the research paper which has further practical applications in social life and financial markets.

Recognizing the importance of forecasting "Financial health" and offering solutions to limit the risk of bankruptcy for SMEs in the post-COVID-19 period is urgent and necessary for the development of the country's economy, the research team decided to implement the project "Forecasting the financial health of small and medium enterprises in Vietnam: Comparing and explaining the results between classic models and machine learning models".

The project is implemented with the desire to contribute to diversifying domestic research as well as contributing to the assessment of the financial potential of SMEs, helping businesses have a better overview of their financial capacity and have an appropriate financial plan for sustainable development. The study will be evaluated by each group of enterprises based on relevant indicators and indicators to bring optimal results and consistency to the study.

The objective of the project is to develop a model for forecasting the financial health of SMEs in Vietnam. Based on the study of SME theories, on the risk of financial distress and the development of financial health forecasting models.

The research topic uses a combination of literature and quantitative research. Document research was conducted by systematizing existing research, finding research gaps and building model ideas to overcome shortcomings in the connection between research variables and put research hypotheses for the topic. Quantitative research with wstimating parameters, testing models and hypotheses set out to make development recommendations. Refer to the expert method, based on the opinions and models proposed by the expert to increase the practicality of the topic. This article used descriptive statistics and quantitative models from classical to machine learning. The models used are: Z - score, X - score, S - Score, H - Score, Logistics Regression, Linear Discriminant Analysis, Random Forest, Support Vector Machine, XGBoost… From there, it is suggested what is the best model to use to assess financial health, or in other words, the risk of financial distress. At the same time, it provides solutions to prevent and limit the risk of financial distress as soon as possible to ensure stable, long-term and sustainable financial operations.

2. Theoretical framework

2.1. SMEs

Small and medium enterprises (SMEs) is a relative concept used to compare the size of an enterprise compared to large enterprises. The determination of criteria and norms for assessing the size of SMEs differs in each country, depending on the level of economic development, cultural context and the purpose of classifying SMEs. However, in general, most countries define SMEs according to three basic criteria: the average number of employees that enterprises use in the year, the total investment capital of the enterprise, the total annual revenue of the enterprise. In which the criteria of labour and investment capital are more widely used. In Vietnam, there are many different definitions of small and medium enterprises,these concepts change over time and the way this type of business is perceived.

Table 1. Agriculture, Forestry, Fishery, Industry and Construction

	Number of labourers	Total capital	Total Revenue
Medium sized enterprises	200	≤ 100	200
Small sized enterprises	100	20	50
Very small sized enterprises	10	3	3

Source: Author's collection

Table 2. Trade and Service

	Number of labourers	Total capital	Total Revenue
Medium sized enterprises	100	100	≤ 300
Small sized enterprises	50	50	100
Very small sized enterprises	10	3	10

Source: Author's collection

2.2. Financial distress

Financial distress is a temporary lack of liquidity, making it difficult to pay financial obligations. This situation increases when there are high fixed costs, illiquid assets or revenue sensitive to bad fluctuations of the economy. Financial distress can lead to bankruptcy. There are many different views and signs of financial distress, but the general definition is when cash flow is not enough to ensure financial obligations, former shareholders lose ownership and creditors hold the assets of the business. This situation can be solved by restructuring business activities or economic organization structure. Financial distress is only the stage in the process of failure and restructuring of the business.

Signs of financial distress of the business:

A business runs into financial distress when there is insufficient cash flow to meet its financial obligations, and this can best be reflected by the cash flow of the business. Financially exhausted businesses often have liabilities greater than the total assets or interest payment ratio of less than one. In general, financial distress goes through three main stages: early, middle and later. At an early stage, the business will face many problems such as reduced operating profits, declining sales The middle stage will make the business in a state of "insolvency". Finally, in the later stage, when the problems cannot be overcome, the business is forced to end, this is the stage of "insolvency, bankruptcy".

2.3. The importance of financial ratios

In order for a business to maintain sustainable operations and long-term growth, it needs to have a solid financial foundation, much like how an individual needs good health to live and work effectively. To assess the financial health of business, important financial ratios need to be examined and analyzed in financial statement, as a way to measure the "health" of the company. Below are some essential groups of financial ratios needed for analyzing and evaluating the financial health of a business:

(i) **Quick ratios:** is one of the important indicators in assessing the financial capacity of a business and helps improve financial management effectiveness. It indicates the ability of the business to quickly pay off short-term debts based on short-term assets that can be converted into cash as quickly as possible.

(ii) **Inventory turnover:** is a financial ratio that assesses a business's ability to manage inventory, indicating the number of times a business sells and replaces its stock of goods during a given period. This ratio helps businesses understand the performance of each product and plan for future development. Effective inventory management is highly important for asset management within a business.

(iii) **Average Collection Period:** is a financial ratio that measures the average time it takes for customers to pay their debts to a business. It needs to be considered in conjunction with other ratios to assess the financial condition and business efficiency of a company. While a lower average collection period is generally favourable, if it becomes too strict, it can also impact customer attraction and lead to other business issues.

(iv) **Fixed asset turnover ratio:** is a ratio used to assess the efficiency of a business's utilization of its fixed assets to generate revenue. However, it is influenced by various factors such as pricing, useful life, and investment in fixed assets. Depreciation rate, residual value, and the rate of increase in fixed assets also affect this ratio. However, fixed asset turnover has limitations in evaluating the speed of capital turnover for a business.

(v) **Return On Sales:** is an important ratio for evaluating business performance and comparing it to other companies within the industry or the general market. Evaluating ROS also helps investors and other stakeholders assess the financial performance of a business. However, ROS also has limitations and needs to be considered in conjunction with other indicators to make informed decisions about the business's operations.

(vi) **Return On Assets:** is a measure of a company's efficiency in using its assets to generate earning after tax. It helps assess the effectiveness of a company's investment activities and serves as an important basis for lenders or creditors to evaluate the profit-generating capability of the business. ROA also helps owners evaluate the impact of financial leverage and make capital mobilisation decisions. It is a significant ratio in financial analysis and provides valuable information for investors and managers to assess the efficiency of a company's operations.

3. Research method

3.1. Data of research

In this research, the data includes the financial information of SMEs in Vietnam, which was collected from the FiinPro database. This data comprises financial indicators such as assets, liabilities, revenue, profit, and other indicators. Data collection took place from 2018 to 2021, but some cases were excluded from the dataset to ensure the integrity and accuracy of the research results.

This study utilizes financial indicators to evaluate the financial health of SMEs on the UPCOM, HOSE, and HNX stock exchanges. Only businesses with a capital scale of 100 billion VND or less, established before 2018, and with at least 1-year financial activity were selected for analysis to obtain financial data. Financial distress prediction of SMEs was carried out 1 year prior to the distressing event.

3.2. Data preprocessing

In the process of predicting the financial health of SMEs in Vietnam, processing the financial reports of small and medium-sized enterprises is a complex task that requires caution to ensure the accuracy and reliability of the forecasting results. Data preprocessing helps eliminate incorrect, missing, inaccurate, and irrelevant data before inputting them into the forecasting models.

After completing the data preprocessing process, the data will be cleaned and ready to be applied to the forecasting models and their effectiveness evaluated. The research team divided the dataset into training and testing sets as follows: using the year 2018 for training and testing in 2019, using the year 2019 for training and testing in 2020, and finally using the year 2020 for training and forecasting for 2021 to test.

3.3. Expected variables

3.3.1. Dependent variable

The research study calculates the dependent variable based on two factors to determine when a company is labeled as distressed:

Negative free cash flow: Free cash flow is represented by the three cash flows in variables X_2, X_3 and X_4. When the free cash flow is negative, the company will not have any sources of funds to pay for its short-term debts, which is one of the signs of financial distress when the company cannot generate profits.

S-Score index < 0.862: The S-Score index is currently the most suitable index for evaluating the market in Vietnam, according to research by (Le Hoang Vinh and colleagues, 2022).

Therefore, determining the label for distressed companies is based on meeting at least one of the above conditions.

3.3.2. Independent variables

When researching the financial health forecasting model of Vietnamese SMEs, financial ratio variables are a crucial part. These variables measure and analyze the financial performance of the enterprise, helping managers, investors, and other stakeholders to assess the financial health of the enterprise and make appropriate decisions.

In this study, the research team synthesized variables from classic models such as Z-Score, X-Score, S-Score, H-Score, and added a number of commonly used variables to evaluate an enterprise.

Table 3. Expected variables in the model

Variable	Description of variables
X_1	(Short_term assets – Short_term debt) / total assets
X_2	Dummy operation cash flow (1 if $X_2 > 0$, 0 if $X_2 \leq 0$)
X_3	Dummy investment cash flow (1 if $X_3 > 0$, 0 if $X_3 \leq 0$)
X_4	Dummy financial cash flow (1 if $X_4 > 0$, 0 if $X_4 \leq 0$)
X_5	Earning before interest and tax / total assets
X_6	Net revenue / total assets
X_7	Earning after tax / total assets
X_8	Earning before tax / short-term debts
X_9	Earning before interest and tax / equity
X_{10}	Net cash flow / total debts
X_{11}	Logarithm(Tangible property)
X_{12}	Logarithm(Earning before interest and tax / interest expenses)
X_{13}	(Short_term assets - inventory) / short_term debts
X_{14}	Money / short_term debts
X_{15}	Cost of goods sold / inventory
X_{16}	Short-term receivables / net revenue
X_{17}	Cost of goods sold / payable accounts

X_{18}	Net revenue / fixed assets
X_{19}	Earning after tax / net revenue
X_{20}	Short_term debt / total assets
X_{21}	Total debts / total assets
X_{22}	Short_term assets / short_term debts
X_{23}	Earning after tax / equity

Source: Author's collection

3.4. Research models

3.4.1. Random Forest

The Random Forest model is a machine learning algorithm used in classification and prediction problems. This model combines multiple decision trees to create a better classification or prediction model.

Random Forest uses Bootstrapping technique to randomly sample a subset of data from the initial training set to build a decision tree. Then, Random Forest combines these decision trees to create a more general classification or prediction model.

The decision trees are built by finding the most important features to divide the data into groups. The decision trees are built independently, thus, Random Forest minimizes the overfitting phenomenon.

The Random Forest also provides methods to evaluate the accuracy and importance of features. It is also capable of handling missing and imbalanced data. Another evaluation method of Random Forest is the Out-of-Bag (OOB) error, which is calculated by using data points not used in the tree building process to evaluate the model. The Random Forest model is an effective classification and prediction model, widely used in real-world problems.

3.4.2. eXtreme Gradient Boosting (XGBoost)

The XGBoost model is a powerful and widely used machine learning algorithm for classification and prediction problems, including financial distress prediction. It is built on the idea of using decision trees to create a high-performance classification or prediction model.

The decision trees in XGBoost are created through a boosting process, in which a sequence of decision trees is generated. Each decision tree learns from the errors of the previous decision tree and is modified to produce a new decision tree with better performance. Each decision tree is trained to predict the value of the dependent variable based on the values of the independent variables.

XGBoost combines a loss function and a regularization function to create an objective function for model optimization. The mathematical formula for the objective function F in XGBoost is expressed as follows:

$$\text{Objective}(F) = L(y, F) + \Omega(F)$$

where:

Objective(F): the objective function

L(y, F): the loss function

Ω(F): the regularization function

The XGBoost model is a variant of Gradient Boosting, in which some improvements have been made to enhance the speed and performance of the algorithm. An important improvement of XGBoost is the use of a differentiable loss function to optimize the model. Specifically, the loss function used is the log loss, similar to that in logistic regression.

XGBoost also uses decision trees to build the model, but instead of using independent decision trees, XGBoost uses a series of level-wise decision trees, each decision tree is built to optimize the remaining error after the previous decision trees have been built.

3.4.3. Explain machine learning model by using SHapley Additive exPlanations (SHAP)

Machine learning models are tools used to predict outcomes based on previously trained data. They can be seen as the artificial brain of a system, capable of learning from input data and optimizing parameters to make the most accurate predictions. However, some types of machine learning models, such as black box models, can make it difficult to explain their workings and decision-making processes, leading to difficulties in explaining why a decision was made or how the model arrived at its prediction. To address this issue, Lundberg and Lee introduced the SHAP (SHapley Additive exPlanations) explanation method in 2017. This method is based on Shapley values theory, a concept introduced in 1953 by Shapley and used to allocate value to a group of players based on their contributions to winning a game. SHAP values calculate the contribution of each feature to the model's prediction, helping users understand which features the model is predicting based on and why. The formula for calculating Shapley values for a feature is obtained by taking the average difference between the predicted value of the model with and without that feature.

$$\phi_i(f,x) = \sum_{z' \subseteq x'} \frac{|z'|!\,(M - |z'| - 1)!}{M!}\left[f_x(z') - f_x(z' \backslash i)\right]$$

Where:

$\phi_i(f,x)$ is the SHAP value of the input variable ith

x is the input vector

z' is the subset of X without variables ith

$f_x(z')$ is the prediction of the model on the z'

$f_x(z' \backslash i)$ Is the prediction of the model on the z' added variable ith

M is the number of input variables

The formula calculates the Shapley value of a feature by comparing the model's predicted value when that feature is present and when it is absent. Shapley values are computed for all features and summed to obtain the overall Shapley value for that data point.

3.4.4. Model evaluation

The confusion matrix is a tool for evaluating the performance of a classification model. It helps assess the model's predictive ability by comparing the predicted results to the ground truth. The confusion matrix consists of four main parts: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). Performance evaluation metrics such as Accuracy, Precision, Recall, and F1-score are computed based on the confusion matrix. The Type 1 and Type 2 error rates are important metrics for evaluating the model's classification ability on both Positive and Negative classes. If the error rate is too high, the classification model needs improvement to reduce classification errors.

Accuracy is the ratio of the number of correctly classified cases to the total number of cases and is calculated by the formula: Accuracy = (TP + TN) / (TP + TN + FP + FN). Accuracy reflects the model's ability to classify correctly across the entire data set.

Recall is the ratio of the number of correctly classified Positive cases to the total number of actual Positive cases and is calculated by the formula: Recall = TP / (TP + FN). Recall reflects the model's ability to classify correctly on the Positive class.

AUC (Area Under the ROC Curve) is the area under the Receiver Operating Characteristic (ROC) curve and measures the model's ability to distinguish between Positive and Negative classes. The closer the AUC is to 1, the better the classification model.

F1-score is the harmonic mean of Precision and Recall and is calculated by the formula: F1-score = 2 * Precision * Recall / (Precision + Recall). F1-score reflects the balance between Precision and Recall.

4. Research Results

4.1. Data preprocessing and results

The research team conducted Exploratory Data Analysis on a dataset of 507 companies. The team created a target variable using the S-Score model and free cash flow as the criteria. If a company had either an S-Score < 0.862 or negative free cash flow, it would be unable to pay its short-term debts and would be labeled as 1; otherwise, if the S-Score ≥ 0.862 and free cash flow is positive, it would be labeled as 0. As a result of this labeling, the study identified 97 bankrupt companies and 410 non-bankrupt companies.

After labeling the dependent variable, the research team constructed independent variables from financial statement to fit the list of expected variables entered into the model, including 23 financial indicators. Variables used to calculate the S-Score and those with high correlation were removed to avoid duplication.

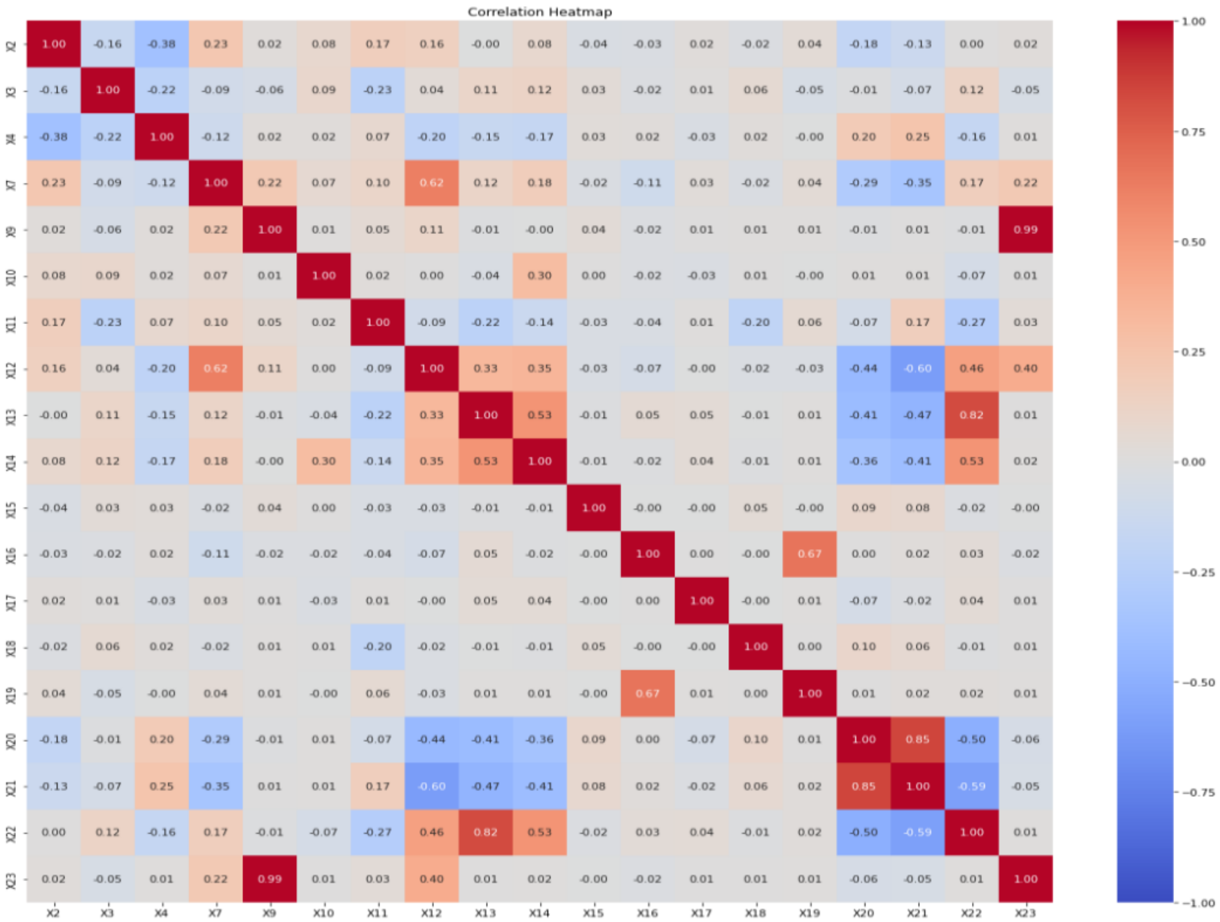

Figure 1. Correlation matrix between variables

Source: Author's calculation

Based on the correlation graph, the research team removed variables with high correlation, such as X_{21}, X_{22}, and X_{23}. In addition, variables used as conditions for the dependent variable calculation, such as X_1, X_5, X_8, and X_6, were also removed to avoid duplication.

Six best variables were selected to be included in the machine learning models for comparison with the classical models that uses fewer variables, to examine the superiority of the machine learning methods over the classical ones. After data calculation, the model selected variables X_7, X_{13}, X_{16}, X_{17}, X_{18}, and X_{19} for machine learning computation.

The research team performed data splitting into training and testing sets, and tested the predictions based on training and testing over the years. Year 2018 was used for training and predicting for year 2019, year 2019 was used for training and predicting for year 2020, and year 2020 was used for training and predicting for year 2021.

4.2. Comparison and evaluation of the results between the classical models and the machine learning models

Table 4. Comparison of predictive power and error types between the machine learning models and the classical models

	Accuracy	Type 1 Error	Type II Error
XGBoost	**94%***	**3,41%*****	**10,25%*****
Random Forest	76%	7,95%	**7,69%****
X – Score	**85,6%****	12,97%	**1,42%***
Z – Score	**85,1%*****	**0,23%***	18,35%
H – Score	81,9%	**1,09%****	17%

*With * being the first rank, ** being the second rank, and *** being the third rank*

Source: Author's calculation

In the model evaluation table, XGBoost and X-Score performed the best with accuracies of 94% and 85.6%, respectively. Although XGBoost had a higher accuracy, X-Score misclassified the fewest distressed samples. Random Forest and Z-Score had lower performances, with Random Forest achieving only 76% accuracy and Z-Score achieving 85.1%. However, both error types and accuracy need to be considered when evaluating a model. Therefore, XGBoost and X-Score are noteworthy models, while Random Forest and H-Score need improvement to achieve better performance.

The results show that the XGBoost model is suitable for predicting the financial health of small and medium-sized enterprises. This model provides a more modern approach and prediction in the digitalization process of enterprises. On the other hand, the X-Score model still demonstrates outstanding ability in predicting for businesses despite some limitations. This helps businesses prevent risks and make appropriate adjustments to avoid bankruptcy.

4.3. Explanation of machine learning model results

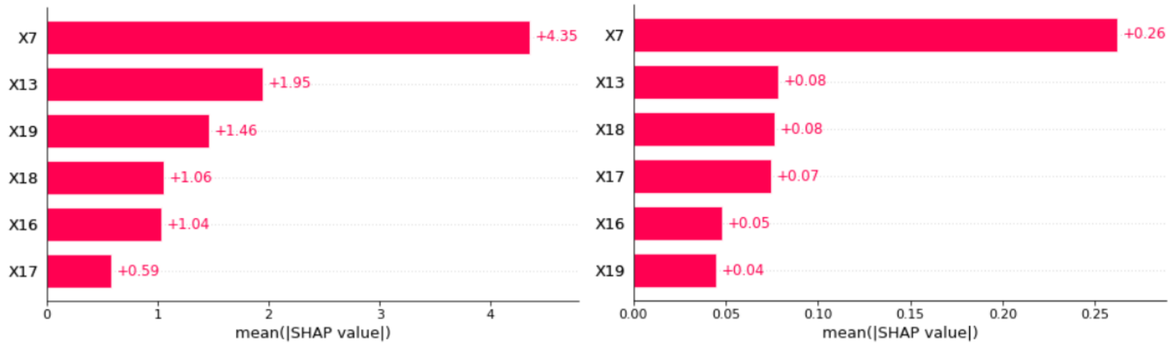

Figure 2: SHAP evaluation plots of the XGBoost (left) and Random Forest (right)

Source: Author's calculation

Based on the calculated SHAP values, it can be seen that both machine learning models evaluate variable X_7 as the most important variable and having a strong impact on the likelihood of a small and medium-sized enterprise falling into financial distress. Additionally, variable X_{13} also has an impact at a moderate level for the XGBoost model, which evaluates it as high after variable X_7, while for the Random Forest model, it is evaluated as having the same impact as variable X_{18}. Therefore, it can be seen that for variable X_7, which represents ROA, the profitability level based on the assets of an enterprise has a significant impact on whether that enterprise may fall into financial distress or not. Further consideration of X_{13}, which represents the quick ratio of an enterprise, may also affect the ability to predict financial distress.

To have a clearer evaluation of the impact level of these 2 variables on the predictive ability, the research team visualized the dependency graphs of each variable.

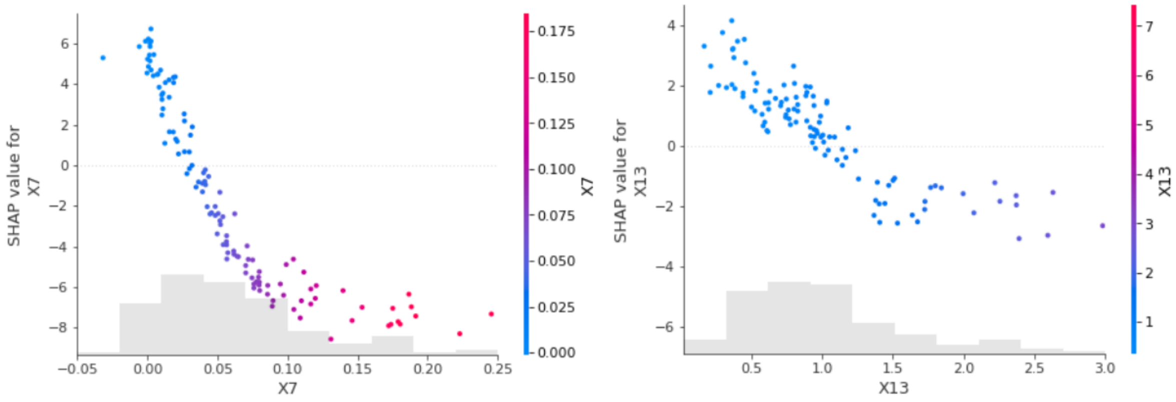

Figure 3: Dependency plot of variable X_7 (left) and variable X_{13} (right)

Source: Author's calculation

It can be seen that these are two opposite variables. For variable X_7, which represents ROA, the SHAP value analysis of the XGBoost model's predicted value shows that the higher the after-tax profit ratio on total assets, the lower the likelihood of financial distress. A significant decrease in after-tax profit may lead to a decrease in the company's ability to repay debts, as well as a lack of capital for business development. Maintaining a reasonable and stable level of profit will help the company achieve sustainable development and avoid the risk of financial distress.

The analysis of the XGBoost model's SHAP value prediction shows that the higher the quick ratio, the lower the likelihood of financial distress. If a company's quick ratio is too low, the company may not have enough current assets to pay off its short-term debts. This means that the company may have to rely on borrowing or selling long-term assets to meet its short-term obligations. Based on the results from SHAP values, companies should maintain this ratio above 1 to have a stable financial health and minimize the risk of financial distress.

5. Discussion

The use of the XGBoost machine learning model to forecast financial health for small and medium-sized businesses is a clear advantage. Compared to classic models such as Z-score, X-score and H-score, XGBoost has better predictability with higher accuracy and better categorization. By using machine learning algorithms and data mining techniques, XGBoost can learn from the historical data of the business and make forecasts about the future financial situation of the business in a more accurate and effective way.

However, to achieve the best results when using XGBoost, it is necessary to have a complete and accurate database to be able to train the model. At the same time, it is necessary to invest in and develop new techniques and technologies to enhance the performance of the model.

In general, the use of the XGBoost machine learning model is an effective solution to improve forecasting and financial management for small and medium enterprises in Vietnam. However, it takes investment and research to be able to apply the model effectively and meet the requirements of the market.

In addition, based on the SHAP algorithm, it can also be seen that the importance of interpreting the machine learning model to be able to understand more about the problem. Because without explaining the internal problems, small and medium enterprises cannot know the directions to overcome their situation when they know the forecast results are exhausted. That's why it's important to explain the machine learning model has given important financial indicators that small and medium enterprises need to pay attention and pay special attention to improve their situation. In addition, other indicators also contribute a lot to the forecast of financial health of businesses, so businesses should not ignore these indicators. In summary, the study has made comparative results between the classical model and the machine learning model. As a result, businesses can see the importance of digital transformation, applying machine learning models and checking their financial health in addition to using classic models that have many shortcomings.

6. Conclusion

6.1. Using Machine Learning Models to Forecast the Financial Health of Enterprises

For small and medium-sized enterprises (SMEs) in Vietnam, using machine learning models to forecast the financial health of businesses can bring numerous benefits, not only in making accurate and effective business development decisions.

One of the benefits of using machine learning models is their ability to help businesses forecast economic and market trends in the future. This enables businesses to prepare appropriate plans and strategies to respond to changes in the business environment.

Furthermore, using machine learning models also helps businesses identify potential risks and take preventive measures before they become severe. This enhances the sustainability and stability of the business.

Lastly, using machine learning models can enable businesses to seize new opportunities and develop their operations more effectively. With accurate forecasting capabilities, businesses can make timely and informed decisions to capitalize on market opportunities.

Therefore, employing machine learning models to forecast the financial health of enterprises is an effective solution to improve strategic decision-making and enhance the sustainability of businesses.

6.2. Enhancing Investment in Research and Development of Machine Learning Models

To improve forecasting capabilities and make appropriate strategic decisions in the market, small and medium-sized enterprises in Vietnam need to increase investment in research and development of machine learning models for financial health forecasting.

One way to enhance forecasting capabilities is to analyze historical data of enterprises and utilize machine learning models to identify trends and relationships among different financial variables. The results can be used to make strategic decisions such as investment, product development, and business expansion.

Moreover, increasing investment in research and development of machine learning models can help businesses discover new approaches to enhance forecasting capabilities. Therefore, strengthening investment in research and development of machine learning models brings multiple benefits to small and medium-sized enterprises in Vietnam, enabling them to improve forecasting abilities and make market-appropriate strategic decisions.

6.3. Introducing Support Policies and Encouraging Businesses to Adopt Machine Learning Models

To support small and medium-sized enterprises in Vietnam, it is necessary to introduce policies that encourage the use of machine learning models for financial health forecasting. However, applying these models still poses challenges, such as insufficient technical knowledge, lack of resources, and the accuracy of forecasts. Enhancing training, providing financial support, and building better machine learning systems for accurate and cost-effective financial health forecasting can enhance business efficiency in a fiercely competitive market.

6.4. Limitations and Difficulties of the Research Topic

During the research and analysis process, the thesis encountered certain limitations and difficulties. One of these challenges was the scarcity of financial health data for small and medium-sized enterprises in Vietnam. This limitation affected the accuracy of the analysis and evaluation results, as well as the construction of financial health forecasting models for businesses.

Additionally, the differences in scale and experience among researchers were also limitations of the research topic. Furthermore, the diversity of external factors affecting the financial health of enterprises complicated the process of drawing conclusions. However, with relentless effort and dedication from researchers, this thesis still provides noteworthy and valuable results for the business community in Vietnam.

REFERENCES

[1] Dung, B. K., & Ngân, M. T. T. (2021). Kiệt quệ tài chính và dòng tiền của các doanh nghiệp phi tài chính niêm yết tại Việt Nam. Tạp chí Khoa học & Đào tạo Ngân hàng, 226.

[2] Hà, H. T. C., & Uyên, N. T. U. (2017). Sử dụng các mô hình cây phân lớp dự báo kiệt quệ tài chính cho doanh nghiệp Việt Nam. Tạp chí Khoa học Đại học Mở Thành phố Hồ Chí Minh – Kinh tế và Quản trị Kinh doanh, 12(3), 62-76.

[3] Vinh, L. H., Quang, P. L. & Dung, B. K. (2022). Mô Hình Nào Phù Hợp Để Đo Lường Kiệt Quệ Tài Chính Cho Công Ty Phi Tài Chính Niêm Yết Tại Việt Nam?. Tạp chí Quản lý và Kinh tế Quốc tế, 144.

[4] Vũ, T. H. T. (2018). Mô hình dự báo khả năng phá sản của các doanh nghiệp Việt Nam.

[5] Hà, H. T. C. (2020). Kiệt quệ tài chính và các chiến lược tái cấu trúc doanh nghiệp Việt Nam theo chu kỳ sống (Doctoral dissertation). Trường Đại học Kinh tế Tp. Hồ Chí Minh).

[6] Hà, N. M., & Khang, N. B. (2019). Các yếu tố tác động đến phá sản doanh nghiệp tại tỉnh Đồng Nai. Tạp chí phát triển kinh tế, 26-38.

[7] Vy, L. T. P. (2020). Kiệt quệ tài chính và quản trị thu nhập: bằng chứng thực nghiệm ở các công ty niêm yết tại Việt Nam. Đại học Kinh tế Tp. Hồ Chí Minh. JED, Vol.31(02).

[8] Tran, K.L., Le, H.A., Nguyen, T.H., Nguyen, D.T. Explainable Machine Learning for Financial Distress Prediction: Evidence from Vietnam. Data 2022, 7, 160.

[9] Christidis, A., & Gregory, A. (2010). Some new models for financial distress prediction in the UK. Xfi-Centre for Finance and Investment Discussion Paper, (10).

[10] Idrees, S., & Qayyum, A. (2018). The impact of financial distress risk on equity returns: A case study of non-financial firms of Pakistan Stock Exchange. Journal of Economics Bibliography, 5(2), 49-59.

[11] Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. International review of financial analysis, 30, 394-419.

[12] Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. The journal of finance, 23(4), 589-609.

[13] Altman, E. I., Sabato, G., & Wilson, N. (2008). The value of non-financial information in SME risk management. Available at SSRN 1320612.

[14] Wruck, K. H. (1990). Financial distress, reorganization, and organizational efficiency. Journal of Financial Economics, 27, 419–444.

[15] Beaver, W.H., (1966). Financial ratios as predictors of failure. Journal of Accounting Research, 4: 71-111.

[16] Theodossiou, P. T. (1993). Predicting shifts in the mean of a multivariate time series process: An application in predicting business failures. Journal of the American Statistical Association, 88, 441–449.