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ĐỀ TÀI NGHIÊN CỨU KHOA HỌC SINH VIÊN

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PROFIT PREDICTION OF LISTED ENTERPRISES IN VIETNAM BY MACHINE LEARNING

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Đại diện nhóm nghiên cứu	**Giảng viên hướng dẫn**	**Chủ tịch Hội đồng**
(Ký, họ tên)	*(Ký, họ tên)*	*(Ký, họ tên)*

Lãnh đạo Khoa/Bộ môn/Trung tâm
(Ký, họ tên)

ABSTRACT

This study uses Machine Learning models to predict and evaluate profits and also identify factors that influence organizational profitability. The research was based on actual data from the financial statements of 512 companies listed on the Vietnamese stock exchange from 2010 to 2020. Recognizing the limits of past studies' techniques, the team proposes to perform profit forecasting research using two ways: by year and by industry, which yields two important results. First, the model's profit or loss performance is fairly strong, particularly for the 2012 and 2020 models, as well as the healthcare model. Second, in the data fields, ROA, Net profit margin, ROE, and DSO are qualities that have a significant impact on profit forecasting. Furthermore, unlike the model decomposed by industry, the model decomposed by years does not account for the effect of macro variables.

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Avg. Inv days	Average Inventory days
Avg. Payable days	Average Payable days
Avg.Receivable	Average Receivable
FA turnover ratio	Fixed asset turnover
DSO	Days sale outstanding
CCC	Cash conversion cycle
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
CPI	Consumer Price Index
GDP	Gross Domestic Product

CHAPTER 1: INTRODUCTION

1.1. Background and justification for the research project

Along with the rapid development of digital transformation, contributing to the diversification of financial activities, the use of Machine Learning in applied finance is becoming more and more popular in many countries. around the world, especially in Vietnam, where the financial market is emerging and vibrant. The research team understood the concept and conducted the study "Forecasting profitability of listed companies in Vietnam over time using Machine Learning". The traditional approach is said to be effective and has a lot of practical experience, but it has disadvantages that are difficult to overcome such as: time consuming and human potential, difficult data collection, lack of characterization, slow update,... To overcome those disadvantages, the research team has applied Machine Learning to analyze and forecast business profits.

In addition to applying technology to the research paper, the research team also selects suitable features to evaluate the impact on the target variable. The target variable here is the profitability or loss of a business at a specified time based on the factors of net income and net cash flow from operating activities. Currently, studies using Machine Learning to forecast profits are quite popular, but there are no studies that combine the above two profit factors to produce results. Besides, Machine Learning's Random Forest algorithm performs quite well in financial forecasts. In addition, this study also contributes to complement previous studies through the following outstanding features: (1) Disaggregation of data by industry; (2) Decay data by year; (3) Using a combination of 2 variables net income and net cash flow from operating activities.

1.2. Study overview

Profit has always been one of the most important aspects for users of financial information, such as investors, creditors, and administrators, because it is the consequence of production and business. However, concentrating just on the quantitative component of profit is insufficient; it is also vital to assess if the quality of that profit is truly sustainable and reliable.

Companies in Vietnam build a positive image to attract outside investment by altering profits to minimize corporate income tax. As a result, firms may change subjective aspects to generate high profitability. This may have an impact on the enterprise's business performance evaluation. Furthermore, there are objective affecting elements outside of the corporate environment, known as macro variables. There is state management in the context of a market economy. These elements have access to the enterprise's business processes and are in close contact with one another. The aforesaid components are then studied and analyzed to find the subjective and objective aspects that influence business earnings. On that basis, forecast business earnings in order to make management or investment decisions in the context of market processes managed by the state.

1.2.1. Domestic studies

There are many studies on forecasting corporate profits.

Specifically, domestic studies on factors affecting business operations and profits such as:

Factors affecting the profit of enterprises listed on HOSE (Nguyen Hoang Anh, Nguyen Thi Tu, 2017) used variables such as: Enterprise size (Size), Financial leverage (LEV), Investment ratio capital asset investment (PPE). After the regression, the author has found that the higher the firm size, the better the earnings quality and the financial leverage is inversely related to the earnings quality.

Measuring business performance through market value index and book value index by machine learning method (Nguyen Anh Phong, 2021). The author used the variables Return on assets (ROA), Return on Equity (ROE) to measure the performance of the business by machine learning. In addition, the author also used some other control variables such as Operating Cash Flow (OCF), Age of the enterprise (Age) which we also studied and applied in this study.

1.2.2. Foreign studies

Besides, there are also international studies on the factors affecting the profitability of enterprises:

Factors affecting profitability in Malaysia (Alarussi, A.S. and Alhaderi, S.M, 2018). This study aims to identify profitability factors in Malaysian listed companies specifically through factors such as company size (measured by total revenue), liquidity and financial leverage. The results highlight a strong positive relationship between total revenue and profitability. The results also show a negative relationship between leverage and profitability. Also, liquidity did not show any significant relationship with profitability.

Determinants of corporate profitability: An empirical study of Indian drugs and pharmaceutical industry (Chander, S., & Aggarwal, P, 2008). The main objective of this study was to examine the relationship between Indian drugs and pharmaceutical companies in terms of characteristics and profitability. The author used factors such as Size, Age, Liquidity and R&D intensity in this study. The results show that variables such as Age, Liquidity Ratio and R&D intensity have positive results on the profitability of enterprises.

Factors Influencing the Companies' Profitability (Camelia Burja, 2011). Research shows that among the factors that have a good influence on profitability are inventory efficiency, debt level, financial leverage, capital efficiency. In addition, the study also demonstrates a close relationship between the company's performance and the way available resources are managed.

Using Machine Learning to Forecast Future Earnings (Xinyue Cui, Zhaoyu Xu, Yue Zhou, 2020) the model in this study was able to serve as a convenient auxiliary tool for

analysts to conduct predictions better than the traditional statistical models that are widely used in the industry including Logistic Regression. This model has made significant progress in both accuracy and speed of prediction.

Predicting profitability using machine learning (V Anand, R Brunner, K Ikegwu, T Sougiannis, 2019). The study explores whether a method from machine learning, a classification tree, can produce predictions of out-of-sample returns that outperform random walk predictions. The authors implement a machine learning approach using a large sample of US companies with required data valid for the period 1963-2017 and generate out-of-sample predictions of changes in direction (increase or decrease) in five profitability measures: return on equity (ROE), return on assets (ROA), return on operating assets (RNOA), cash flow from operations (CFO) and free cash flow (FCF). The results show that their machine learning method achieves classification accuracy ranging from 57-64% compared to 50% for random walk, and the difference in classification accuracy rate between machine learning and Random walk is very meaningful. In summary, the study provides some evidence that machine learning methods have the potential to be useful in predicting profitability.

1.3. Objectives of the study

Identify and evaluate factors affecting business income in order to more accurately estimate business profit. Profitability is one of the most important criteria that external investors and internal management must understand when examining a company's performance. As a result, by using Machine Learning applications to guide groups of information to seek out the drivers of business results and forecast the state of business operations at a given point in time. based on profitability metrics. Apply Machine Learning to research to be able to process a huge data collection with a high degree of diversity, freeing up factors other than the underlying factor, and maximizing prediction accuracy. Furthermore, the study is based on current data of Vietnamese enterprises in order to be relevant and relevant to the Vietnamese economy and provide important information for domestic and foreign investors and managers objectively and reasonably.

1.4. Research subjects

Factors influencing company profits that are subjective (financial statements, business sector, business size, growth rate, capital asset investment ratio, liquidity ratio, leverage ratio ...).

Profit is influenced by both objective and macro variables (GDP, CPI, interest rate).

1.5. Research scope

Scope of space: 512 enterprises listed on Vietnam stock exchange.

Time scope: 11-year research period from 2010 to 2020.

1.6. Research Methods

Data collection method: using the data collection method from secondary sources such as Thomson Reuters and the State Bank of Vietnam.

Qualitative methods: calculating and integrating elements impacting the enterprise's profit, and seeking for new factors. This method requires the researchers deeply understanding the nature of the research issue, specifically, the target variable and features.

Quantitative methods: Profit forecasting for enterprises based on Machine Learning models using historical figures and scale them to the same rule. From there, the direction of future profit movement may be determined.

Empirical research method: After collecting a quantitative data set, researchers can analyze, build the model and print the results, then verify the results by measuring the experimental probability of the study based on the real data.

Theoretical research method: researchers collect information through articles, documents, and other scientific studies to find and select the basic concepts and ideas that are the basis for the theory of the topic, form scientific hypotheses, predict the properties of research objects, and build the model.

1.7. Expected results

If effectively applied and investigated, the study will give firms with more accurate profit estimates. At the same time, the study examines related uncertainties and factors affecting the profits of publicly traded companies, such as economic figures, enterprises' subjective factors, which assists managers and investors in making sound investment decisions, hence reducing company risks.

1.8. New point of research

The analysis in two directions is a new element of the research model that will assist the analyst understand the nature of his model and generate solid forecasts in the direction of industry analysis (specifically, the profit forecast of each enterprise in the industry) or annual analysis (profit forecasts for all publicly traded firms on the stock exchange each year) to aid in making better investment selections. Specifically:

- Industry analysis aids in determining which industries are best projected for the model, as well as which elements, such as macro variables, have a significant impact on each industry and the market economy, and how much influence each type of industry has.

- Year-to-year analysis can assist in determining whether there is a substantial change in the elements that influence a company's profitability indicators from one year to the next. If yes, what caused the shift (from objective market mechanism variables) so that the analyst can capture the market's major trend throughout time in the future.

CHAPTER 2: THEORETICAL BASIS AND REALITY OF THESIS

2.1. Theoretical basis

2.1.1. Machine learning

Machine Learning, according to Arthur Samuel, is "the branch of research that makes computers capable of learning without being explicitly programmed."

Machine Learning, as defined by Tom Mitchell, is "a computer program that learns from experience E to do task T, and its effectiveness is evaluated by P, if its efficacy in executing task T is measured by performance P, enhanced by experience E."

In this study, T E P is defined as:

- Task T is to determine whether the business is profitable or not.
- Experience E is the characteristic to classify businesses that profit from available data.
- The performance P metric is the accuracy of the determination process.

Machine learning is the activity of learning from data in an iterative fashion using various algorithms to develop models and predict outcomes. The data set is divided into two pieces by machine learning: the training set and the test set. Algorithms employ training data to build machine learning models. The test data set will be used to assess the correctness of the produced model.

Popular machine learning algorithms such as: Artificial Neural Networks - ANN, Support Vector Machines - SVM, Genetic Programming - GPN, K-nearest neighbors (KNN), Logistic regression, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Decision Tree, Random Forest…

2.1.2. Reasons for choosing Machine learning

Both Machine Learning and Statistical Estimation techniques can generate forecasts. However, each type has different strengths and purposes. In it, machine learning models are designed to make the most accurate predictions possible. Statistical models are designed to make inferences about relationships between variables.

Statistics is the mathematical study of data. You can't make statistics unless you have the data. A statistical model is a model for data that is used to infer something about relationships within the data or to create a model that can predict future values. Therefore, there are many statistical models that can make predictions, but the accuracy of the predictions is not their strong point.

In contrast, Machine Learning models provide varying degrees of interpretability, from highly interpretable Lasso Regression to impenetrable neural networks, but they often sacrifice interpretability for predictability. The purpose of machine learning is to obtain a model that can make reproducible predictions without regard to whether the model is

interpretable or not, although you should still experiment to make sure. ensure that the model's predictions make sense.

So, which method is better depends on what you use it for. If you just want to create an algorithm that can predict house prices with great accuracy, or use data to determine if someone is likely to have certain types of disease, then machine learning might be the better approach. If you are trying to prove relationships between variables or make inferences from data, statistical modeling may be a better approach.

In this study, our goal is to be able to most accurately predict which businesses are profitable. Therefore, using Machine Learning will be a more optimal method and also a newer method than previous studies using regression statistics to predict results.

Econometrics is mainly concerned with model interpretation, which is the evaluation of the effects of independent variables on a large number of dependent variables in an econometric model. Machine learning is exclusively concerned with the model's prediction results; ML models attempt and fail to find the best accurate prediction. Machine learning is better suited to prediction than econometrics.

2.1.3. Supervised learning

Supervised learning is a method of Machine Learning that uses labeled data with the main goal of determining the relationship between input and output variables. Supervised learning is divided into two problems: regression and classification. Regression is used to predict continuous data, while classification is used for discrete data.

2.1.4. Random forest

According to the definition of Breiman (2001): random forest is “a classifier consisting of a collection of tree-structured classifiers {h(x, Θk), k = 1, . . .} where the {k} are independently identically distributed random vectors and each tree casts a unit vote for the most popular class at input x”.

The random forest classification algorithm is an enhanced version of the decision tree classification technique. This algorithm, which is built from several decision trees, aids in overcoming the problem of overfitting. To pick trees in the forest, the algorithm utilizes a voting mechanism.

There are two ways to vote on a random forest. One is to choose the decision tree with the highest number of votes. The second is to select the results based on the proportion of votes, these votes are the weight of the results.

Random forest generates random trees by: bootstrapping and criteria selection.

- Bootstrapping technique: Each tree is created with a unique data set that is made up of a subset of the same size of the available data.

- Criteria: Decision trees will choose features for the tree to branch.

The random forest can indicate the importance of the model's features. It helps us to know the most important features and the unimportant features. This helps to focus more on the essentials and can be considered to remove low-impact features.

2.1.5. ROC curve

ROC Curve stands for Receiver Operating Characteristics Curve, which is a metric to evaluate the performance of a classification model. Each point along the ROC Curve corresponds to a classification model. The ROC curve shows the sensitivity of the classification model to the ratio between true positive and false negative. The ROC that compares two operating characteristics as the criteria change is called a relative operating characteristic curve. These two performance characteristics are True Positive Rate (TPR) and False Positive Rate (FPR). An ROC with a ratio between True Positive and False Positive corresponding to 1:0 is considered ideal.

Important points in ROC Curve:

- TPR = 0, FPR = 1: the model predicts all cases to be negative class
- TPR = 1, FPR = 1: The model predicts all cases to be positive class
- TPR = 1, FPR = 0: Ideal model with 0 false classifications.

2.1.6. AUC

AUC, also known as Area Under Curve, is a metric commonly used to evaluate machine learning models, which is the area below the ROC curve. The AUC helps the classifier to distinguish between classes. The higher the Area Under Curve, the better the positive and negative discrimination performance of the model.

The classifier is considered perfect when AUC = 1. And AUC=0 if the algorithm only makes random guesses.

2.1.7. Enterprise profit

Profit is the difference between a company's income and costs in a certain time. Profit has an impact on the company's liquidity and financial situation. The profit gained is used to reinvest, grow, and develop the business in the future. This is also one of the factors used to evaluate enterprise business activity and assist investors in making investment decisions. Profits may be classified into two types: economic profit and accounting profit. Accounting profit is only concerned with monetary expenses, not sunk and opportunity costs, as economic profit is. This study simply takes into consideration the accounting earnings of businesses.

2.1.8. Operating cash flow

Operating cash flow (OCF) is the amount of money generated from business activities of a business during a certain period. This is an important metric on a business' cash flow statement because it shows the financial health of the business. This cash flow represents a company's liquidity including its ability to pay debts and pay expenses. If

OCF > 0, the business pays its expenses and repays its debt with the cash it receives. In contrast, with OCF<0, the business must find other sources of money (such as loans, or liquidation of assets) to pay these costs. Operating cash flow helps to check the real income situation of the business, if the business has extremely high profits but the OCF is negative, it is likely that the business has used accounting tricks for financial statements.

2.2. Real state of affairs

Profit optimization is always the top concern of businesses. Therefore, methods to predict profits and revenue of enterprises need to be improved and gradually increased accuracy. Traditionally, doing fundamental analysis requires three stages. The first and most important stage is to accurately predict the future profitability of the company over a given period of time. Without accurate predictions, the calculation of the next period's intrinsic values will be inaccurate and lead to high-risk, wrong investment choices in subsequent steps, when the value market is compared to intrinsic value. Fundamental analysis requires out-of-sample forecasts of profitability in addition to accurate forecasts because these are the forecasts that investors demand in practice.

Many studies and many tests have really shown that using historical data sets, it is possible to easily predict and identify trends in corporate financial results with reasonable error from 2-8%. However, the biggest challenge for this approach is not making predictions on their own, but collecting data and building models with a large amount of variables. Just building a simple model and getting results takes hours, not months or even days. Therefore, with a huge amount of variables and data, it will take a lot of time and effort. On the other hand, when the study is completed, the results may be outdated and no longer useful and timely.

The task of predicting profits for a particular period is very important. Because if a business can generate a lot of profit with the amount of capital, policies, and projects implemented, then a business can earn more than the expected profit provided that the value can be achieved. guess. And investors will also be easier to make decisions. The profit that a company earns in a particular period of time depends on several factors such as the amount of time and money.... So to predict the profit of a company over a period of time. Specifically, we need to train a machine learning model with a dataset containing historical data about the profits generated by the company.

Monahan (2017) examined empirical research that revealed that the out-of-sample profitability estimates provided by various regression models are not more accurate than those generated by the regression model. Furthermore, Bradshaw et al. (2012) demonstrate that even financial experts' profitability estimations are no more accurate than those obtained by a random walk model. According to Monahan (2017), the random walk model's greater performance over existing methodologies is problematic from both a theoretical and practical standpoint. Furthermore, the team views the failures of

previous approaches as an impetus to employ new ways that are more optimum as well as optimal in terms of limiting the weaknesses of basic analysis.

CHAPTER 3: PREPROCESSING DATA AND BUILDING MODELS

3.1. Data resources

The data used is a secondary data source with 2 types of micro data and macro data:

Micro data is collected from Thomson Reuter from 2009 to 2020. The data used are financial figures of 684 Vietnamese enterprises listed on 2 exchanges HOSE (Hochiminh Stock Exchange) and HNX (HaNoi Stock Exchange). These businesses operate in 10 industries such as: Utilities, Basic Materials, Industrials, Consumer Cyclicals, Consumer Non-Cyclicals, Energy, Healthcare, Real Estate, Technology, Academic & Educational Services.

Macro data includes 3 indicators GDP, CPI and Real interest rate of Vietnam central bank. These indicators are collected from the World Bank from 2009 to 2020.

3.2. Preprocessing data

3.2.1. Data Cleaning

To ensure that the data is not too much missing, we drop businesses listed on the stock exchange for less than 5 years. Then check the missing value of the variables with the count_missing function. The ratio of missing value variables from 12.46% or less, the variables with the missing value rate above 7% are Quick ratio, Cash conversion cycle, Inventory turnover ratio, ROE, FA turnover ratio, Operating margin, BEP, Expense of revenue ratio, and DSO. Use the fill missing value method to reduce the problem of missing values of these 9 variables with the interpolate function. The missing values in the first and last years will be filled by the backfill and first fill method. The missing values in the middle will be filled by the regression method. After filling data, only variable avg inventory days has 48 missing values and 4 companies VNF.HN, TVC.HN, VNT.HN, VNL.HM cannot be filled due to empty full and will be removed completely. Check the missing value value ratio again, there are variables with missing value. Drop all rows with at least 1 missing value. After cleaning, the remaining data sets are businesses in 9 industries except Academic & Educational Services.

3.2.2. Data transforming

We convert some unreasonable negative values into positive variables such as: Cost of revenue, Accounts receivable, Avg. Inv days, Avg. Payable days, Avg.Receivable days. Next, we create 20 independent variables from the available data source. After the calculation, the Growth variable is missing data because there is no 2008 to calculate, so the 2009 drop should be performed on all variables. Age variable is calculated from the year of company establishment, companies established from 2011-2020 will be converted to NaN and dropped.

The Target variable is created from Net income and Operating cash flow. The value of Target is 1 if Net income and Operating cash flow are greater than 0; and zero if Net income and Operating cash flow are less than 0. The profit forecast associated with

Operating cash flow shows the business's ability to pay its debts and reduce the risk of fraudulent financial statements for investors. 23 feature variables (independent variables) and 1 target variable (dependent variable) after being calculated are merged into 1 dataframe with 21 columns and 5676 rows.

We found 13 variables with outliers: Growth, PPE, Liquidity, Quick ratio, Inventory turnover ratio, FA turnover ratio, DSO, Capital intensity, Expense of revenue ratio, Operating margin, Net profit margin, ROE, CCC. Dealing with outlier by assigning a new value to the variable with:

- Highest values = Mean value + 3*Standard deviation.

- Lowest values = Mean value - 3*Standard deviation.

3.3. Variables

The study uses 24 observed variables including 23 feature variables (independent variables) and 1 target variable (dependent variable). The independent variables used are: Growth, Size, Age, Liq, Lev, PPE, Quick ratio, Inv turnover ratio, FA turnover ratio, TA turnover ratio, DSO, Capital intensity, Expense revenue ratio, Operating margin, Net profit margin, BEP, ROA, ROE, EPS, CCC, GDP, CPI, Interest rates. The target variable is Target.

3.3.1. Target variable

The target variable is created from 2 values net income and operating cash flow with the below condition:

- Net income > 0 and Operating cash flow > 0: Target = 1.
- Net income < 0 and Operating cash flow < 0: Target = 0.

3.3.2. Sale growth rate (Growth)

$$Growth = \frac{Sale_t - Sale_{t-1}}{Sale_{t-1}}$$

Growth is the growth rate of a business's revenue. Businesses with this high ratio are often in a strong growth phase. The growth rate of the joint also affects the quality of profits. Specifically, Nissimi and Penman (2001), Dechow and et al (2011), Gopalan and Jayaraman (2012), Nguyen Hoang Anh (2017) said that firms with high this ratio have lower quality of profits.

3.3.3. Size

$$Size = ln(Market\ value)$$

Size is the size of the business. Large companies are often highly profitable. This is also found in the studies of Ball and Foster (1982), Liu and et al (2017). However, Gopalan and Jayaraman (2012) and Watts and Zimmerman (1990) show a negative relationship between firm size and profitability.

3.3.4. Age

The company's age variable is calculated in 2020 minus the company's founding year. The longer a business has been in operation, the greater its profitability. This is because long-standing businesses have created a reputation, have high product recognition and experience in production. Chander and Aggarwal (2008) show a positive influence of age on firm profitability.

3.3.5. Liquidity ratio (Liq)

$$Liq = \frac{Total\ current\ asset}{Current\ liabilities}$$

Liquidity ratio indicates a company's ability to pay short-term debts in the short term. Cerf (1961) found that the higher the liquidity ratio, the higher the profit of the enterprise.

3.3.6. Leverage ratio (Lev)

$$Lev = \frac{Total\ liabilities}{Total\ asset}$$

A highly leveraged company means a lot of debt, which makes it possible for managers to tamper with financial statements to inflate profits. Gopalan and Jayaraman (2012) suggest that financial leverage is negatively correlated with profitability. However, Barton and Waymire (2003) find profitability and financial leverage positively correlated.

3.3.7. Capital investment ratio (PPE)

$$PPE = \frac{Tangible\ Fixed\ Asset}{Sales}$$

Capital investment ratio shows the ratio of the company's investment in tangible assets. This high ratio makes it easy for investors to track and encourages managers to adjust profits accordingly.

3.3.8. Quick ratio

$$Quick\ ratio = \frac{Total\ current\ asset - Inventory}{Current\ liabilities}$$

Quick ratio shows the ability of a business to pay its short-term debts in the short term, regardless of its inventory.

3.3.9. Inventory turnover ratio

$$Inventory\ turnover = \frac{365}{Average\ inventory\ days}$$

Inventory turnover ratio measures the number of times a company sells new inventory and replacements. For a business with low inventory turnover ratio, inventory costs will increase which can potentially reduce profits.

3.3.10. Fixed asset turnover ratio

$$Fixed\ asset\ turnover\ ratio\ = \frac{Sales}{Fixed\ assets}$$

Fixed asset turnover ratio measures the efficiency of a company's fixed assets such as machinery and equipment.

3.3.11. Total asset turnover ratio

$$Total\ asset\ turnover = \frac{Sales}{Total\ asset}$$

Total asset turnover ratio measures how effectively a company's total assets are used in generating revenue. Alarussi and Alhaderi (2018), Alghusin (2015) and Agiomirgianakis and et al (2006) show that total asset turnover has a positive effect on profitability.

3.3.12. Days sale outstanding (DSO)

$$DSO\ = \frac{Account\ receivable}{Sale/365}$$

Days sales outstanding measures the average time it takes for a company to collect money from making a sale. DSO is too high, potentially bad debt, reducing the company's profit.

3.3.13. Capital intensity

$$Capital\ intensity\ = \frac{Total\ asset}{Sales}$$

Capital intensity refers to the need for large amounts of investment for production of some industries. Gopalan and Jayaraman (2012) find a positive correlation between capital intensity and profitability.

3.3.14. Expense revenue ratio

$$Expense\ revenue\ = \frac{Costs\ of\ revenue}{Sales}$$

Expense revenue ratio measures the performance between revenue and expenses.

3.3.15. Operating margin

$$Operating\ margin\ = \frac{EBIT}{Sales}$$

Operating margin is a profitability ratio that measures operating income per dollar of sales.

3.3.16. Net profit margin

$$Net\ profit\ margin\ =\ \frac{Net\ income}{Sales}$$

Net profit margin is a profitability ratio that measures net income per dollar of sales.

3.3.17. Basic earning power (BEP)

$$BEP\ =\ \frac{EBIT}{Total\ asset}$$

Basic earning power indicates the ability of a business' assets to generate operating income against the effects of taxes and debt. This ratio is used to compare a business's ability to make money when taxes and debt are different.

3.3.18. Return on total asset (ROA)

$$ROA\ =\ \frac{Net\ income}{Total\ asset}$$

ROA measures profitability per dollar of assets. ROA can result from using a lot of debt, which will result in a fairly low net income.

3.3.19. Return on equity (ROE)

$$ROE\ =\ \frac{Net\ income}{Total\ equity}$$

ROE measures profitability on common equity. This ratio is of great interest to investors. The higher the ROE, the more efficient the company is in using shareholder capital and increasing profits, which is a great attraction for investors.

3.3.20. Earning per share (EPS)

Earning per share is the profit earned from a share. EPS is used to assess a company's profitability.

3.3.21. Cash conversion cycle (CCC)

Cash conversion cycle = Average inventory days + Average receivable days - Average payable days

Cash conversion cycle is the time period from when the company pays its creditors to when it receives money from its customers.

3.3.22. Gross Domestic Index (GDP)

The Gross Domestic Index reflects the growth rate of gross domestic product year over year. A growing economy helps to increase business efficiency, which in turn also affects profits.

3.3.23. Consumer Price Index (CPI)

Consumer Price Index is the rate of increase in the general price level of goods and services over time and the devaluation of a currency. High CPI increases the instability of production, affecting the profits of enterprises.

3.3.24. Real interest rate

Real interest rate is the lending rate as measured by the GDP deflator. Real interest rates are influenced by terms and conditions across countries, so comparability is limited.

3.4. Drawing correlation matrix of variables

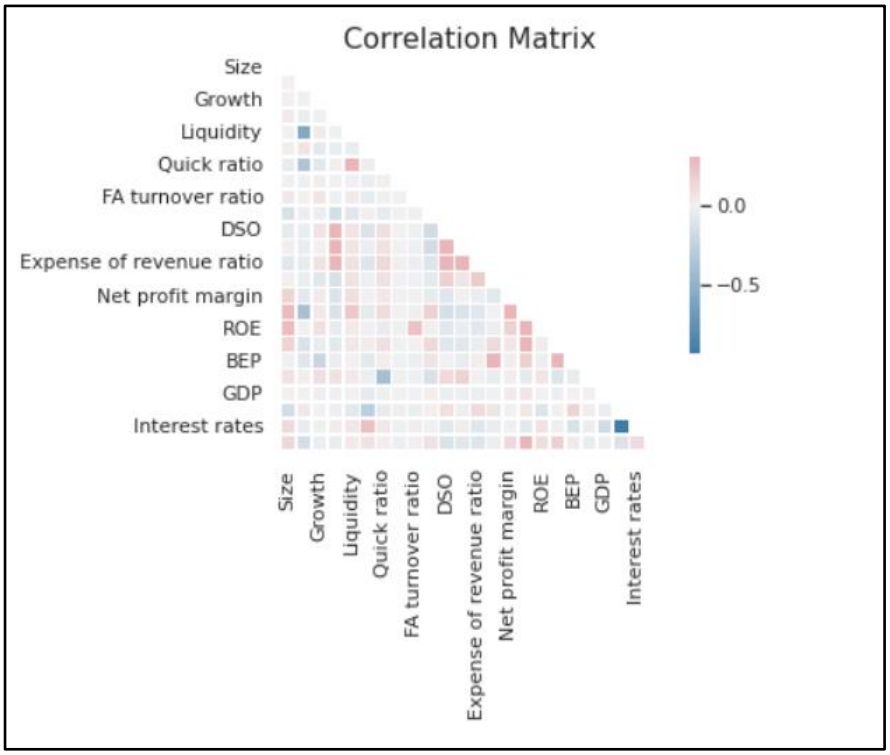

Figure 3.1. Correlation matrix of variables

Almost all variables have no correlation, except for the variable inflation index (CPI) which has a negative correlation with the variable real interest rate (Interest real rate) about -90%.

3.5. Building models and visualizing of results

3.5.1. Building models

We build models on python3 programming language combined with open source software packages.

To construct the machine learning model, divide the data into two parts, a training set and a testing set with a ratio of 80:20. The training set is used to train the machine learning model, and the testing set is used to test the model. We test machine learning algorithms to find the most optimal algorithm: Logistic Regression, K-nearest

neighbors, Decision above, Support vector Machine (Linear and RBF Kernel), Neural Network, and Random forest.

Algorithm	**Model score**
Logistic Regression	70.93%
K-Nearest Neighbors	67.93%
Decision Tree	66.43%
Support Vector Machine (Linear Kernel)	71.83%
Support Vector Machine (RBF Kernel)	71.03%
Neural Network	70.73%
Random Forest	74.53%

Table 3.1. Table of various models' scores in order to search for the best one

The score shows that Random forest is the best model to forecast corporate profits with 74.53%.

We perform GridSearch from 1 to 100 random forest to find the optimal number of trees. The results show that the model stopping at the 81nd tree is optimal. We train the random forest model with the 81nd optimal number of trees.

Research model:

$$\text{Target} = \beta_0 + \beta_1 \text{Growth}_{it} + \beta_2 \text{Size}_{it} + \beta_3 \text{Age}_{it} + \beta_4 \text{Liq}_{it} + \beta_5 \text{Lev}_{it} + \beta_6 \text{Ppe}_{it} + \beta_7 \text{Quick}_{it} + \beta_8 \text{Inv turnover ratio}_{it} + \beta_9 \text{FA turnover ratio}_{it} + \beta_{10} \text{TA turnover ratio}_{it} + \beta_{11} \text{DSO}_{it} + \beta_{12} \text{Capital intensity}_{it} + \beta_{13} \text{Expense revenue ratio}_{it} + \beta_{14} \text{Operating margin}_{it} + \beta_{15} \text{Net profit margin}_{it} + \beta_{16} \text{BEP}_{it} + \beta_{17} \text{ROA}_{it} + \beta_{18} \text{ROE}_{it} + \beta_{19} \text{EPS}_{it} + \beta_{20} \text{CCC}_{it} + \beta_{21} \text{GDP}_{it} + \beta_{22} \text{CPI}_{it} + \beta_{23} \text{Interest Rate}_{it} + \varepsilon_{it}$$

In there:

- Target variable: We use 2 figures net income (NI) and operating cash flow (OCF) as the condition to create binary values (0 and 1).
- Dependent variables: Capital investment rate (PPE), Inventory turnover ratio, Fixed asset turnover ratio, total asset turnover ratio, day sales outstanding

(DSO), Capital intensity, Expense revenue ratio, operating margin, net profit margin, basic earning power (BEP), return on total asset (ROA), return on equity (ROE), earning per share (EPS), cash conversion cycle (CCC).

- Control variables: business's size variable (Size), business's Age variable (Age), sale growth variable (Growth), financial leverage (Lev), liquidity variable (Liq).

- In addition we also use macro variables: Gross Domestic Product (GDP), Consumer Price Index (CPI), Interest Real Rate (Interest Rate).

The above model includes data of businesses with industries in the dataset from 2010 - 2020. In addition, we disaggregate data by year and by industry to compare differences with variables like the model above. Specifically, for model decomposition by year, we form 11 models corresponding to 11 years from 2010 to 2020. For model decomposition by industry, we form 9 models corresponding to 9 industries: Utilities, Basic Materials, Industrials, Consumer Cyclicals, Consumer Non-Cyclicals, Energy, Healthcare, Real Estate, Technology.

3.5.2. Results and evaluation of models

First, we will evaluate the predictive model for the entire business. When the number of estimators is 81, the model has a relatively decent accuracy index (0.71), as shown in Figure 4.1.

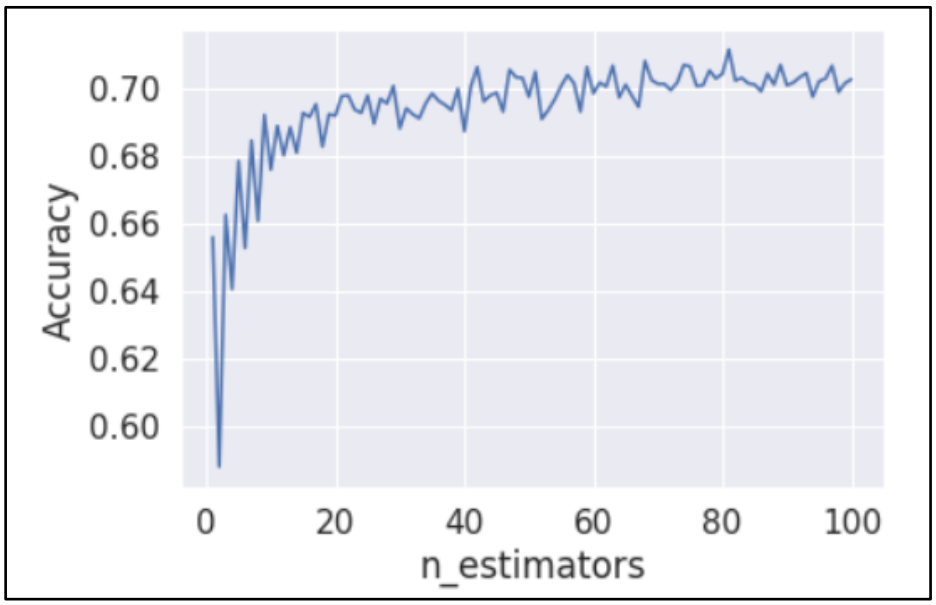

Figure 3.2. Chart of accuracy line with the various number of n_estimators in the total industries model

Also, the ROC-AUC findings of this model are pretty good, as shown in Figure 4.2. The 5-fold AUC values vary from 0.75-0.81, showing that the model is doing well.

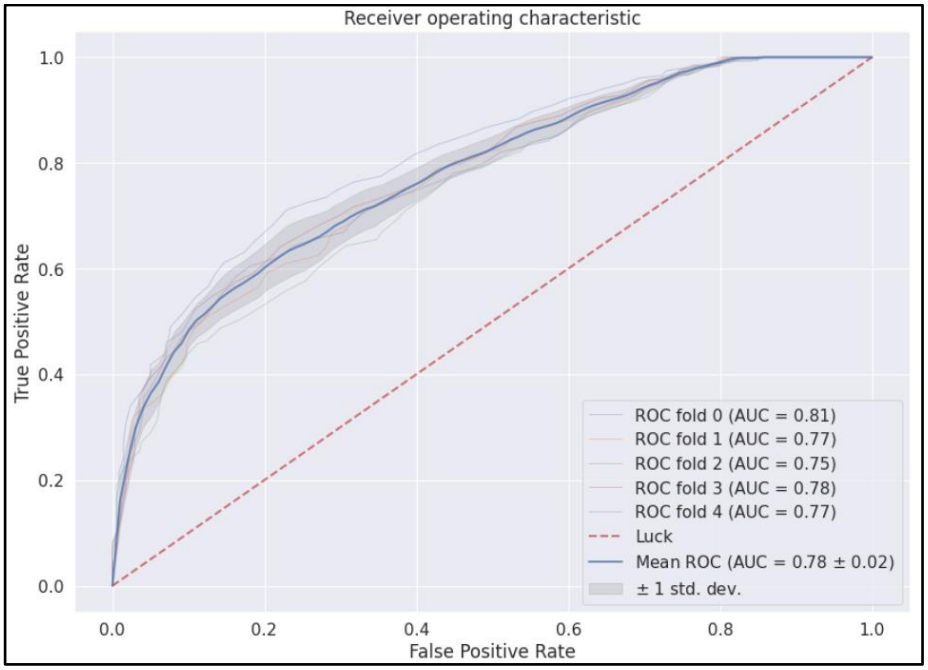

Figure 3.3. Chart of ROC curve in the total industries model

Furthermore, We discovered that the Precision of the Profit group and the Recall of the Loss group were fairly good based on the indications in the classification report (Figure 4.3). Demonstrates the model's ability to anticipate the accuracy of profit estimates for the market as a whole. In addition, the capacity to foresee nearly entire business losses in the market. However, the Profit group's Recall index is relatively low, indicating that the model overlooks many investment possibilities from organizations that are actually lucrative in the market but are expected to lose money.

Formulae for Classification report:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = \frac{2 * precision * recall}{precision + recall}$$

	precision	recall	f1-score	support
0.0	0.37	0.94	0.54	338
1.0	0.87	0.20	0.32	663
accuracy			0.45	1001
macro avg	0.62	0.57	0.43	1001
weighted avg	0.70	0.45	0.40	1001

Figure 3.4. Classification report of the total industries model

3.5.2.1. Decomposition of the years

Phân rã theo năm	Obs	Training set							Test set						
		Train-set obs	Accuracy	AUC score	Precision		Recall		Test-set obs	Accuracy	AUC score	Precision		Recall	
					Profit	Loss	Profit	Loss				Profit	Loss	Profit	Loss
2010	393	314	61%	**100%**	**61%**	0%	99%	**0%**	79	48%	**76%**	**48%**	0%	100%	**0%**
2011	430	344	46%	**100%**	**83%**	41%	16%	**95%**	86	53%	**71%**	**75%**	51%	14%	**95%**
2012	445	356	55%	**100%**	**89%**	43%	37%	**91%**	89	52%	**81%**	**96%**	32%	38%	**95%**
2013	459	367	65%	**100%**	**80%**	51%	60%	**73%**	92	60%	**72%**	**79%**	44%	54%	**71%**
2014	470	376	34%	**100%**	**100%**	32%	3%	**100%**	94	35%	**71%**	**100%**	34%	2%	**100%**
2015	504	403	54%	**100%**	**89%**	40%	38%	**90%**	101	59%	**72%**	**88%**	45%	45%	**88%**
2016	490	392	58%	**100%**	**79%**	43%	49%	**75%**	98	58%	**76%**	**84%**	42%	48%	**81%**
2017	476	380	57%	**100%**	**87%**	45%	39%	**90%**	96	57%	**80%**	**91%**	47%	35%	**94%**
2018	454	363	49%	**100%**	**81%**	37%	32%	**85%**	91	46%	**70%**	**86%**	33%	29%	**88%**
2019	447	357	33%	**100%**	**84%**	28%	10%	**95%**	90	40%	**73%**	**78%**	36%	12%	**94%**
2020	434	347	42%	**100%**	**89%**	33%	20%	**94%**	87	52%	**81%**	**100%**	41%	28%	**100%**

Table 3.2. Table of models' scores decomposed by years

When the number of estimators is 55, the algorithm achieves optimal accuracy (0.75), In general, the model is of quite high quality.

From the 4 indicators of the confusion matrix (TP, TN, FP, FN), we have a classification report to evaluate the reliability of the model.

	precision	recall	f1-score	support
0.0	0.39	1.00	0.56	29
1.0	1.00	0.21	0.34	58
accuracy			0.47	87
macro avg	0.69	0.60	0.45	87
weighted avg	0.80	0.47	0.41	87

Figure 3.5. Classification report of the model decomposed by years

The forecast model gives good results with a high precision value of 85% and y = 1 indicates that the accuracy of the points obtained is high, indicating that the rate of selecting the proper firm provides high profits of about 85%. However, with a recall rate of 43%, we can see that we have relatively zoned out for fear of risk, resulting in missing out on many really profitable companies.

Our testing sample ranges from 2010 to 2020. In addition to presenting the model's overall AUC, the team also presents the AUC score for each year, which is displayed in Table 4.1.1. In general, the AUC ratings for each year are in the 70-81% range (highest in 2012 and 2020).

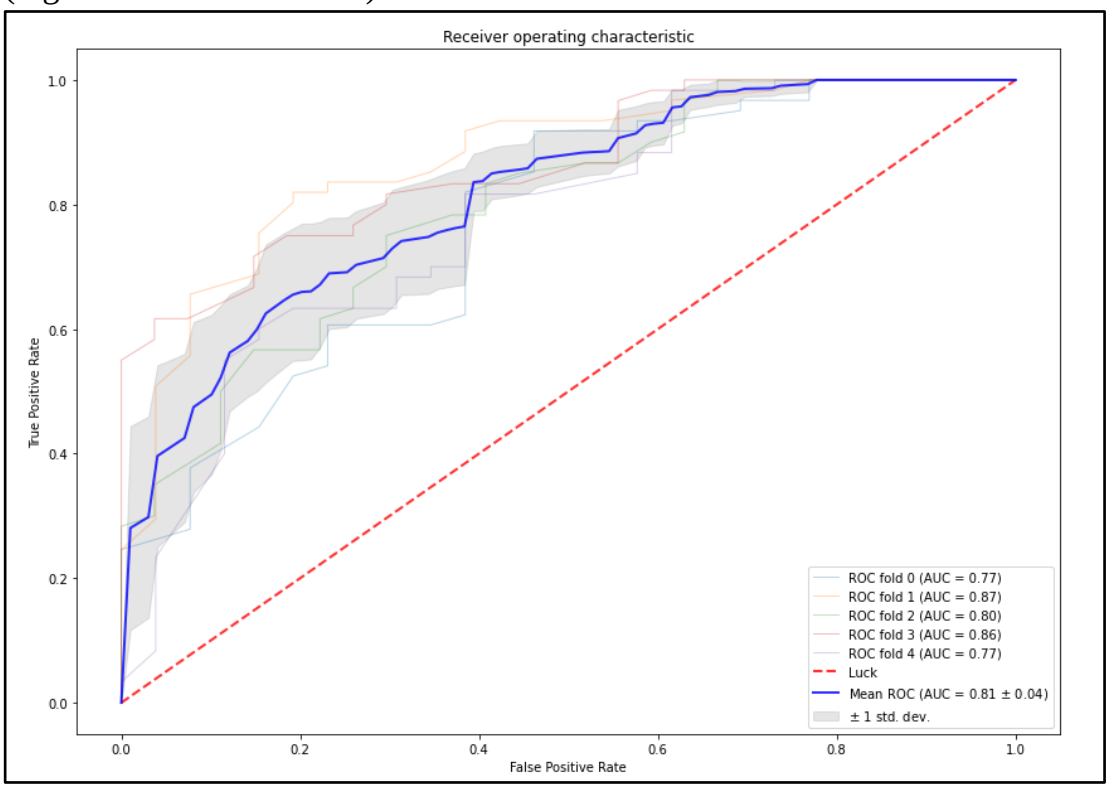

Figure 3.6. Chart of ROC curve of the year 2020 model

With the year 2020 model, we evaluated the model's output quality using ROC utilizing cross-validation and obtained the findings given in Figure 4.1.2.

ROC curves normally have a Y axis for true positive rate and an X axis for false positive rate. This suggests that the "ideal" point is in the plot's upper left corner, with a false positive rate of zero and a real positive rate of one. This is far from practical, but it does imply that a greater area under the curve (AUC) is typically preferable.

It displays the ROC response of several datasets created by 5-fold cross validation. Using all of these curves, the mean area under the curve can be calculated and the variance of the curve can be shown when the training set is divided into different subsets. This approximately depicts how changes in the training data impact the classifier's output, as well as the difference between the splits created by the 5-fold cross-validation versus each other.

The 5-fold AUC scores range from 0.77-0.87, indicating that the model's performance is stable.

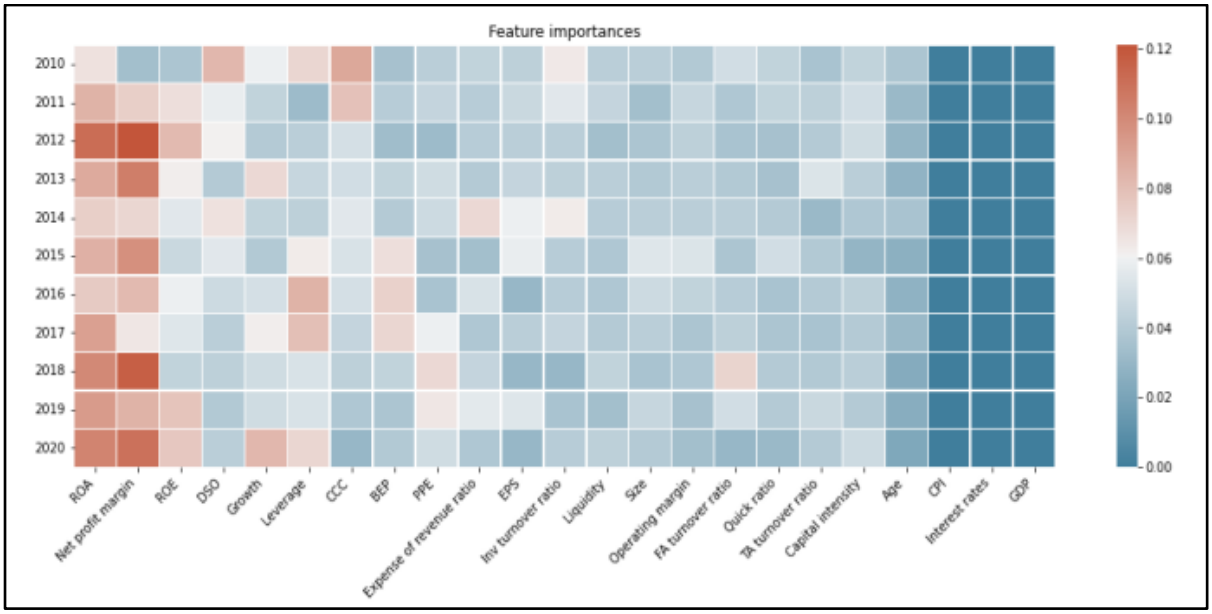

Figure 3.7. Heatmap of features' importance in the model decomposed by years.

We next examined the model's feature importances. Figure 4.1.3 shows that, in general, the impact ratio of the factors does not change much over time. ROA, Net profit margin, and ROE are more essential than other factors and grow year after year from 2010 to 2020 (particularly, in the Appendix 5, ROA: 0.067-0.103, Net profit margin: 0.034-0.11, ROE: 0.037-0.77). This demonstrates the need of paying more attention to these values, as changes in them in the future might have an impact on the profitability of businesses. Furthermore, it can be observed that macro variables have no effect on the analysis over time. The remaining factors have an influence but are not significant.

3.5.2.2. Decomposition of the industries

Decomposition by industries	Obs	Training set							Test set						
		Train-set obs	Accuracy	AUC score	Precision		Recall		Test-set obs	Accuracy	AUC score	Precision		Recall	
					Profit	Loss	Profit	Loss				Profit	Loss	Profit	Loss
All industries	5002	4001	45%	**100%**	**85%**	37%	20%	**93%**	1001	46%	**78%**	**86%**	38%	22%	**93%**
Basic materials	841	672	37%	**100%**	**94%**	32%	11%	**99%**	169	50%	**80%**	**94%**	40%	26%	**96%**
Consumer cyclicals	769	615	33%	**100%**	**94%**	30%	7%	**99%**	154	36%	**76%**	**100%**	33%	6%	**100%**
Consumer non-cyclicals	478	382	35%	**100%**	**100%**	34%	2%	**100%**	96	46%	**77%**	**100%**	43%	9%	**100%**
Energy	375	300	50%	**100%**	**86%**	27%	43%	**75%**	75	52%	**64%**	**90%**	25%	46%	**79%**
Health care	161	128	50%	**100%**	**92%**	32%	36%	**91%**	33	76%	**89%**	**95%**	46%	73%	**86%**
Industrials	1461	1168	48%	**100%**	**78%**	43%	18%	**92%**	293	48%	**73%**	**85%**	41%	21%	**94%**
Real estate	534	427	55%	**100%**	**57%**	54%	24%	**83%**	107	43%	**63%**	**57%**	39%	20%	**77%**
Technology	166	132	39%	**100%**	**100%**	36%	6%	**100%**	34	65%	**66%**	**100%**	60%	25%	**100%**
Utilities	217	173	85%	**100%**	**92%**	13%	92%	**13%**	44	25%	**83%**	**83%**	16%	14%	**86%**

Table 3.3. Table of models' scores decomposed by industries

According to Table 4.2.1, the AUC of each industry varies greatly. In comparison to all industries, the AUC in real estate, energy, and technology is quite low (lower than 12-15 percent). Besides, the health-care business has the greatest AUC index (89% - 11 percent higher than the all industries model). From there, the Health care sector forecasting model may be rated as extremely good in terms of predicting lucrative firms in this discipline.

	precision	recall	f1-score	support
0.0	0.46	0.86	0.60	7
1.0	0.95	0.73	0.83	26
accuracy			0.76	33
macro avg	0.71	0.79	0.71	33
weighted avg	0.85	0.76	0.78	33

Figure 3.8. Classification report of the Healthcare industry model

The Healthcare industry forecasting model has an accuracy index of 0.95, indicating a high ability to accurately forecast firms in this industry, and a recall index of 0.73, indicating a strong ability to properly anticipate companies in this sector. The likelihood of losing out on truly lucrative businesses is minimal. The healthcare business has a robust data collection and few missing numbers, making it a stable growth and low volatility market with few outliers. Furthermore, the nature of the healthcare business is closely regulated by the government and market processes in order to mitigate detrimental effects on community services. As a result, the model is rated as the best and most stable in comparison to the other industries, with a very high AUC value (0.78-0.92, Figure 4.2.3) and a high accuracy of 0.76.

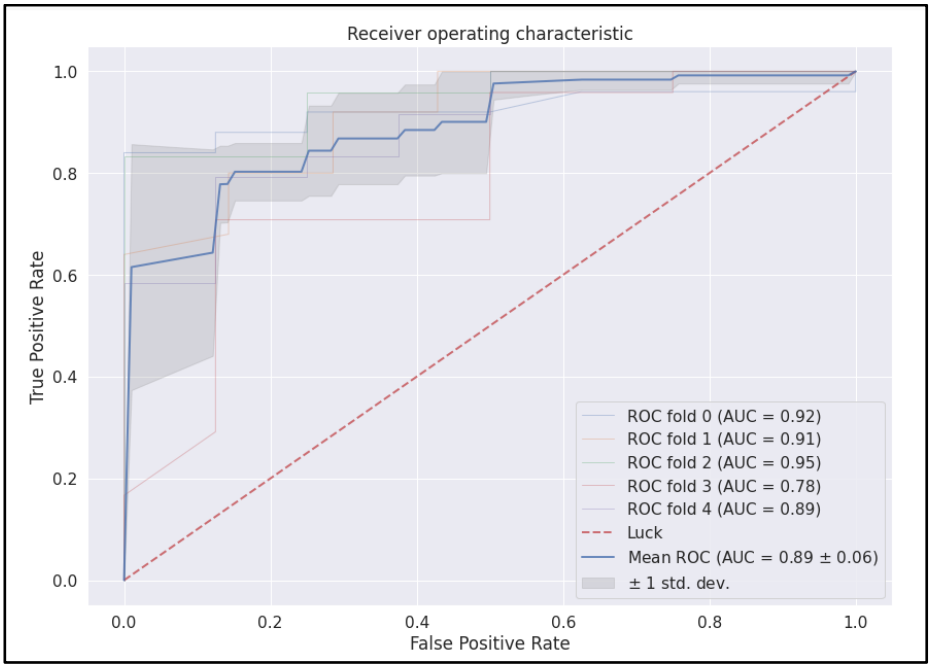

Figure 3.9. Chart of ROC curve of the Healthcare industry model

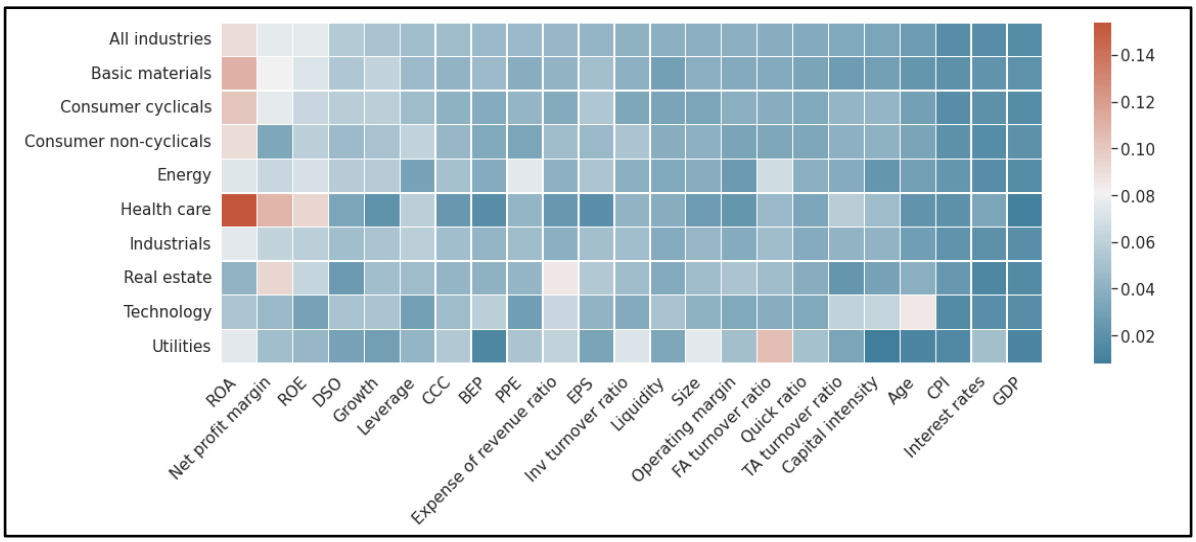

Figure 3.10. Heatmap of features' importance in the model decomposed by industries

The influence of the factors may be seen in Figure 4.243. In general, characteristics are classified into three classes based on their effect degree (2-14 percent). The most essential set of characteristics are the fundamental metrics used to assess the company's success, such as ROA, Net profit margin, ROE, and DSO. Other financial indicators such as Growth, Leverage, CCC, EPS... are the second most essential category of attributes. The remaining characteristics are macro variables. Although the level of impact of macro variables is low, it does show the influence of variables when classifying by industry; when looking at the year, all companies are subject to the same systematic risk, so the annual forecast model does not show the influence of macro factors, which is a significant difference when compared to the model decomposed by industries.

CHAPTER 4: DISCUSSION AND CONCLUSION

4.1. Conclusion

We investigate whether a machine learning (ML) approach, random forests can provide out-of-sample profitability forecasts that outperform classical forecasts. We are motivated to use the Machine Learning method because a) the literature and training show that traditional regression methods cannot produce out-of-sample forecasts that are superior to random walk forecasts, and Logistic Regression, K-Nearest Neighbors, Decision Tree, Support Vector Machine (Linear Kernel), Support Vector Machine (RBF Kernel), Neural Network, and, in particular, Random Forest. b) Because they are focused on prediction and optimizing prediction accuracy, ML approaches have certain benefits over regression methods in generating out-of-sample predictions.

Examples of such advantages include insensitivity to econometric issues such as multicollinearity, better handling of nonlinearity in the data than traditional regression-based methods, and discovery of the functional form that best fits the data. We implement the ML method using a large sample of Vietnamese firms with valid required data over the period 2010-2021 and generate out-of-sample predictions of directional changes (increases or decreases) in more than twenty variables profitability measures: quick ratio, cash conversion cycle (CCC), inventory turnover ratio, return on equity (ROE), fix asset turnover ratio (FA turnover ratio), operating margin, basic earning power (BEP), expense of revenue ratio, days sales outstanding (DSO), size, net profit margin, return on assets (ROA), growth, earnings per share (EPS), Property, Plant, & Equipment Turnover Ratio (PPE), total asset turnover ratio (TA turnover ratio), capital intensity, leverage, liquidity, age , gross domestic product (GDP), consumer price index (CPI), interest real rates (interest rates), target. Results based on a minimum set of independent variables show that our ML method achieves classification accuracies ranging from 47% to 76% for our profitability measures, and that the differences in proportions of accurate classifications between ML and random walk are highly significant.

The main factor affecting the profitability of the majority of companies drawn after the study is Return on Assets ratio. The findings of the investigation using standard analytical methods are comparable and supported by the findings of the research. Return on Assets (ROA), for example, can still be frequently employed by market analysts as a measure of financial success when calculating accounting profit, because it gauges the efficiency of assets in generating revenue. ROA is an important number for assessing a company's profitability even in the banking industry since it is unaffected by a high equity ratio. The researchers' findings also demonstrate that ROA may be utilized to anticipate business profitability efficiently.

After obtaining the study's findings by sector and year, we can see that, by industry, AUC on the health care test set is the best at roughly 89 percent, while real estate is the

worst at about 63 percent. Otherwise, when analyzing the model by year, the most accurate years are 2012 and 2020, with accuracies of roughly 81 percent. The efficacy of the data collection and the reality of each industry must be the cause of these results.

As we can see, the Vietnamese health care industry has attracted a big number of investors while also creating a high level of income and accuracy. The profit forecasting model of the healthcare industry is the best because of the good data set, few missing values, the industry's steady growth, little volatility, few outliers, the nature of the Healthcare industry is tightly controlled by the state and the market mechanism. schools to combat negative impacts on health care and public health services, that might help with the evaluation process. Because medical equipment is a significant component in deciding the efficiency and quality of medical work, it actively assists doctors in properly diagnosing and treating patients. It is quick, safe, and effective. Today, medical equipment not only helps prolong the senses, but also allows doctors to easily access and treat injuries inside the body, such as: laparoscopic surgery, surgery, robotics... can even replace the human brain (using artificial intelligence) to help make the most informed, correct, and effective decisions in diagnosing, treating, and caring for people's health sick. However, the data set of real estate not only contains more missing values, but it also includes primarily short-term loans, which result in high finance leverage and, as a result, worse accuracy and low AUC score.

Furthermore, we judge that the results obtained from the study by year are not as good as by the industries. AUC scores, which get from model evaluation by year, are changing around 71% and 81% and have no significant change over year and its accuracy, which ranges between 35% and 60%, is quite low when compared to the model by industries. In addition, the macro features' importance in the year model equal zero over years. This is because these variables affects in the same way on companies and industries and the systematic risk in that year is the same to all business, so the difference cannot be seen and the forecast is accurate. However, for different people and different purposes, we may choose different ways of modeling. As researchers require high accuracy prediction for investment and taking risk, evaluation model by fields is more suitable with higher AUC score and higher accuracy.

4.2. Discussion and future study

Because of the large number of decision trees involved in the test, random forests are regarded as an accurate and powerful approach. It does not have any overfitting issues. The fundamental reason for this is that it takes the average of all forecasts, canceling out the bias. The approach is applicable to our research. Missing values can also be handled using random forests. We use an effective approach to dealing with these numbers: utilizing linear regression method to replace continuous variables missing values. That may obtain relative feature importance, which aids in determining which characteristics contribute the most to the classifier.

However, this method has some limitations. Since there are so many decision trees in random forests, it takes a long time to make predictions. Every time it makes a forecast, all of the trees in the forest must make a prediction for the same supplied input and then vote on it. This entire procedure takes time. Models are more perplexing than decision trees, which allow you to readily make judgments by following a path through the tree. In addition, the selected data has some unreasonable points such as net income (NI) is higher than earnings before interest and taxes (EBIT) and higher than sales; inventory is higher than current assets. This should be improved in the next extended research.

Additionally, our Machine Learning model has issues with anticipated loss companies, and there is a precision-to-recall mismatch. The results reveal that the model is unable to forecast which companies would lose money, but it can anticipate which companies will benefit in the future. This needs to be improved in the future.

We feel that these results can be further improved, especially if we are willing to sacrifice model interpretability. For example, we could add more features, employ different ML methods, explode the feature space to properly handle categorical variables, and expand the set of hyperparameters over which we searched. Future work can also explore the use of accruals as features in the prediction of cash flows. Finally, our results can be compared to the results of a recent study by Vorst and Yohn (2018), who perform out-of-sample predictions using a regression methodology, but without using the random walk as a benchmark.

The applicability of research in management and investment:

+ Administrators

  These outcomes help internal users (such as managers, shareholders and employees). They may identify the drivers of increasing their company's profitability after comparing it to the industry index and general profitability index in the results, and so focus more on the elements that increase their company's profitability to make the performance best. In each specific case of market, macro variables maybe help internal users to find out the market rule at this time in general and the main movement trends of each particular industry. Also, this research helps the managers make decisions in operating activities by assessing that the company will probably lose or profit with the year-similar project.

+ Investors

  Other external users (such as investors, creditors, new established companies, tax authority) also may get advantages from these results. It is clear that those users concern about the profitability of companies and the determinants of their profitability.

Furthermore, investors will be able to remark and assess which prospectively potential industry to invest in for maximum earnings. Investors might be more confident and reduce the risk of their decisions as a consequence of the research findings.Also, they can avoid cooking the book problem. It helps the users analyze and invest with spending much less time than the fundamental analysis.

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APPENDICES

Appendix 1. Table of raw data

Variable	**Code**
Date Became Public	"Public Date" sheet, "Date Became Public" column
Organization Founded Year	"Public Date" sheet, "Organization Founded Year" column
Company Code	"Name" sheet, "Identifier" column
Industry Code	"Name" sheet, "TRBC Economic Sector Name" column
Operating Cash Flow	"OCF" sheet
Return On Asset	"ROA" sheet
Total Asset	"TA" sheet
Market Value	"MV" sheet
Total Liability	"Total Lia" sheet
Sales	"Sales" sheet
Tangible Fixed Asset	"Tangible FA" sheet
Total Current Asset	"Total CA" sheet
Current Liability	"Total Current Lia" sheet
Fixed Asset	"Fixed assets" sheet
Accounts Receivable	"Accounts Receivable" sheet
Cost Of Revenue	"Cost of revenue" sheet
Earning Before Interest And Tax	"EBIT" sheet
Earning Per Share	"EPS" sheet
Equity	"Equity" sheet
Average Receivable Day	"Avg. Receivable days" sheet
Average Payable Day	"Avg. Payable days" sheet
Average Inventory Day	"Avg. Inventory days" sheet

Gross Domestic Product	"GDP" sheet
Consumer Price Index	"CPI" sheet
Interest Real Rate	"Interest rates" sheet

Appendix 2. Table of intermediate variables

Variable	**Code**	**Formula**
Net Income	NI	ROA * TA
Inventory	Inv	Sales/Inventory Turnover Ratio

Appendix 3. Table of independent variables

Variable	**Code**	**Formula**
Growth Of Sales	Growth	$\frac{Sale_t - Sale_{t-1}}{Sale_{t-1}}$
Market Size Of Company	Size	ln(Market value)
Age Of Company	Age	2020 - Founding year
Liquidity Ratio	Liq	$\frac{Total\ current\ asset}{Current\ liabilities}$
Leverage Ratio	Lev	$\frac{Total\ liabilities}{Total\ asset}$
Property, Plant, & Equipment Turnover Ratio	PPE	$\frac{Tangible\ Fixed\ Asset}{Sales}$
Quick Ratio	Quick ratio	$\frac{Total\ current\ asset - Inventory}{Current\ liabilities}$
Inventory Turnover Ratio	Inventory turnover ratio	$\frac{365}{Average\ inventory\ days}$
Fixed Asset Turnover Ratio	FA turnover ratio	$\frac{Sales}{Fixed\ assets}$
Total Asset Turnover Ratio	TA turnover ratio	$\frac{Sales}{Total\ asset}$
Days Sale Outstanding	DSO	$\frac{Account\ receivable}{Sale/365}$
Capital intensity	Capital intensity	$\frac{Total\ asset}{Sales}$
Expense Of Revenue Ratio	Expense of revenue ratio	$\frac{Costs\ of\ revenue}{Sales}$
Operating margin	Operating margin	$\frac{EBIT}{Sales}$
Net profit margin	Net profit margin	$\frac{Net\ income}{Sales}$

Return On Total Asset	ROA	$\frac{Net\ income}{Total\ asset}$
Return On Equity	ROE	$\frac{Net\ income}{Total\ equity}$
Earnings Per Share	EPS	None
Basic Earning Power Ratio	BEP	$\frac{EBIT}{Total\ asset}$
Cash Conversion Cycle	CCC	Average inventory days + Average receivable days - Average payable days
Gross Domestic Product	GDP	None
Consumer Price Index	CPI	None
Interest Real Rate	Interest rates	None

Appendix 4. Table of target variables

Variable	**Code**
Net Income	NI
Operating Cash Flow	OCF

Appendix 5. Variables' importance in the model decomposed by years

	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
ROA	0.067	0.085	0.112	0.088	0.074	0.086	0.076	0.092	0.101	0.094	0.103
Net profit margin	0.034	0.074	0.121	0.105	0.071	0.098	0.082	0.065	0.117	0.085	0.11
ROE	0.037	0.068	0.082	0.062	0.055	0.047	0.059	0.054	0.044	0.078	0.077
DSO	0.083	0.058	0.061	0.04	0.067	0.055	0.048	0.042	0.043	0.039	0.042
Growth	0.059	0.044	0.04	0.07	0.044	0.039	0.051	0.062	0.049	0.049	0.083
Leverage	0.071	0.032	0.042	0.046	0.043	0.063	0.085	0.08	0.052	0.052	0.071
CCC	0.089	0.079	0.051	0.05	0.055	0.052	0.051	0.045	0.043	0.038	0.03
BEP	0.035	0.041	0.033	0.044	0.04	0.068	0.073	0.071	0.044	0.037	0.039
PPE	0.042	0.045	0.032	0.049	0.048	0.035	0.036	0.059	0.07	0.065	0.049
Expense of revenue ratio	0.044	0.041	0.041	0.04	0.07	0.034	0.052	0.038	0.045	0.056	0.038
EPS	0.043	0.047	0.042	0.045	0.059	0.058	0.030	0.042	0.03	0.054	0.03
Inv turnover ratio	0.064	0.055	0.042	0.043	0.063	0.041	0.041	0.045	0.03	0.036	0.041
Liquidity	0.042	0.045	0.034	0.042	0.041	0.038	0.038	0.04	0.044	0.034	0.043

Size	0.042	0.034	0.037	0.039	0.042	0.054	0.048	0.042	0.036	0.046	0.04
Operating margin	0.039	0.046	0.043	0.042	0.042	0.053	0.044	0.037	0.038	0.035	0.034
FA turnover ratio	0.05	0.038	0.036	0.039	0.042	0.037	0.041	0.043	0.072	0.05	0.03
Quick ratio	0.044	0.044	0.035	0.035	0.04	0.05	0.036	0.037	0.04	0.04	0.031
TA turnover ratio	0.036	0.043	0.04	0.053	0.031	0.039	0.04	0.036	0.039	0.047	0.04
Capital intensity	0.044	0.05	0.049	0.042	0.038	0.029	0.043	0.04	0.042	0.04	0.048
Age	0.037	0.031	0.029	0.028	0.036	0.026	0.027	0.031	0.024	0.025	0.022
CPI	0	0	0	0	0	0	0	0	0	0	0
Interest rates	0	0	0	0	0	0	0	0	0	0	0
GDP	0	0	0	0	0	0	0	0	0	0	0

Appendix 6. Variables' importance in the model decomposed by industries

	All industries	**Basic materials**	**Consumer cyclicals**	**Consumer non-cyclicals**	**Energy**	**Health care**	**Industrials**	**Real estate**	**Technology**	**Utilities**
ROA	0.091	0.111	0.101	0.091	0.074	0.154	0.075	0.042	0.053	0.075
Net profit margin	0.076	0.081	0.076	0.034	0.064	0.109	0.062	0.094	0.045	0.048
ROE	0.076	0.073	0.064	0.059	0.07	0.094	0.059	0.063	0.031	0.044
DSO	0.056	0.054	0.058	0.046	0.057	0.033	0.048	0.026	0.051	0.031
Growth	0.051	0.062	0.059	0.051	0.057	0.021	0.052	0.048	0.052	0.029
Leverage	0.048	0.046	0.047	0.062	0.031	0.059	0.059	0.047	0.029	0.043
CCC	0.047	0.042	0.041	0.044	0.05	0.025	0.048	0.043	0.047	0.055
BEP	0.045	0.046	0.037	0.035	0.037	0.018	0.043	0.041	0.059	0.014
PPE	0.045	0.038	0.043	0.033	0.075	0.043	0.047	0.043	0.028	0.052
Expense of revenue ratio	0.044	0.042	0.036	0.047	0.04	0.025	0.039	0.086	0.064	0.062
EPS	0.043	0.049	0.054	0.045	0.053	0.019	0.049	0.055	0.042	0.032
Inv turnover ratio	0.041	0.040	0.034	0.052	0.039	0.042	0.048	0.047	0.036	0.072
Liquidity	0.039	0.030	0.032	0.038	0.035	0.038	0.037	0.036	0.051	0.034
Size	0.039	0.039	0.033	0.04	0.038	0.027	0.044	0.047	0.041	0.075
Operating margin	0.039	0.036	0.039	0.032	0.026	0.023	0.037	0.052	0.035	0.049
FA turnover ratio	0.038	0.036	0.038	0.034	0.067	0.045	0.047	0.047	0.038	0.105

Quick ratio	0.036	0.032	0.035	0.034	0.039	0.033	0.037	0.038	0.035	0.05
TA turnover ratio	0.035	0.027	0.043	0.04	0.037	0.058	0.042	0.023	0.061	0.033
Capital intensity	0.033	0.029	0.043	0.041	0.023	0.047	0.042	0.031	0.063	0.008
Age	0.027	0.023	0.030	0.032	0.029	0.022	0.028	0.039	0.085	0.013
CPI	0.018	0.02	0.018	0.02	0.023	0.02	0.022	0.025	0.016	0.015
Interest rates	0.018	0.022	0.020	0.017	0.018	0.033	0.02	0.014	0.019	0.049
GDP	0.017	0.021	0.017	0.02	0.017	0.01	0.019	0.016	0.018	0.013

Appendix 7. Table of percent missing values occupied in each variable for the total industries model

	(%)
Quick ratio	12.455955
CCC	10.095137
Inventory turnover ratio	9.355180
ROE	9.249471
FA turnover ratio	8.192389
Operating margin	7.998591
BEP	7.892882
Expense of revenue ratio	7.716702
DSO	7.646230
Size	5.761099
Net profit margin	5.056378
ROA	4.844961
Growth	4.474982
EPS	4.439746
PPE	3.488372
TA turnover ratio	3.312192
Capital intensity	3.312192
Leverage	3.100775
Liquidity	3.100775
Age	0.088090
GDP	0.000000
CPI	0.000000
Interest rates	0.000000
Target	0.000000

Appendix 8. Tables of features' importance in the total industries model *(1)*, the two models decomposed by industries (Healthcare industry) *(2)*, decomposed by years (year 2020) *(3)*

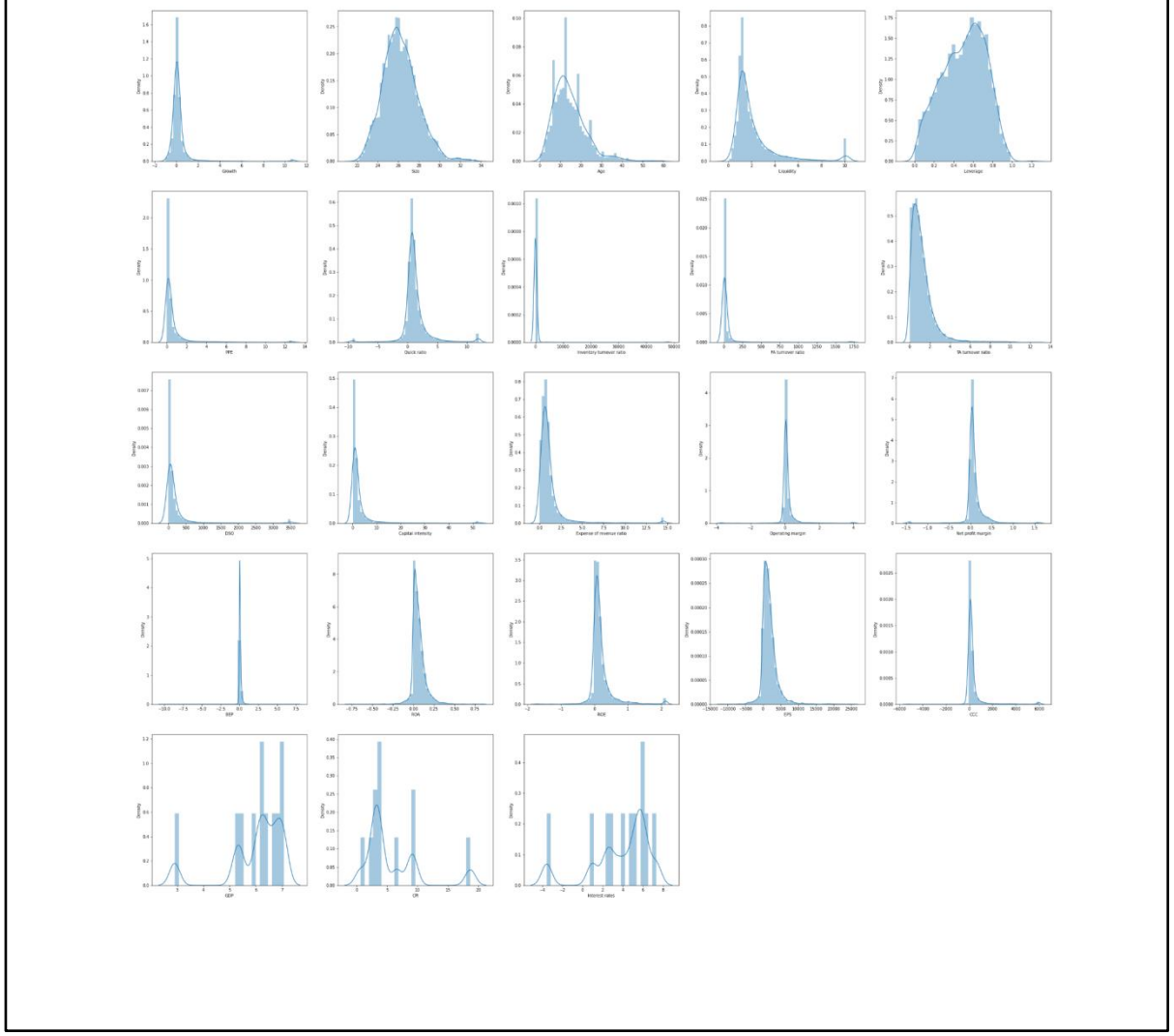
(1) (2) (3)

	(%)
ROA	0.089889
Net profit margin	0.077182
ROE	0.076106
DSO	0.056026
Growth	0.050740
Leverage	0.048209
CCC	0.047006
BEP	0.044831
PPE	0.044354
Expense of revenue ratio	0.043395
EPS	0.043180
Inventory turnover ratio	0.040494
Liquidity	0.039150
Size	0.039076
Operating margin	0.038699
FA turnover ratio	0.038274
Quick ratio	0.036344
TA turnover ratio	0.035160
Capital intensity	0.032499
Age	0.026629
CPI	0.018445
Interest rates	0.017795
GDP	0.016520

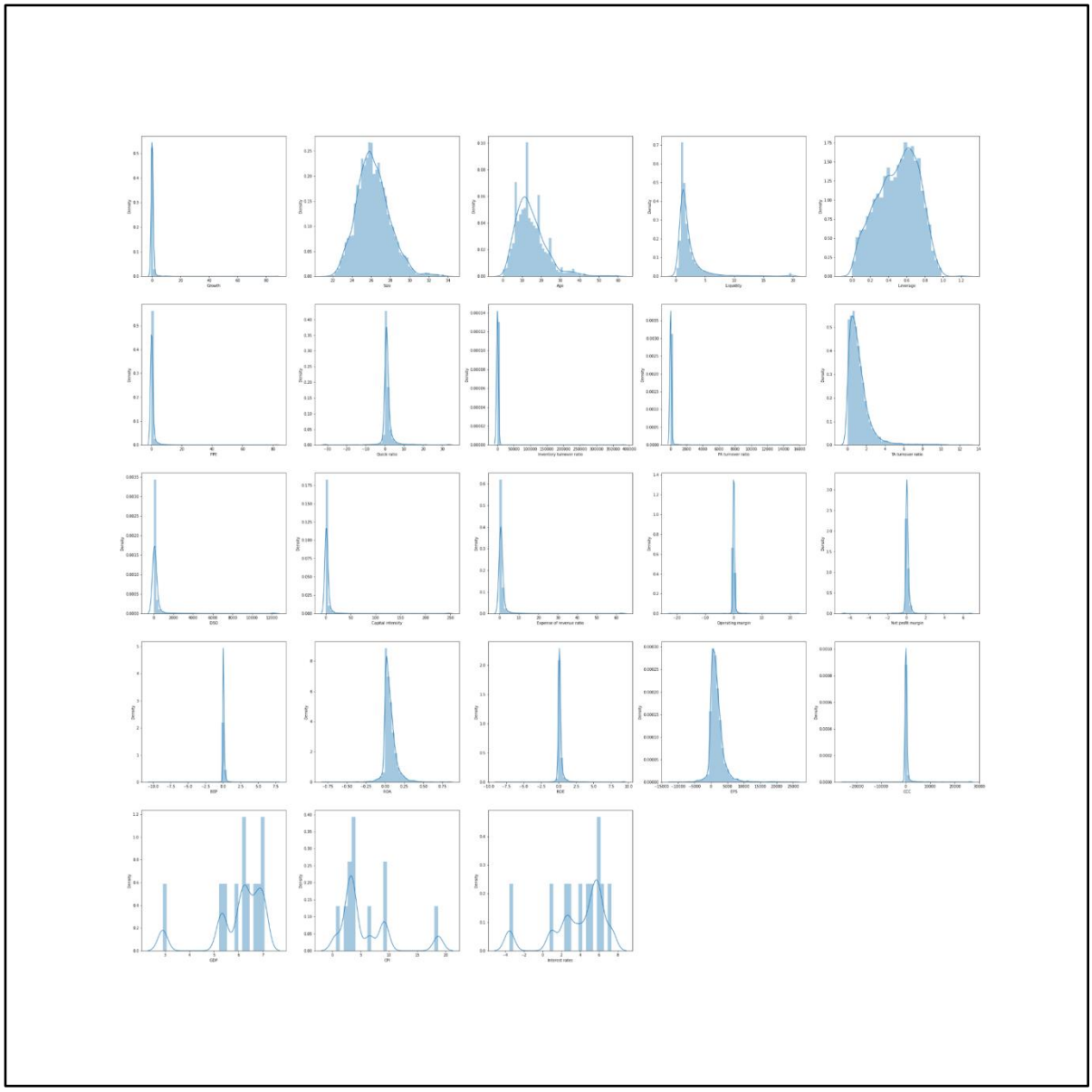
	(%)
ROA	0.152503
Net profit margin	0.107874
ROE	0.092146
TA turnover ratio	0.060019
Leverage	0.058353
FA turnover ratio	0.051188
Capital intensity	0.047730
PPE	0.043960
Inventory turnover ratio	0.041703
Liquidity	0.037320
Interest rates	0.033550
DSO	0.032460
Quick ratio	0.032281
Size	0.027716
Expense of revenue ratio	0.025562
CCC	0.023973
Operating margin	0.023077
Growth	0.021283
Age	0.021095
CPI	0.019816
EPS	0.018863
BEP	0.017713
GDP	0.009817

	(%)
Net profit margin	0.109058
ROA	0.098060
Growth	0.083994
ROE	0.081257
Leverage	0.071470
PPE	0.048940
Capital intensity	0.048569
BEP	0.041972
TA turnover ratio	0.041967
Expense of revenue ratio	0.041538
Inventory turnover ratio	0.041219
DSO	0.040435
Liquidity	0.039447
Size	0.037474
Operating margin	0.035791
FA turnover ratio	0.032517
CCC	0.030755
EPS	0.028522
Quick ratio	0.027636
Age	0.019378
GDP	0.000000
CPI	0.000000
Interest rates	0.000000

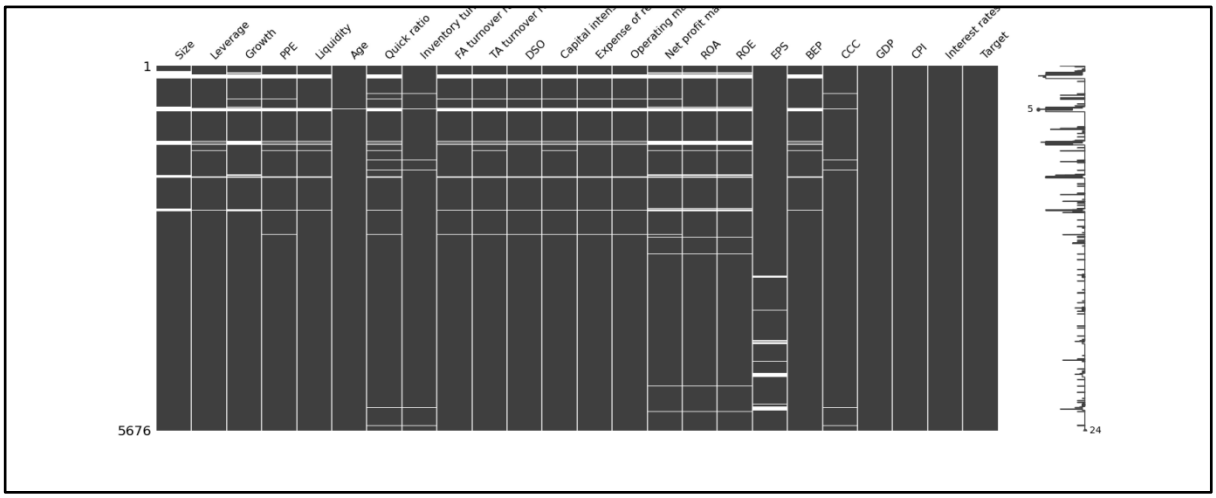
Appendix 9. Chart of values' distribution before fixing outliers in the total industries model



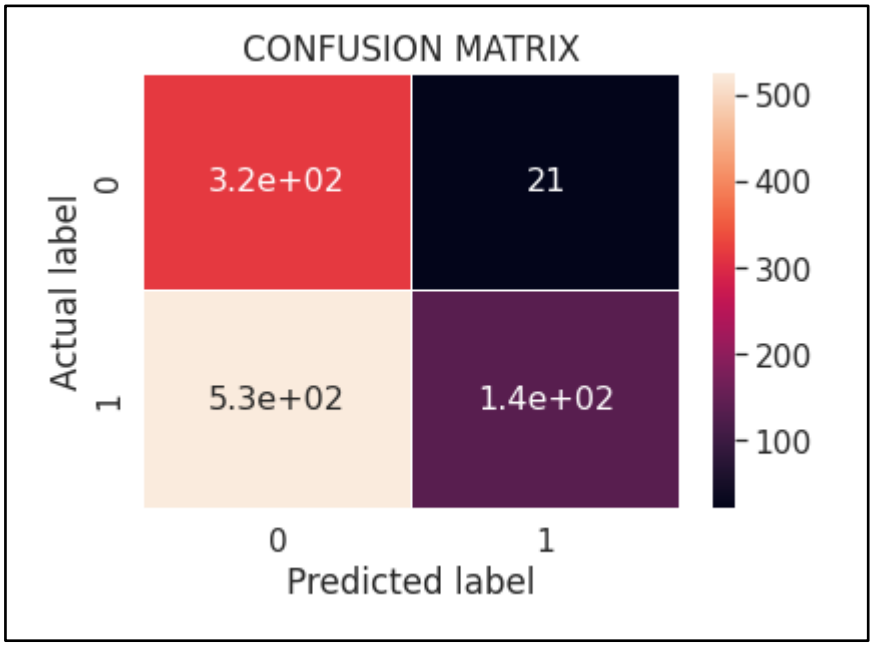
Appendix 10. Chart of values' distribution after fixing outliers in the total industries model



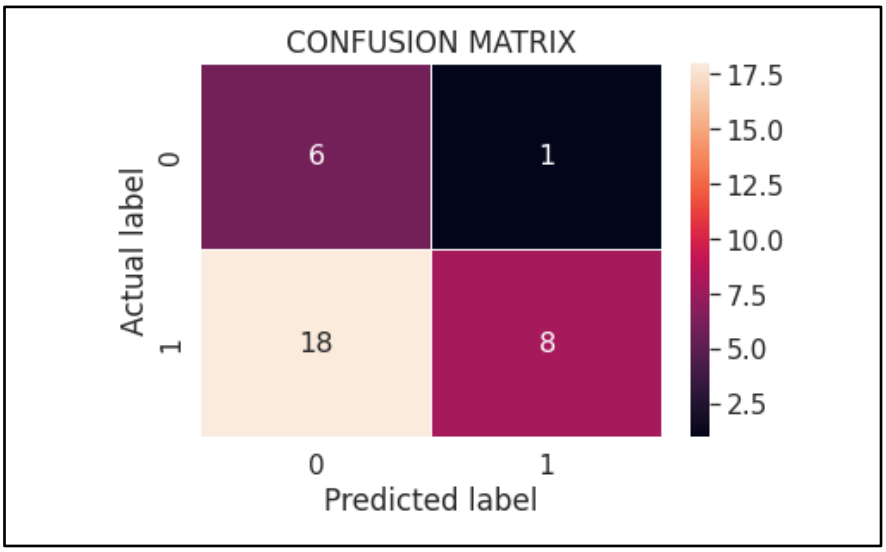
Appendix 11. Chart of missing values' distribution in the total industries model



Appendix 12. Chart of confusion matrix in the total industries model



Appendix 13. Chart of confusion matrix in the Healthcare model



Appendix 14. Chart of confusion matrix in the year 2020 model