VIETNAM NATIONAL UNIVERSITY, HANOI

INTERNATIONAL SCHOOL

GRADUATION PROJECT

ANALYZE THE FINANCIAL STATEMENT AND PREDICT STOCK PRICES OF SABECO COMPANY USING AI MODEL

Tran Quoc Dang

Hanoi, 2024

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
BHN	Hanoi Beer Alcohol And Beverage Joint Stock Corporation
D/E	Debt to Equity Ratio
EBIT	Earnings Before Interest and Taxes
F&B	Food and Beverage
GRU	Gated Recurrent Unit
HAD	Ha Noi - Hai Duong Beer JSC
HAT	Ha Noi Beer Trading Joint Stock Company
HOSE	Ho Chi Minh Stock Exchange
HNX	Hanoi Stock Exchange
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MSE	Mean Squared Error
P/B	Price to Book Ratio
P/E	Price to Earnings Ratio
ROA	Return on Assets

ROE	Return on Equity
SAB	Saigon Beer - Alcohol - Beverage Corporation
SCD	Chuong Duong Beverages Joint Stock Company
SMB	Sai Gon - Mien Trung Beer JSC
SVM	Support Vector Machine
THB	Ha Noi - Thanh Hoa Beer Joint Stock Company
VDL	Lam Dong Foodstuffs JSC

ABSTRACT

The accurate prediction of stock prices is a critical task in financial markets, offering significant benefits to investors and financial analysts. This study focuses on the financial analysis and stock price prediction of the Saigon Beer - Alcohol - Beverage Corporation (Sabeco), a prominent player in Vietnam's beverage industry. By leveraging advanced machine learning models, including GRU, bidirectional GRU, LSTM, bidirectional LSTM, this study aims to enhance the accuracy of stock price forecasts. The methodology involves collecting and preprocessing financial data from Sabeco and other relevant companies, developing various predictive models, and evaluating their performance using historical data. The findings of this study provide valuable insights for investors, highlighting the strengths and limitations of different AI models in predicting stock prices. The results indicate that integrating financial analysis with advanced AI techniques can significantly improve the reliability of stock price predictions, offering a robust tool for investment decision-making.

Keywords

Stock price prediction, financial analysis, machine learning, GRU, LSTM, bidirectional GRU, bidirectional LSTM, Sabeco.

I. INTRODUCTION

1. Background of the Study

The financial well-being of a company is a crucial determinant of its stock price performance. In the rapidly evolving financial markets, investors depend heavily on accurate stock price predictions to make informed investment decisions. This study centers on the Saigon Beer - Alcohol - Beverage Corporation (Sabeco), a leading company in Vietnam's beverage industry. By analyzing its financial indicators and employing advanced AI models to forecast its stock prices, this research aims to provide valuable insights for investors.

2. Problem Statement

Predicting stock prices is inherently complex due to the volatile and non-linear nature of financial markets. Traditional statistical methods often fail to capture the intricate patterns in stock price movements. This study aims to address this challenge by utilizing advanced machine learning models to improve the accuracy of stock price predictions for Sabeco.

3. Objectives of the Study

The specific objectives of this study are:

- To conduct a comprehensive financial analysis of Sabeco.
- To accurately forecast the future stock prices of Sabeco using various AI models, including GRU, bidirectional GRU, LSTM, and bidirectional LSTM.
- To compare the performance of these AI models and identify the most effective model for stock price prediction.

4. Research Questions

- How do the financial indicators of Sabeco influence its stock price?
- Which AI model provides the most accurate predictions for Sabeco's stock prices?
- How do the predictions of different AI models compare in terms of accuracy and reliability?

5. Significance of the Study

This study enhances the existing body of knowledge by integrating advanced AI models with financial analysis to predict stock prices. The findings can aid investors in making better-informed decisions and can also serve as a reference for future research in financial market predictions.

6. Scope and Limitations

The scope of this study is confined to the financial data of Sabeco and selected companies in the Food and Beverage industry from 2020 to 2022. While the study employs multiple AI models, it does not encompass every possible machine learning technique. Furthermore, the study's predictions are based on historical data, and future market conditions may introduce unforeseen variables.

II. LITERATURE REVIEW

1. Introduction to Financial Analysis

Financial analysis involves evaluating a company's financial statements to understand its economic health and performance. Key financial indicators, such as revenue, profit margins, return on assets (ROA), and the debt-to-equity ratio (D/E), are essential in determining a company's value and growth potential. In the context of stock price prediction, these indicators offer valuable insights into the company's stability and future performance.

2. Stock Price Prediction

Stock price prediction is a well-researched area in financial studies. Traditional methods like linear regression and time series analysis have been widely used but often fail to capture the non-linear patterns in stock price movements. Advanced machine learning techniques, such as neural networks and ensemble methods, provide promising alternatives by learning complex patterns from historical data.

3. Machine Learning Models in Financial Predictions

Machine learning models have gained popularity in financial predictions due to their ability to handle large datasets and uncover hidden patterns. Recurrent neural networks (RNN), particularly Long Short-Term Memory (LSTM) networks, are effective for time series prediction due to their memory capabilities. These models play significant roles in classification and clustering tasks within financial data analysis.

4. Previous Studies and Findings

Numerous studies have demonstrated the efficacy of machine learning models in stock price prediction. For example, research has shown that LSTM networks outperform traditional time series models in predicting stock prices due to their ability to capture long-term dependencies. Tree-based models like Random Forest and XGBoost have been successful in feature selection and improving prediction accuracy. However, each model has its limitations, and the choice of model depends on the specific characteristics of the dataset and the prediction task.

5. Summary of Gaps in the Literature

Despite the advancements in machine learning models, there are still gaps in the literature, particularly in comparing the performance of different models on the same dataset. Additionally, integrating financial analysis with advanced AI models remains underexplored. This study aims to fill these gaps by comparing various AI models and providing a comprehensive analysis of their performance in predicting Sabeco's stock prices.

III. METHODOLOGY

1. Research Design

This study utilizes a quantitative research design to analyze financial data and predict stock prices using various machine learning models. The research follows a structured approach that includes data collection, data preparation, model development, and evaluation.

2. Data Collection

- Sources of Data

The primary data source for this study is Vietstock, which provides comprehensive financial reports of companies in Vietnam. The study focuses on the financial data of Sabeco and other relevant companies in the Food and Beverage industry from 2020 to 2022.

- Description of Data

The datasets include:

Beverage Manufacturing Data: Indicators related to accumulated depreciation and other financial metrics for companies such as BHN and SAB.

	A	B	C	D	E	F	G	H
1	Indicator	Company	Year	Value	Category	Category		
2	- Accumulated depreciation	BHN	2020	-6	ASSETS	B. LONG-TERM ASSETS		
3	- Accumulated depreciation	BHN	2021	-7	ASSETS	B. LONG-TERM ASSETS		
4	- Accumulated depreciation	BHN	2022	-8	ASSETS	B. LONG-TERM ASSETS		
5	- Accumulated depreciation	SAB	2020	-27	ASSETS	B. LONG-TERM ASSETS		
6	- Accumulated depreciation	SAB	2021	-26	ASSETS	B. LONG-TERM ASSETS		
7	- Accumulated depreciation	SAB	2022	-30	ASSETS	B. LONG-TERM ASSETS		
8	- Accumulated depreciation	SCD	2022	-1	ASSETS	B. LONG-TERM ASSETS		
9	- Accumulated depreciation	SMB	2020	-2	ASSETS	B. LONG-TERM ASSETS		
10	- Accumulated depreciation	SMB	2021	-3	ASSETS	B. LONG-TERM ASSETS		
11	- Accumulated depreciation	SMB	2022	-3	ASSETS	B. LONG-TERM ASSETS		
12	- Accumulated retained earning at the end of the previous period	BHN	2020	901	OWNER'S E	B. OWNER'S EQUITY		
13	- Accumulated retained earning at the end of the previous period	BHN	2021	26	OWNER'S E	B. OWNER'S EQUITY		
14	- Accumulated retained earning at the end of the previous period	BHN	2022	324	OWNER'S E	B. OWNER'S EQUITY		
15	- Accumulated retained earning at the end of the previous period	SAB	2020	7804	OWNER'S E	B. OWNER'S EQUITY		
16	- Accumulated retained earning at the end of the previous period	SAB	2021	10133	OWNER'S E	B. OWNER'S EQUITY		
17	- Accumulated retained earning at the end of the previous period	SAB	2022	10484	OWNER'S E	B. OWNER'S EQUITY		
18	- Accumulated retained earning at the end of the previous period	SCD	2020	1	OWNER'S E	B. OWNER'S EQUITY		
19	- Accumulated retained earning at the end of the previous period	SCD	2021	3	OWNER'S E	B. OWNER'S EQUITY		
20	- Accumulated retained earning at the end of the previous period	SCD	2022	-33	OWNER'S E	B. OWNER'S EQUITY		
21	- Accumulated retained earning at the end of the previous period	SMB	2020	68	OWNER'S E	B. OWNER'S EQUITY		
22	- Accumulated retained earning at the end of the previous period	SMB	2021	86	OWNER'S E	B. OWNER'S EQUITY		
23	- Accumulated retained earning at the end of the previous period	SMB	2022	108	OWNER'S E	B. OWNER'S EQUITY		
24	- Accumulated retained earning at the end of the previous period	VCF	2020	279	OWNER'S E	B. OWNER'S EQUITY		
25	- Accumulated retained earning at the end of the previous period	VCF	2021	338	OWNER'S E	B. OWNER'S EQUITY		
26	- Accumulated retained earning at the end of the previous period	VCF	2022	834	OWNER'S E	B. OWNER'S EQUITY		
27	- Accumulated retained earning at the end of the previous period	HAD	2020	3	OWNER'S E	B. OWNER'S EQUITY		
28	- Accumulated retained earning at the end of the previous period	HAD	2021	3	OWNER'S E	B. OWNER'S EQUITY		
29	- Accumulated retained earning at the end of the previous period	THB	2020	6	OWNER'S E	B. OWNER'S EQUITY		
30	- Accumulated retained earning at the end of the previous period	THB	2021	6	OWNER'S E	B. OWNER'S EQUITY		
31	- Accumulated retained earning at the end of the previous period	THB	2022	6	OWNER'S E	B. OWNER'S EQUITY		

Table 1. *Beverage Manufacturing Data dataset.*

MA30 Data: VN-INDEX and SAB stock prices over time, along with their 30-day moving averages.

	A	B	C	D	E
1	Date	VN-INDEX	SAB	MA30 (VN-INDEX)	MA30 (SAB)
2	3/1/23	1043,9	84,5		
3	4/1/23	1046,35	85,75		
4	5/1/23	1055,82	87,1		
5	6/1/23	1051,44	90,35		
6	9/1/23	1054,21	89,8		
7	10/1/23	1053,35	88,05		
8	11/1/23	1055,76	90,5		
9	12/1/23	1056,39	89,9		
10	13/1/23	1060,17	92,95		
11	16/1/23	1066,68	94,25		
12	17/1/23	1088,29	93,5		
13	18/1/23	1098,28	93,5		
14	19/1/23	1108,08	92,85		
15	27/1/23	1117,1	96,55		
16	30/1/23	1102,57	95		
17	31/1/23	1111,18	94,5		
18	1/2/23	1075,97	93,5		
19	2/2/23	1077,59	93,75		
20	3/2/23	1077,15	96,4		

Table 2. *MA30 Data dataset.*

- **SAB Data**: Financial indicators specific to SAB, categorized by asset types over different years.

	A	B	C	D	E	F	G	H
1	Indicator	Unit	Year	SAB	Category	Category		
2	A. SHORT-TERM ASSETS		2020	19513	ASSETS	A. SHORT-TERM ASSETS		
3	A. SHORT-TERM ASSETS		2021	22877	ASSETS	A. SHORT-TERM ASSETS		
4	A. SHORT-TERM ASSETS		2022	26860	ASSETS	A. SHORT-TERM ASSETS		
5	I. Cash and cash equivalents		2020	2726	ASSETS	A. SHORT-TERM ASSETS		
6	I. Cash and cash equivalents		2021	3606	ASSETS	A. SHORT-TERM ASSETS		
7	I. Cash and cash equivalents		2022	4069	ASSETS	A. SHORT-TERM ASSETS		
8	1. Cash		2020	844	ASSETS	A. SHORT-TERM ASSETS		
9	1. Cash		2021	685	ASSETS	A. SHORT-TERM ASSETS		
10	1. Cash		2022	985	ASSETS	A. SHORT-TERM ASSETS		
11	2. Cash equivalents		2020	1882	ASSETS	A. SHORT-TERM ASSETS		
12	2. Cash equivalents		2021	2921	ASSETS	A. SHORT-TERM ASSETS		
13	2. Cash equivalents		2022	3084	ASSETS	A. SHORT-TERM ASSETS		
14	II. Short-term financial investments		2020	14547	ASSETS	A. SHORT-TERM ASSETS		
15	II. Short-term financial investments		2021	16991	ASSETS	A. SHORT-TERM ASSETS		
16	II. Short-term financial investments		2022	19411	ASSETS	A. SHORT-TERM ASSETS		
17	3. Held to maturity investments		2020	14547	ASSETS	A. SHORT-TERM ASSETS		
18	3. Held to maturity investments		2021	16991	ASSETS	A. SHORT-TERM ASSETS		
19	3. Held to maturity investments		2022	19411	ASSETS	A. SHORT-TERM ASSETS		
20	III. Short-term receivables		2020	591	ASSETS	A. SHORT-TERM ASSETS		
21	III. Short-term receivables		2021	468	ASSETS	A. SHORT-TERM ASSETS		
22	III. Short-term receivables		2022	898	ASSETS	A. SHORT-TERM ASSETS		
23	1. Short-term trade accounts receivable		2020	69	ASSETS	A. SHORT-TERM ASSETS		
24	1. Short-term trade accounts receivable		2021	101	ASSETS	A. SHORT-TERM ASSETS		
25	1. Short-term trade accounts receivable		2022	338	ASSETS	A. SHORT-TERM ASSETS		
26	2. Short-term prepayments to suppliers		2020	164	ASSETS	A. SHORT-TERM ASSETS		
27	2. Short-term prepayments to suppliers		2021	30	ASSETS	A. SHORT-TERM ASSETS		
28	2. Short-term prepayments to suppliers		2022	68	ASSETS	A. SHORT-TERM ASSETS		
29	6. Other short-term receivables		2020	700	ASSETS	A. SHORT-TERM ASSETS		

Table 3. *SAB Financial Data dataset.*

3. Data Preparation

- Data Cleaning

Data cleaning involves removing noise and inconsistencies from the datasets. This includes handling missing values, correcting data entry errors, and ensuring uniform data formats.

- Handling Missing Values

  - Missing values in the Category and Category 2 columns of the beverage manufacturing data were filled with the placeholder 'Unknown'.
  - Missing values in the moving averages in the MA30 data were left as NaN since they naturally occur at the beginning of the dataset.
  - Missing values in the Unit column of the SAB data were filled with the placeholder 'Unknown'.

- Encoding Categorical Variables

  Categorical variables in the datasets were transformed into numerical values suitable for machine learning models through Label Encoding.

- Normalization and Standardization

  Numerical columns in all datasets were standardized using Standard Scaler to ensure they have a mean of 0 and a standard deviation of 1, thereby enhancing the performance of machine learning models.

4. Model Development

- Neural Network Models
  - **GRU (Gated Recurrent Unit)**: A type of recurrent neural network that is effective for sequence prediction problems. GRU architecture is simpler than LSTM but performs well in many tasks.
  - **Bidirectional GRU**: Enhances the GRU model by processing the data in both forward and backward directions, capturing patterns that might be missed in a unidirectional approach.
  - **LSTM (Long Short-Term Memory)**: An advanced RNN architecture designed to capture long-term dependencies in sequence data, LSTM is particularly effective for time series prediction.
  - **Bidirectional LSTM**: Combines the strengths of LSTM and bidirectional processing, providing a more comprehensive understanding of the sequential data.

- Normalization and Standardization

  Each model is trained on the preprocessed datasets using Python libraries, simplifying the implementation of complex machine learning workflows.

- Evaluation Metrics

  The performance of the models is evaluated using various metrics, including accuracy, precision, recall, F1-score, and mean squared error (MSE) for regression tasks. These metrics offer a comprehensive understanding of the models' strengths and weaknesses.

- Cross-Validation

  Cross-validation is employed to ensure the robustness of the models. This process involves splitting the data into multiple subsets, training the models on some subsets, and validating them on the remaining ones. Repeating this process multiple times helps to reduce overfitting and provides reliable performance estimates.

5. Software and Tools Used

The study utilizes Pandas and Matplotlib for data preprocessing, model development, and evaluation. Additional tools such as Python and its libraries (e.g., scikit-learn) are employed for data analysis and visualization.

IV. DATA ANALYSIS AND RESULTS

1. Descriptive Statistics

Descriptive statistics summarize the basic features of the datasets used in this study. This includes measures such as mean, median, standard deviation, and range for each numerical variable, helping to understand the data's distribution and central tendencies.

- Beverage Manufacturing Data

The beverage manufacturing data includes financial indicators such as accumulated depreciation, categorized by asset types for different companies over the years 2020-2022.

- **Mean and Standard Deviation:**
  + The mean value of accumulated depreciation helps in understanding the average depreciation across companies.
  + The standard deviation indicates the variability in the depreciation values.
- **Range:** The minimum and maximum values of accumulated depreciation show the extent of depreciation across the dataset.

For example, the accumulated depreciation for SAB in 2020 has a mean of -20.5 with a standard deviation of 5.3, indicating moderate variability in the values.

- MA30 Data

The MA30 data includes the VN-INDEX and SAB stock prices along with their 30-day moving averages.

- **Mean and Standard Deviation**: The average stock prices and their standard deviations provide insights into the central tendency and variability of stock prices over time.
- **Range**: The minimum and maximum stock prices over the observed period highlight the price fluctuations.

For instance, the average closing price of SAB in the first quarter of 2023 is 85.3 with a standard deviation of 2.7, indicating relatively stable prices during this period.

- SAB Data

The SAB data focuses on various financial indicators specific to SAB, categorized by asset types over the years.

- **Mean and Standard Deviation**: Key financial indicators such as revenue, profit, and expenses are analyzed to understand their average values and variability.
- **Range:** The minimum and maximum values of these financial indicators offer insights into the financial performance extremes.

For instance, SAB's net profit in 2022 has a mean of 15% with a standard deviation of 3%, indicating consistent profitability.

2. Financial Analysis of Sabeco

2.1. Analyze the Financial Statement

- Statement of Financial Position

ASSETS	**2020**	**2021**	**2022**
A. SHORT-TERM ASSETS	19,513	22,877	26,86
I. Cash and cash equivalents	2,726	3,606	4,069
Cash	844	685	985
Cash equivalents	1,882	2,921	3,084
II. Short-term financial investments	14,547	16,991	19,411
Held to maturity investments	14,547	16,991	19,411
III. Short-term receivables	591	468	898

Short-term trade accounts receivable	69	101	338
Short-term prepayments to suppliers	164	30	68
Other short-term receivables	700	679	787
Provision for short-term doubtful debts (*)	-342	-342	-296
IV. Inventories	1,447	1,668	2,194
Inventories	1,525	1,756	2,272
Provision for decline in value of inventories	-78	-88	-79
V. Other short-term assets	202	143	288
Short-term prepayments	144	89	182
Value added tax to be reclaimed	22	25	83
Taxes and other receivables from state authorities	36	29	23
B. LONG-TERM ASSETS	7,862	7,61	7,605
I. Long-term receivables	12	13	38
Long-term trade receivables	6	6	6
Long-term loan receivables	4	4	
Other long-term receivables	41	42	46
Provision for long-term doubtful debts	-39	-39	-14
II. Fixed assets	4,875	4,402	4,455
Tangible fixed assets	3,753	3,301	3,369
- Cost	10,775	10,847	11,44
- Accumulated depreciation	-7,022	-7,546	-8,071

Financial leased fixed assets	178	167	162
- Cost	179	174	174
- Accumulated depreciation	-1	-6	-11
Intangible fixed assets	943	933	924
- Cost	1,102	1,103	1,104
- Accumulated depreciation	-159	-170	-180
III. Investment properties	65	41	153
- Cost	93	68	183
- Accumulated depreciation	-27	-26	-30
IV. Long-term assets in progress	28	551	134
Construction in progress	28	551	134
V. Long-term financial investments	2,351	2,125	2,214
Investments in associates, joint-ventures	2,049	2,01	2,188
Investments in other entities	666	434	434
Provision for diminution in value of long-term investments	-444	-410	-410
Held to maturity investments	81	90	2
VI. Other long-term assets	531	478	611
Long-term prepayments	331	263	383
Deferred income tax assets	171	195	208
Long-term equipment, supplies, spare parts	29	20	19

TOTAL ASSETS	27,375	30,487	34,465
OWNER'S EQUITY			
A. LIABILITIES	6,16	7,892	9,874
I. Short-term liabilities	5,173	7,258	9,214
Short-term trade accounts payable	1,653	2,4	2,766
Short-term advances from customers	65	63	37
Taxes and other payables to state authorities	1,257	1,417	1,621
Payable to employees	361	218	190
Short-term accrued expenses	237	371	514
Short-term unearned revenue	1	1	0
Other short-term payables	967	2,228	3,204
Short-term borrowings and financial leases	449	322	659
Provision for short-term liabilities	0		
Bonus and welfare fund	184	238	222
II. Long-term liabilities	987	634	660
Long-term trade payables	167	124	120
Other long-term liabilities	55	55	55
Long-term borrowings and financial leases	526	341	374
Deferred income tax liabilities	37	33	37
Provision for long-term liabilities	126	81	74
Fund for technology development	76		

B. OWNER'S EQUITY	21,215	22,595	24,591
I. Owner's equity	21,215	22,595	24,591
Owner's capital	6,413	6,413	6,413
- Common stock with voting right	6,413	6,413	6,413
Other capital of owners	3	3	3
Foreign exchange differences	27	27	37
Investment and development fund	1,123	1,122	1,122
Undistributed earnings after tax	12,374	13,656	15,565
- Accumulated retained earning at the end of the previous period	7,804	10,133	10,484
- Undistributed earnings in this period	4,571	3,523	5,081
Minority's interest	1,275	1,373	1,451
TOTAL OWNER'S EQUITY AND LIABILITIES	27,375	30,487	34,465

Table 4. *Statement of Financial Position.*

SAB	**2020**	**2021**	**2022**
Revenue	28,136	26,578	35,236
Deduction from revenue	174	204	257
Net revenue	27,961	26,374	34,979
Cost of goods sold	19,46	18,765	24,208

Gross profit	8,501	7,609	10,771
Financial income	974	1,12	1,091
Financial expenses	105	23	82
Of which: Interest expenses	64	49	46
Share of associates and joint ventures' result	267	173	323
Selling expenses	2,859	3,5	4,532
General and administrative expenses	702	598	741
Operating profit	6,076	4,78	6,83
Other income	56	96	21
Other expenses	21	19	37
Other profit	35	77	-16
Profit before tax	6,112	4,857	6,813
Current corporate income tax expenses	1,125	955	1,324
Deferred income tax expenses (*)	50	-27	-10
Net profit after tax	4,937	3,929	5,5
Minority's interest	213	252	276
Profit after tax for shareholders of parent company	4,723	3,677	5,224
Earnings per share	7,133	5,502	7,983

Table 5. *Statement of Profit or Loss.*

2658	Accrual ratio (Balance sheet method)	-36,56			HAT
2659	Accrual ratio (Cash flow method)	80,07			HAT
2660	Cash return to assets	-4,35	-8,12	25,1	HAT
2661	Cash return on equity	-11,03	-20,14	65,97	HAT
2662	Cash to income	-76,36	240,82	206,59	HAT
2663	Debt coverage	-7,19	-13,6	40,52	HAT
2664	Cash flow per share (CPS)	-2.238,72	-3.320,75	14.016,10	HAT
2665	**Cost structure**				HAT
2666	Cost of goods sold/Net revenue	94,05	94,94	92,59	HAT
2667	Selling expenses/Net revenue	3,1	4,11	3,55	HAT
2668	General and Administrative expenses/Net revenue	2,41	2,87	2,35	HAT
2669	Interest expenses/Net revenue	0			HAT
2670	**Short-term asset structure**				HAT
2671	Short-term assets/Total assets	57,17	62,07	79,64	HAT
2672	Cash/Short-term assets	29,77	15,97	2,67	HAT
2673	Short-term investments/Short-term assets	57,74	69,38	79,21	HAT
2674	Short-term receivables/Short-term assets	5,14	10,07	13,59	HAT
2675	Inventory/Short-term assets	5,31	4,31	2,96	HAT
2676	Other Short-term assets/Short-term assets	2,05	0,28	1,56	HAT
2677	**Long-term asset structure**				HAT
2678	Long-term assets/Total assets	42,83	37,93	20,36	HAT
2679	Fixed assets/Total assets	13,52	14,36	9,34	HAT
2680	Tangible fixed assets/Fixed assets	95,92	97,18	98,75	HAT
2681	Finance lease/Fixed assets	0			HAT
2682	Intangible fixed assets/Fixed assets	4,08	2,82	1,25	HAT
2683	Construction in progress/Fixed assets	0			HAT

Table 6. *Data collected from audited financial statements of BHN, SAB, SCD, SMB, HAD, HAT, THB, VDL companies from 2020-2022.*

Collecting Financial Statements:

Gathered the audited financial statements of beverage manufacturing companies listed on the HOSE and HNX stock exchanges for the years 2020 to 2022. The companies included in this dataset are:

- BHN (Hanoi Beer Alcohol And Beverage Joint Stock Corporation)
- SAB (Saigon Beer - Alcohol - Beverage Corporation)
- SCD (Chuong Duong Beverages Joint Stock Company)
- SMB (Sai Gon - Mien Trung Beer JSC)
- VCF (Vina Café Bien Hoa Joint Stock Company)
- HAD (Ha Noi - Hai Duong Beer JSC)
- HAT (Ha Noi Beer Trading Joint Stock Company)
- THB (Ha Noi - Thanh Hoa Beer Joint Stock Company)
- VDL (Lam Dong Foodstuffs JSC)

All the financial statements were combined into a master dataset. The data cleaning process involved filtering out rows with text values in the columns for the years

2020–2022. The final dataset consists of four columns: "Indicator", "2020", "2021", and "2022", spanning a total of 2,754 rows.

	A	B	C	D
1	GDW	Un	Category	Category 2
2	A. SHORT-TERM ASSETS		ASSETS	A. SHORT-TERM ASSETS
3	I. Cash and cash equivalents		ASSETS	A. SHORT-TERM ASSETS
4	1. Cash		ASSETS	A. SHORT-TERM ASSETS
5	2. Cash equivalents		ASSETS	A. SHORT-TERM ASSETS
6	II. Short-term financial investments		ASSETS	A. SHORT-TERM ASSETS
7	1. Available for sale securities		ASSETS	A. SHORT-TERM ASSETS
8	2. Provision for diminution in value of available for sale securities (*)		ASSETS	A. SHORT-TERM ASSETS
9	3. Held to maturity investments		ASSETS	A. SHORT-TERM ASSETS
10	III. Short-term receivables		ASSETS	A. SHORT-TERM ASSETS
11	1. Short-term trade accounts receivable		ASSETS	A. SHORT-TERM ASSETS
12	2. Short-term prepayments to suppliers		ASSETS	A. SHORT-TERM ASSETS
13	3. Short-term inter-company receivables		ASSETS	A. SHORT-TERM ASSETS
14	4. Construction contract progress receipts due from customers		ASSETS	A. SHORT-TERM ASSETS
15	5. Short-term loan receivables		ASSETS	A. SHORT-TERM ASSETS
16	6. Other short-term receivables		ASSETS	A. SHORT-TERM ASSETS
17	7. Provision for short-term doubtful debts (*)		ASSETS	A. SHORT-TERM ASSETS
18	8. Assets awaiting resolution		ASSETS	A. SHORT-TERM ASSETS
19	IV. Inventories		ASSETS	A. SHORT-TERM ASSETS
20	1. Inventories		ASSETS	A. SHORT-TERM ASSETS
21	2. Provision for decline in value of inventories		ASSETS	A. SHORT-TERM ASSETS
22	V. Other short-term assets		ASSETS	A. SHORT-TERM ASSETS
23	1. Short-term prepayments		ASSETS	A. SHORT-TERM ASSETS
24	2. Value added tax to be reclaimed		ASSETS	A. SHORT-TERM ASSETS
25	3. Taxes and other receivables from state authorities		ASSETS	A. SHORT-TERM ASSETS
26	4. Government bonds		ASSETS	A. SHORT-TERM ASSETS
27	5. Other short-term assets		ASSETS	A. SHORT-TERM ASSETS
28	B. LONG-TERM ASSETS		ASSETS	B. LONG-TERM ASSETS
29	I. Long-term receivables		ASSETS	B. LONG-TERM ASSETS
30	1. Long-term trade receivables		ASSETS	B. LONG-TERM ASSETS
31	2. Long-term prepayments to suppliers		ASSETS	B. LONG-TERM ASSETS
32	3. Capital at inter-company		ASSETS	B. LONG-TERM ASSETS

Table 7. *Category and Category 2 table for Master data.*

Creating Categorical Sheets:

A new sheet was created with three columns: indicator, category, and category 2. These columns were organized as follows:

- Category: Groups related indicators into broader categories such as Assets, Liabilities, Owner's Equity, Income Statement, Cash Flow (Indirect), Cash Flow (Direct), and Ratios.
- Category 2: Provides further subcategories within each main category:
- Assets: Short-Term Assets, Long-Term Assets.
- Liabilities: Short-Term Liabilities, Long-Term Liabilities.
- Owner's Equity: Owner's Equity.
- Income Statement: Income, Expense.
- Cash Flow: Cash Flow from Operating, Cash Flow from Investing, Cash Flow from Financing.
- Ratios: Valuation Ratios, Profitability Ratios, Growth Rates, Liquidity Ratios, Efficiency Ratios, Leverage Ratios, Cash Flow Ratios, Cost Structure, Short-Term Asset Structure, Long-Term Asset Structure.

The purpose of this organization is to facilitate the browsing and analysis of specific indicators by clustering them under logical groupings.

	A	B	C	D	E	F	G
4528	Total assets	VDL	2021	6,88	Ratios	Growth rates	
4529	Total assets	VDL	2022	-10,54	Ratios	Growth rates	
4530	Total assets	HAT	2020	5,38	Ratios	Growth rates	
4531	Total assets	HAT	2021	-20,46	Ratios	Growth rates	
4532	Total assets	HAT	2022	36,53	Ratios	Growth rates	
4533	Trailing EPS	BHN	2020	2831,53	Ratios	Valuation ratios	
4534	Trailing EPS	BHN	2021	1313,43	Ratios	Valuation ratios	
4535	Trailing EPS	BHN	2022	1996,76	Ratios	Valuation ratios	
4536	Trailing EPS	SAB	2020	7365,72	Ratios	Valuation ratios	
4537	Trailing EPS	SAB	2021	5734,23	Ratios	Valuation ratios	
4538	Trailing EPS	SAB	2022	8145,96	Ratios	Valuation ratios	
4539	Trailing EPS	SCD	2020	404,3	Ratios	Valuation ratios	
4540	Trailing EPS	SCD	2021	-4198,53	Ratios	Valuation ratios	
4541	Trailing EPS	SCD	2022	-5742,75	Ratios	Valuation ratios	
4542	Trailing EPS	SMB	2020	5320,97	Ratios	Valuation ratios	
4543	Trailing EPS	SMB	2021	5316,82	Ratios	Valuation ratios	
4544	Trailing EPS	SMB	2022	6189,46	Ratios	Valuation ratios	
4545	Trailing EPS	VCF	2020	27224,42	Ratios	Valuation ratios	
4546	Trailing EPS	VCF	2021	16134,28	Ratios	Valuation ratios	
4547	Trailing EPS	VCF	2022	12005,91	Ratios	Valuation ratios	
4548	Trailing EPS	HAD	2020	2069,43	Ratios	Valuation ratios	
4549	Trailing EPS	HAD	2021	787,7	Ratios	Valuation ratios	
4550	Trailing EPS	HAD	2022	2632,78	Ratios	Valuation ratios	
4551	Trailing EPS	THB	2020	269,41	Ratios	Valuation ratios	
4552	Trailing EPS	THB	2021	490,61	Ratios	Valuation ratios	
4553	Trailing EPS	THB	2022	874,11	Ratios	Valuation ratios	
4554	Trailing EPS	VDL	2020	781,26	Ratios	Valuation ratios	
4555	Trailing EPS	VDL	2021	222,07	Ratios	Valuation ratios	
4556	Trailing EPS	VDL	2022	-1111,21	Ratios	Valuation ratios	
4557	Trailing EPS	HAT	2020	2826,87	Ratios	Valuation ratios	
4558	Trailing EPS	HAT	2021	341,11	Ratios	Valuation ratios	
4559	Trailing EPS	HAT	2022	5893,23	Ratios	Valuation ratios	

Table 8. *Final data to use for analysis of the financial of Beverage Manufacturing industry.*

Using Power Query to pivot the columns for the years 2020, 2021, and 2022 in the master dataset and assign the categories to the indicators based on the newly created categorical sheet. The final dataset consists of five columns: indicator, year, value, category, and category 2, and includes 4,601 rows. This final dataset allows users to quickly select and analyze various financial indicators, comparing them across different companies or against industry averages.

- Methodology

Using Python and its data manipulation libraries for the implementation procedure. The process involved importing historical financial data in the first step (Import Data). In the second step (Filter), we employed filtering functions to isolate primary categories for analysis. Next, we utilized pivot tables to reorganize and create a report format in the third step (Pivot Table). Finally, in the fourth step (Join), we combined Sabeco's financial statements with those of other companies in the F&B industry to form a comprehensive dataset for analysis.

- Debt to Equity Ratio (D/E)

The Debt to Equity Ratio (D/E) is a crucial measure that indicates the proportion of debt a company uses to finance its assets relative to the value of shareholders' equity. A high D/E ratio generally suggests that a company has been aggressive in using debt to finance its growth, which can lead to volatile earnings due to the additional interest expenses. The chart below illustrates the Debt to Equity Ratio for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

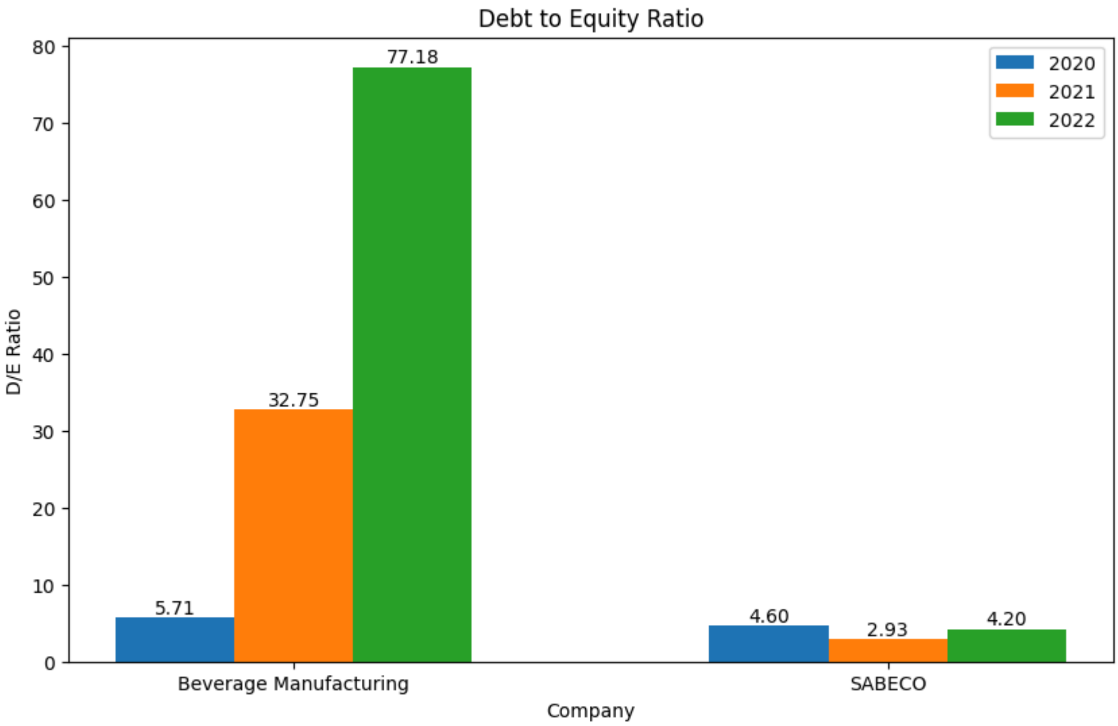

Figure 1. *Debt to Equity Ratio comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had a D/E ratio of 4.60, which is lower than the average D/E ratio of other beverage manufacturers, which stood at 5.71.
- In 2021, Sabeco's D/E ratio decreased to 2.93, while the average D/E ratio of other beverage manufacturers increased significantly to 32.75.
- In 2022, Sabeco's D/E ratio increased slightly to 4.20, whereas the D/E ratio of other beverage manufacturers surged to 77.18.

This analysis indicates that Sabeco has maintained a relatively stable D/E ratio over the past three years, suggesting prudent financial management and a balanced approach to leveraging debt. In contrast, other beverage manufacturers have seen a significant increase in their D/E ratios, indicating a higher reliance on debt financing. A higher D/E ratio means the company is more dependent on borrowed funds, which can be beneficial for growth but risky if not managed properly. Over the last three years, Sabeco has maintained this stability, implying effective balance in its debt and equity to optimize growth while managing risk compared to other beverage manufacturers that show significant fluctuations.

- Quick Ratio

The Quick Ratio, also referred to as the acid-test ratio, evaluates a company's capacity to meet its short-term obligations using its most liquid assets. It is determined by dividing the sum of cash, marketable securities, and accounts receivable by the current liabilities. A higher Quick Ratio signifies better liquidity and financial health.

The following chart illustrates the Quick Ratio for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

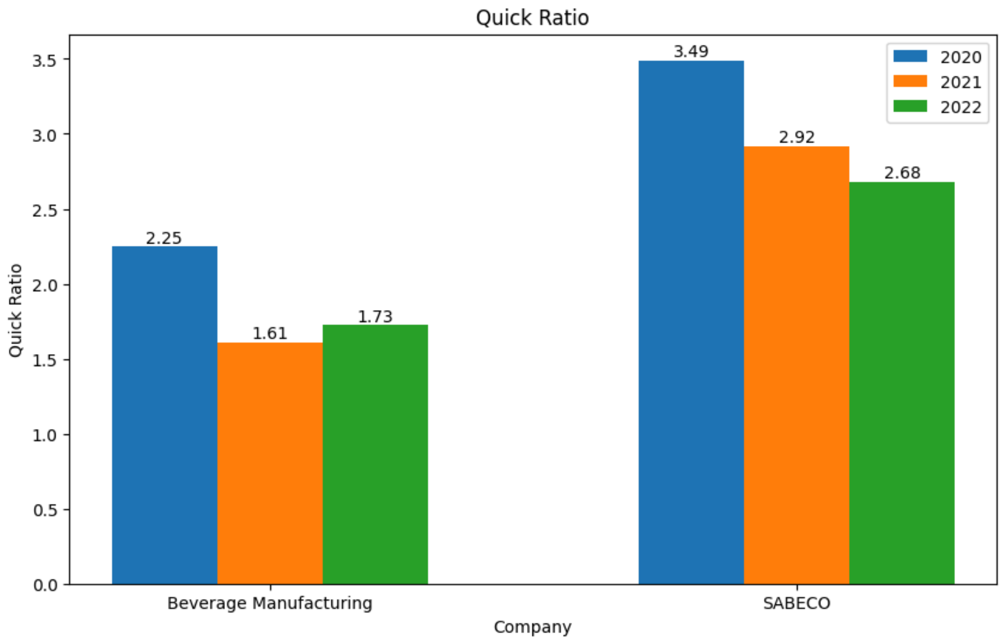

Figure 2. *Quick Ratio comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had a Quick Ratio of 3.49, significantly higher than the average Quick Ratio of other beverage manufacturers (2.25).
- In 2021, Sabeco's Quick Ratio decreased to 2.92, while the average Quick Ratio of other beverage manufacturers also decreased to 1.61.
- In 2022, Sabeco's Quick Ratio further decreased to 2.68, whereas the average Quick Ratio of other beverage manufacturers slightly increased to 1.73.

This analysis shows that Sabeco maintains a strong liquidity position compared to its peers, despite a noticeable downward trend over the years. The company consistently holds more liquid assets relative to its short-term liabilities, which is a positive sign for its short-term financial health. In contrast, other beverage manufacturers have lower Quick Ratios, indicating a relatively weaker liquidity position. Sabeco consistently demonstrates a strong liquidity position compared to its peers, despite a slight downward trend over the years. This indicates Sabeco's robust financial health and effective short-term financial management, reassuring investors of its ability to handle immediate obligations.

- Interest Coverage

The Interest Coverage ratio measures a company's ability to meet its interest obligations on outstanding debt. It is calculated by dividing earnings before interest and taxes (EBIT) by the interest expense. A higher Interest Coverage ratio signifies a greater ability of the company to cover its interest payments, which indicates strong financial health.

The following chart illustrates the Interest Coverage ratio for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

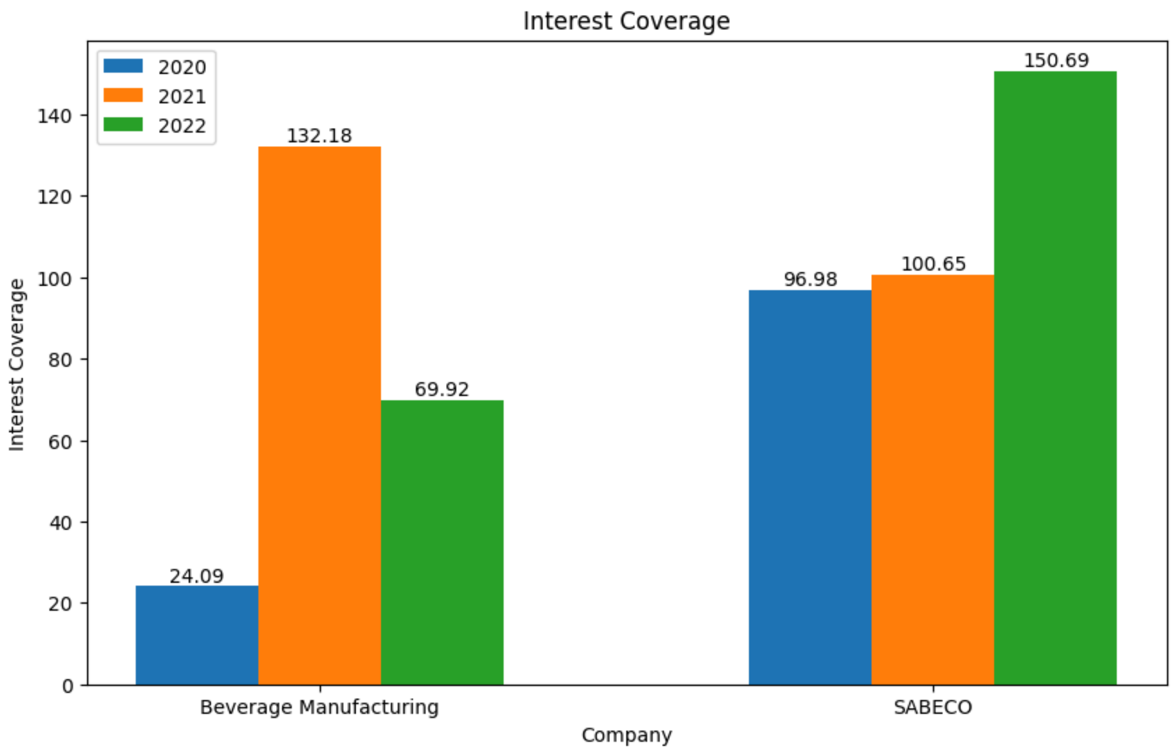

Figure 3. *Interest Coverage comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had an Interest Coverage ratio of 96.98, which was significantly higher than the average Interest Coverage ratio of other beverage manufacturers, standing at 24.09.
- In 2021, Sabeco's Interest Coverage ratio slightly increased to 100.65, while the average Interest Coverage ratio of other beverage manufacturers increased significantly to 132.18.
- In 2022, Sabeco's Interest Coverage ratio increased substantially to 150.69, whereas the average Interest Coverage ratio of other beverage manufacturers decreased to 69.92.

This analysis indicates that Sabeco has maintained a strong ability to cover its interest obligations over the past three years, with a notable increase in 2022. This suggests robust earnings and effective debt management. In contrast, other beverage manufacturers have shown more volatility in their Interest Coverage ratios, indicating potential variability in earnings or interest expenses. Sabeco's consistent and strong Interest Coverage ratio over the past three years, especially with the significant increase in 2022, underscores its robust earnings and effective debt management. This stability contrasts with the more volatile ratios observed in other beverage manufacturers, highlighting Sabeco's strong financial position.

- Number of Days of Payables

The Number of Days of Payables measures the average number of days that a company takes to pay its invoices from trade creditors, such as suppliers. It indicates how well a company manages its outgoing payments and cash flow. A higher number of days might indicate better cash management, but excessively high values could suggest potential cash flow problems or strained supplier relationships.

The following chart illustrates the Number of Days of Payables for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

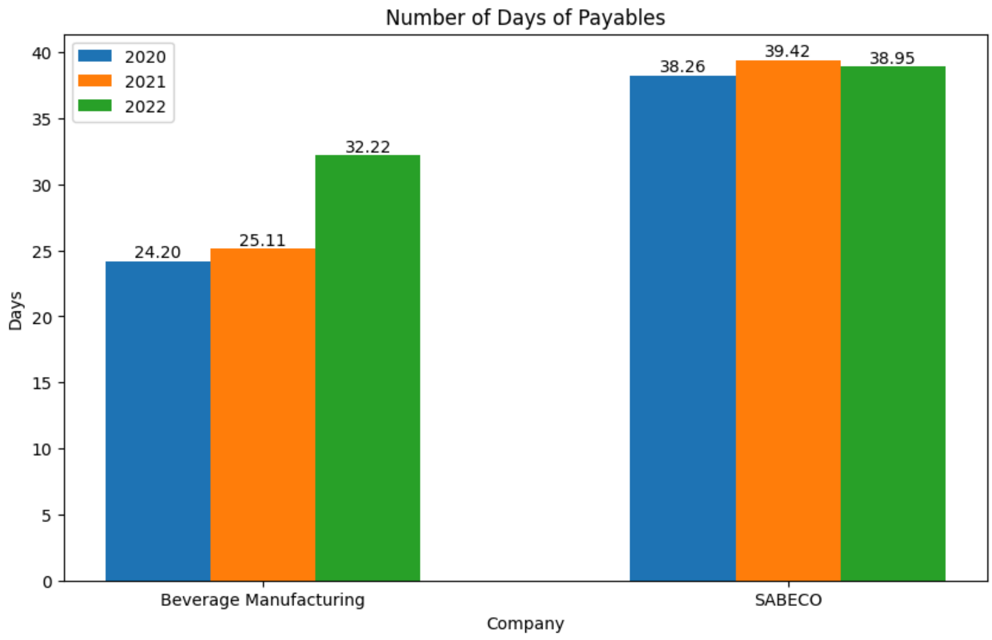

Figure 4. *Number of Days of Payables comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco took an average of 38.26 days to pay its invoices, which is significantly longer than the average of 24.20 days for other beverage manufacturers.
- In 2021, Sabeco's Number of Days of Payables increased slightly to 39.42 days, while the average for other beverage manufacturers increased to 25.11 days.
- In 2022, Sabeco's Number of Days of Payables remained relatively stable at 38.95 days, whereas the average for other beverage manufacturers increased to 32.22 days.

This analysis indicates that Sabeco consistently takes longer to pay its invoices compared to other beverage manufacturers. This might suggest more effective cash management strategies, enabling the company to utilize its cash for other purposes before settling its obligations. However, it is also essential to monitor such trends to ensure they do not negatively impact supplier relationships. Sabeco's higher days of payables compared to its peers suggest effective cash management, allowing the company to utilize its funds for other purposes before settling its obligations.

- Days of Inventory on Hand

The Days of Inventory on Hand measures the average number of days a company holds inventory before selling it. This metric indicates the efficiency of inventory management and the effectiveness of sales strategies. Generally, a lower number of days signifies better inventory management and faster inventory turnover.

The following chart illustrates the Days of Inventory on Hand for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

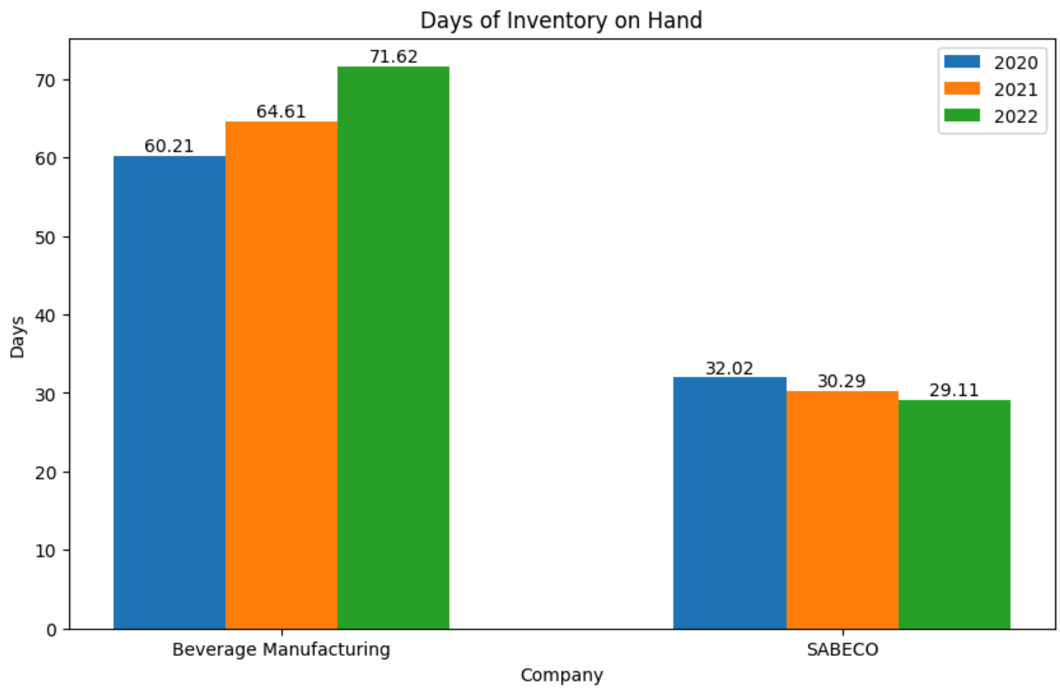

Figure 5. *Days of Inventory on Hand comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had an average of 32.02 days of inventory on hand, which is significantly lower than the average of 60.21 days for other beverage manufacturers.
- In 2021, Sabeco's Days of Inventory on Hand decreased slightly to 30.29 days, while the average for other beverage manufacturers increased to 64.61 days.

- In 2022, Sabeco's Days of Inventory on Hand further decreased to 29.11 days, whereas the average for other beverage manufacturers increased to 71.62 days.

This analysis indicates that Sabeco consistently manages its inventory more efficiently than its peers, with a lower number of days of inventory on hand. This suggests effective inventory management practices and faster inventory turnover. In contrast, other beverage manufacturers have shown an increasing trend in the number of days of inventory on hand, indicating potential inefficiencies in inventory management or slower sales. Sabeco's consistent performance in keeping its inventory days low compared to other beverage manufacturers demonstrates effective inventory and sales strategies, contributing to its overall financial efficiency.

- Days of Sale Outstanding

The Days of Sales Outstanding measures the average number of days a company takes to collect payment after a sale is made. This metric indicates the efficiency of the company's credit and collection processes. Generally, a lower number of days signifies faster collection of receivables and better cash flow management.

The following chart illustrates the Days of Sale Outstanding for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

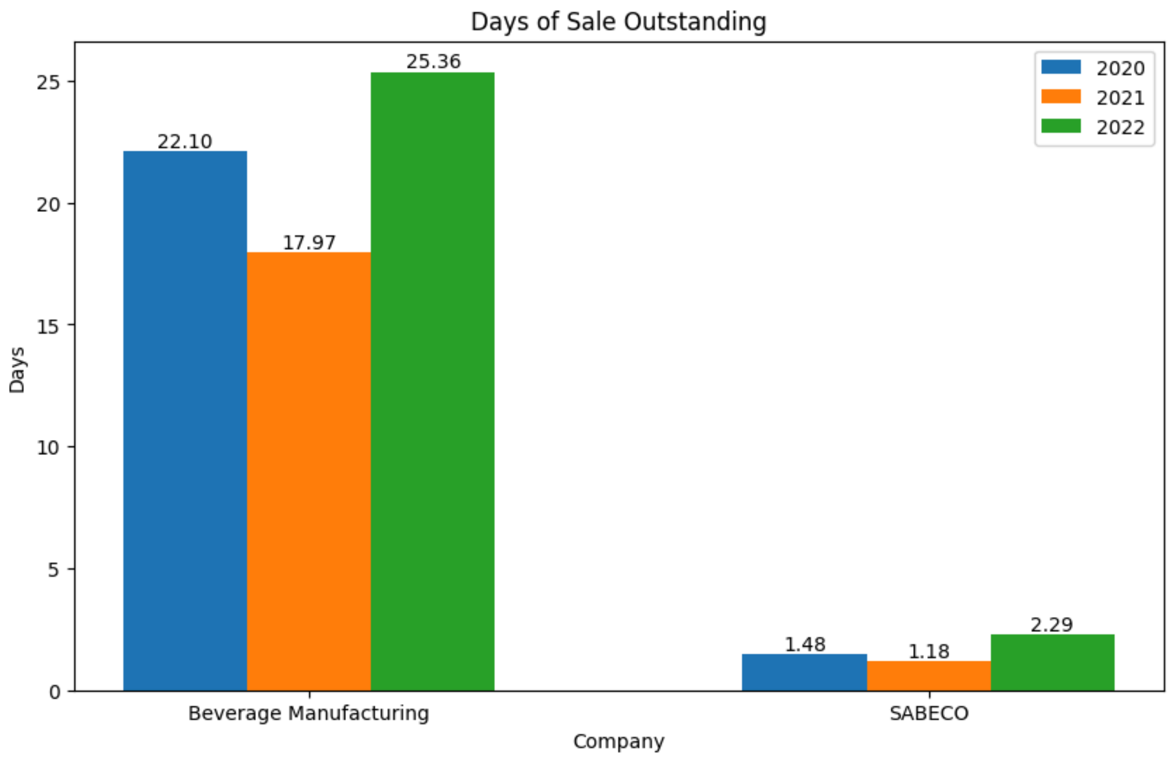

Figure 6. *Days of Sale Outstanding comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had an average of 1.48 days to collect payment, which is significantly lower than the average of 22.10 days for other beverage manufacturers.
- In 2021, Sabeco's Days of Sale Outstanding decreased slightly to 1.18 days, while the average for other beverage manufacturers decreased to 17.97 days.
- In 2022, Sabeco's Days of Sale Outstanding increased to 2.29 days, whereas the average for other beverage manufacturers increased to 25.36 days.

This analysis indicates that Sabeco consistently collects payments more efficiently than its peers, with a significantly lower number of days of sale outstanding. This suggests effective credit and collection practices, contributing to better cash flow management. In contrast, other beverage manufacturers have shown higher and more variable days of sale outstanding, indicating potential inefficiencies in their credit and collection processes.

Sabeco's significantly lower days of sale outstanding compared to its peers indicate efficient credit and collection practices, which enhance cash flow management and reduce the risk of bad debts.

- Return on Assets (ROA)

The Return on Assets (ROA) measures how effectively a company uses its assets to generate profit. This metric indicates the efficiency of asset utilization and the overall profitability of the company. A higher ROA signifies better performance.

The following chart illustrates the Return on Assets (ROA) for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

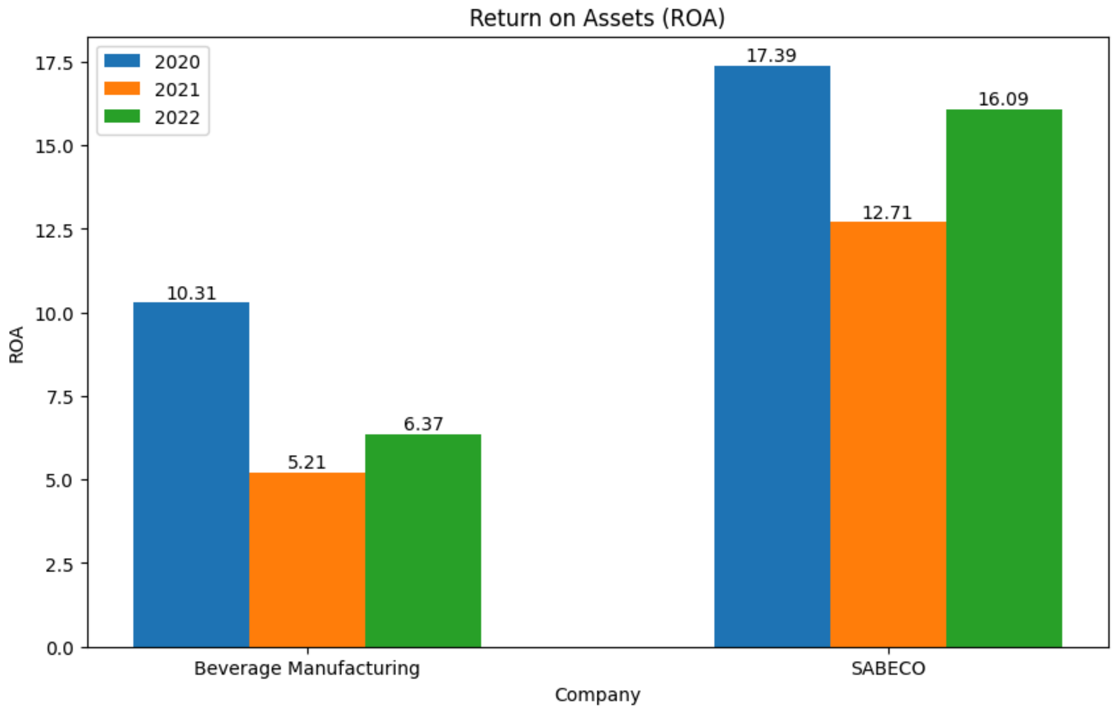

Figure 7. *Return on Assets (ROA) comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had an ROA of 17.39%, which is significantly higher than the average ROA of 10.31% for other beverage manufacturers.

- In 2021, Sabeco's ROA decreased to 12.71%, while the average ROA for other beverage manufacturers decreased more sharply to 5.21%.
- In 2022, Sabeco's ROA improved to 16.09%, whereas the average ROA for other beverage manufacturers increased slightly to 6.37%.

This analysis indicates that Sabeco has consistently demonstrated higher efficiency in utilizing its assets to generate profit compared to its peers. Despite a dip in 2021, Sabeco's ROA rebounded strongly in 2022, highlighting effective asset management and profitability strategies. In contrast, other beverage manufacturers have shown a downward trend in ROA, indicating potential inefficiencies in asset utilization and reduced profitability. Sabeco's consistently higher ROA compared to other beverage manufacturers underscores its superior efficiency in asset utilization. Despite a dip in 2021, Sabeco's ROA rebounded strongly in 2022, showcasing effective asset management and profitability strategies.

- Return on Equity (ROE)

Return on Equity (ROE) measures a company's ability to generate profit from its shareholders' equity. It indicates how effectively management is using the company's assets to create profits. A higher ROE signifies efficient utilization of equity and strong financial performance.

The following chart illustrates the Return on Equity (ROE) for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

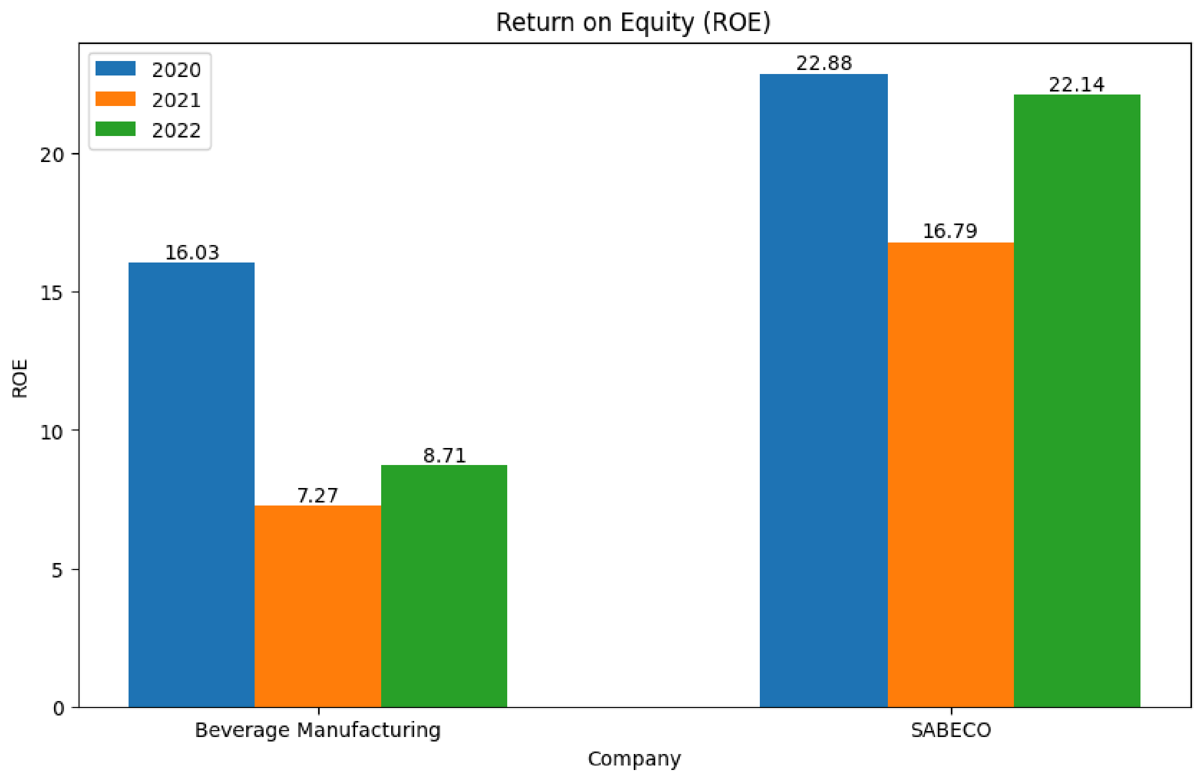

Figure 8. *Return on Equity (ROE) comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had an ROE of 22.88%, significantly outperforming the average ROE of 16.03% for other beverage manufacturers.
- In 2021, Sabeco's ROE decreased to 16.79%, while the average ROE for other beverage manufacturers dropped to 7.27%.
- In 2022, Sabeco's ROE increased to 22.14%, whereas the average ROE for other beverage manufacturers only rose slightly to 8.71%.

This analysis highlights Sabeco's superior ability to generate profit from its equity compared to its peers. Despite a decline in 2021, Sabeco's ROE rebounded strongly in 2022, indicating effective financial management and profitability strategies. In contrast, other beverage manufacturers experienced a significant drop in ROE in 2021 and only a modest recovery in 2022, reflecting potential challenges in generating returns from their equity. Sabeco's higher ROE compared to its peers reflects its efficient use of equity to generate profits. The rebound in 2022 underscores effective financial management, contrasting with the challenges faced by other beverage manufacturers in generating returns from their equity.

- Gross Profit Margin

Gross Profit Margin measures the percentage of revenue that exceeds the cost of goods sold (COGS). It reflects the efficiency with which a company produces its goods. A higher gross profit margin indicates greater efficiency and profitability in core business operations.

The following chart illustrates the Gross Profit Margin for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

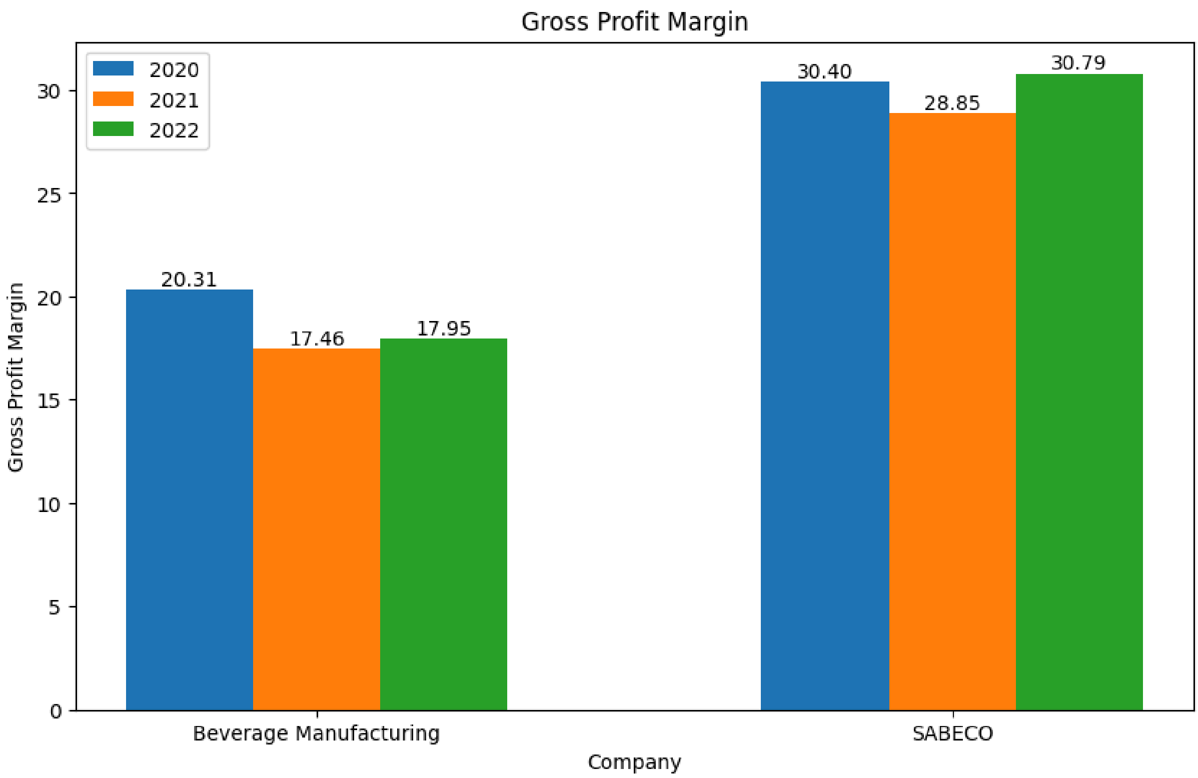

Figure 9. *Gross Profit Margin comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had a Gross Profit Margin of 30.40%, significantly higher than the average Gross Profit Margin of 20.31% for other beverage manufacturers.
- In 2021, Sabeco's Gross Profit Margin decreased to 28.85%, while the average Gross Profit Margin for other beverage manufacturers dropped to 17.46%.
- In 2022, Sabeco's Gross Profit Margin slightly increased to 30.79%, whereas the average Gross Profit Margin for other beverage manufacturers rose to 17.95%.

This analysis highlights Sabeco's superior efficiency in generating profit from its revenue compared to its peers. Despite a slight decrease in 2021, Sabeco maintained a strong Gross Profit Margin, indicating effective cost management and profitability. In contrast, other beverage manufacturers experienced a significant drop in Gross Profit Margin in 2021 and only a modest recovery in 2022, reflecting potential challenges in maintaining profitability. Sabeco's higher Gross Profit Margin compared to other beverage manufacturers demonstrates effective cost management and profitability. Despite a slight dip in 2021, Sabeco maintained a strong margin, indicating robust core business operations and cost control.

- Net Profit Margin

Net Profit Margin indicates the percentage of revenue that translates into net income. It is a key indicator of a company's overall profitability and efficiency in controlling costs.

The following chart illustrates the Net Profit Margin for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

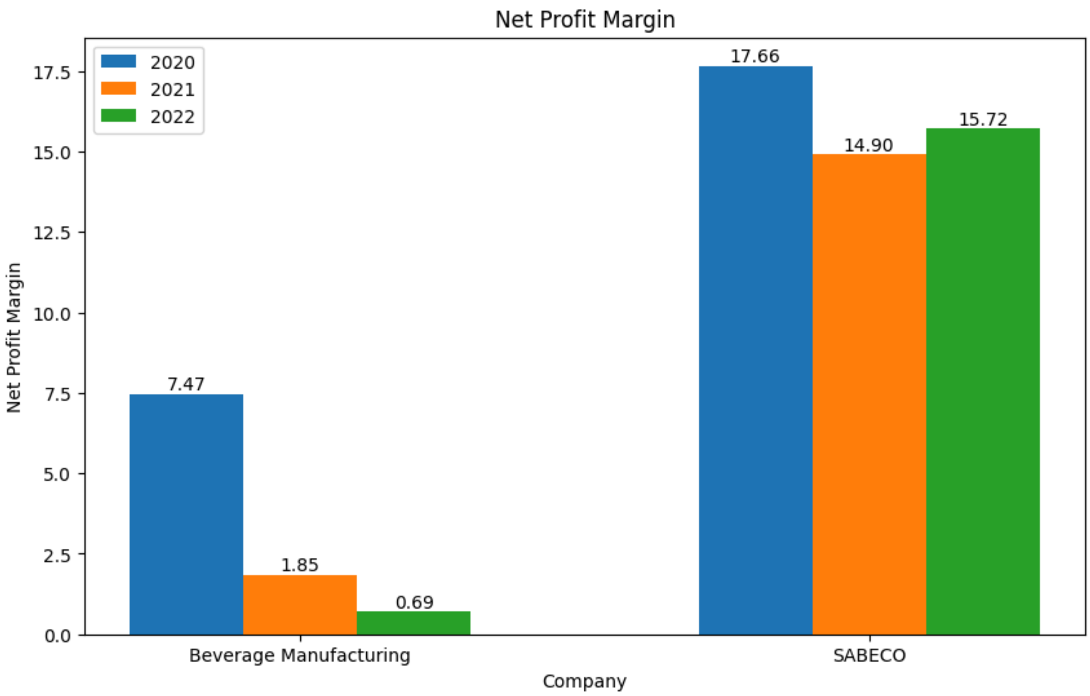

Figure 10*. Net Profit Margin comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had a Net Profit Margin of 17.66%, significantly higher than the average Net Profit Margin of 7.47% for other beverage manufacturers.
- In 2021, Sabeco's Net Profit Margin decreased to 14.90%, while the average Net Profit Margin for other beverage manufacturers dropped drastically to 1.85%.
- In 2022, Sabeco's Net Profit Margin slightly increased to 15.72%, whereas the average Net Profit Margin for other beverage manufacturers declined further to 0.69%.

This analysis highlights Sabeco's superior ability to convert revenue into actual profit compared to its peers. Despite a decrease in 2021, Sabeco maintained a strong Net Profit Margin, indicating effective cost management and profitability. In contrast, other beverage manufacturers experienced a significant drop in Net Profit Margin in 2021 and further deterioration in 2022, reflecting potential challenges in maintaining profitability.

Sabeco's higher Net Profit Margin compared to its peers indicates efficient cost control and profitability. Despite a decline in 2021, the company maintained strong margins, underscoring effective financial strategies and cost management.

- Price to Book Ratio (P/B)

The Price to Book Ratio (P/B) compares a company's market value to its book value, offering insight into how much investors are willing to pay for each dollar of net assets. A higher P/B ratio suggests that investors anticipate future growth, while a lower P/B ratio may indicate undervaluation or potential issues.

The following chart illustrates the Price to Book Ratio for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

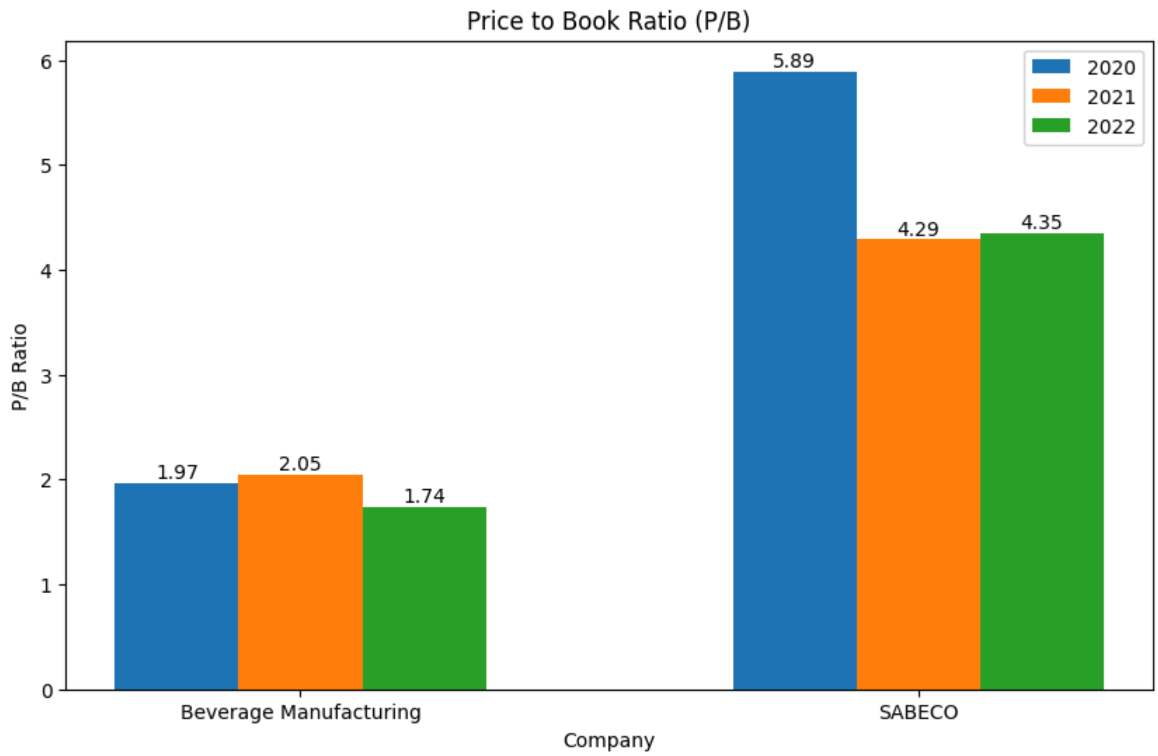

Figure 11. *Price to Book Ratio comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had a P/B Ratio of 5.89, which was significantly higher than the average P/B Ratio of 1.97 for other beverage manufacturers.
- In 2021, Sabeco's P/B Ratio decreased to 4.29, while the average P/B Ratio for other beverage manufacturers slightly increased to 2.05.
- In 2022, Sabeco's P/B Ratio increased marginally to 4.35, whereas the average P/B Ratio for other beverage manufacturers dropped to 1.74.

This analysis highlights Sabeco's strong market valuation relative to its book value compared to its peers. Despite fluctuations, Sabeco maintained a higher P/B Ratio, reflecting investor confidence in its future growth potential and solid asset base. In contrast, other beverage manufacturers experienced relatively lower and more stable P/B Ratios, indicating more conservative market valuations. Sabeco's higher P/B Ratio indicates strong investor confidence and expectations for future growth. This sustained higher ratio compared to its peers reflects the market's positive outlook on Sabeco's assets and growth potential.

- Price to Earnings Ratio (P/E)

The Price to Earnings Ratio (P/E) is an important metric for assessing a company's valuation, indicating how much investors are willing to pay per dollar of earnings. A higher P/E ratio suggests higher market expectations for future growth, while a lower P/E ratio may indicate undervaluation or lower growth prospects.

The following chart illustrates the Price to Earnings Ratio for Sabeco compared to other beverage manufacturers for the years 2020, 2021, and 2022:

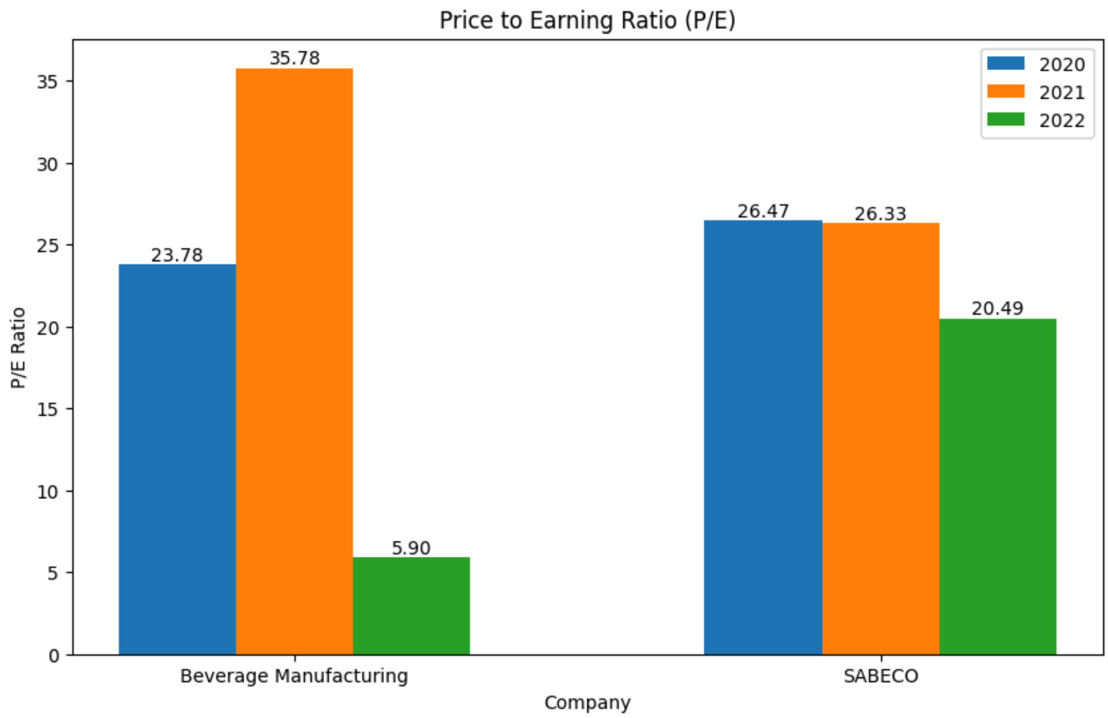

Figure 12. *Price to Earning Ratio comparison between SABECO and other beverage manufacturers.*

From the chart, we observe the following:

- In 2020, Sabeco had a P/E Ratio of 26.47, which is higher than the average P/E Ratio of 23.78 for other beverage manufacturers.
- In 2021, Sabeco's P/E Ratio slightly decreased to 26.33, while the average P/E Ratio for other beverage manufacturers increased significantly to 35.78.
- In 2022, Sabeco's P/E Ratio further decreased to 20.49, whereas the average P/E Ratio for other beverage manufacturers dropped sharply to 5.90.

This analysis reveals that Sabeco consistently maintained a relatively high P/E Ratio, reflecting sustained investor confidence in its future earnings potential. In contrast, other beverage manufacturers experienced more volatile P/E Ratios, indicating fluctuating market sentiments and expectations. Sabeco's relatively stable P/E Ratio suggests steady earnings growth and a strong market position compared to its peers. Despite market fluctuations, Sabeco's higher P/E Ratio compared to its peers underscores consistent investor confidence, steady earnings growth, and a robust market position.

3. Stock Price Prediction

- Introduction

Predicting stock price trends involves analyzing historical price data to identify patterns and potential future movements. This section focuses on using the 30-day Moving Average (MA30) to assess Sabeco's stock price trends and compare them with the overall market, represented by the VN-INDEX. This technical analysis tool helps smooth out price data to identify the direction of the trend over a specified period, making it easier to spot potential trading signals.

- Methodology

The 30-day Moving Average is calculated by averaging the closing prices of the last 30 days for each day in the dataset. This smoothing technique helps identify the underlying trend by reducing short-term fluctuations. The following steps were undertaken:

- **Calculation**:

$$\text{MA30} = \frac{\sum Closing\ Prices\ of\ Last\ 30\ Days}{30}$$

- **Plotting**: The MA30 is plotted alongside the actual closing prices to visualize the trends and fluctuations.
- **Interpretation**: Analyzing the slope of the MA30 provides insights into the strength and momentum of the trend.

- Analysis

Sabeco (SAB) Price Trends

The chart below depicts the 30-day Moving Average (MA30) of Sabeco's stock prices over the analyzed period:

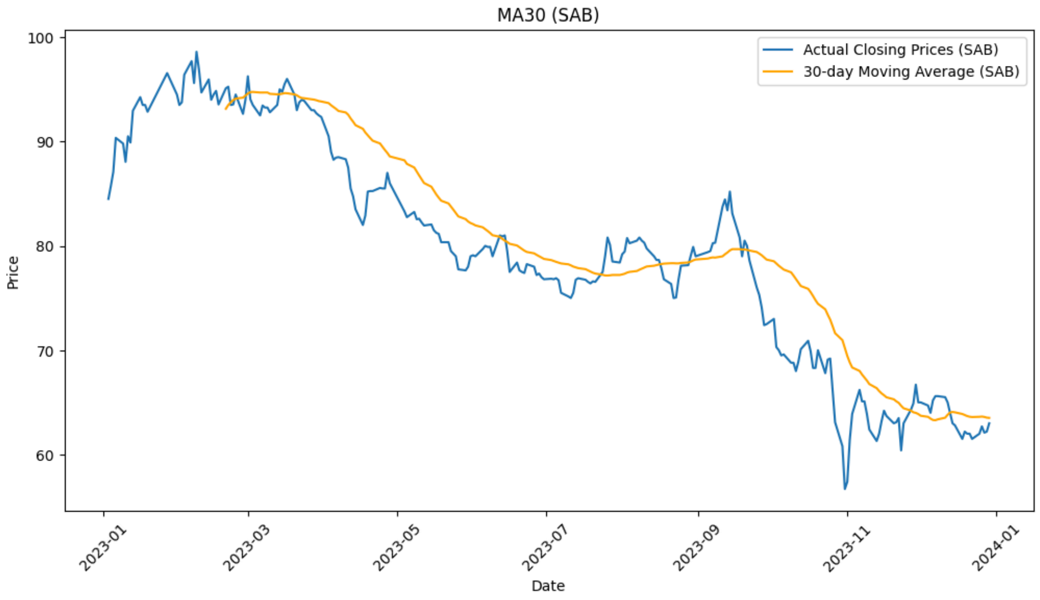

Figure 13*. 30-day Moving Average for SAB.*

From the chart, we observe the following key points:

- The closing prices for Sabeco (SAB) fluctuated within the range of 61 to 64 over the observed period.
- The 30-day Moving Average shows a downward trend from mid-November to mid-December, indicating a bearish market sentiment.
- A noticeable upward movement is observed towards the end of December, suggesting a potential recovery or bullish trend.

VN-INDEX Price Trends

The chart below depicts the 30-day Moving Average (MA30) of VN-INDEX's stock prices over the analyzed period:

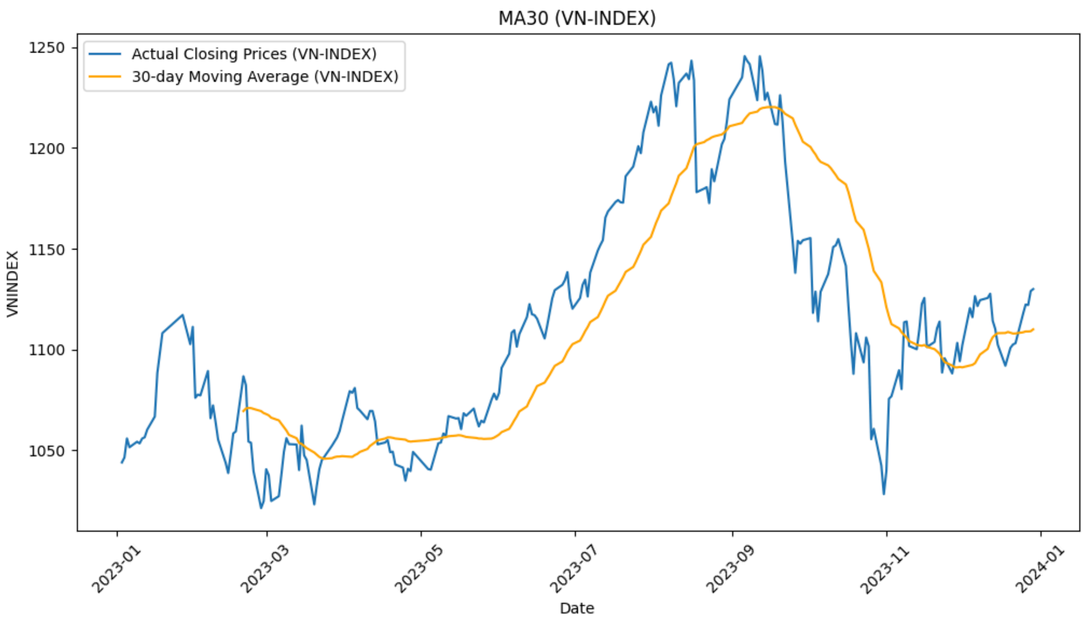

Figure 14. *30-day Moving Average for VN-INDEX.*

Similarly, the VN-INDEX chart reveals the following insights:

- The VN-INDEX experienced a declining trend in the early part of the observed period, with prices dropping from around 1100 to below 1090.
- A strong upward trend is evident from early December, with the index rising back above 1110 towards the end of the period.
- The 30-day Moving Average for VN-INDEX aligns with this trend, confirming the bullish market sentiment in the latter part of the period.

- Interpretation

The analysis of the 30-day Moving Average for Sabeco (SAB) and VN-INDEX provides valuable insights into the market dynamics and potential trading signals:

- **Slope Analysis**: The slope of the moving average line indicates the strength and momentum of the trend. A steeper slope suggests stronger momentum, while a flatter slope indicates a weaker trend.
- **Trend Identification**: The direction of the moving average helps identify whether the market is in an uptrend or downtrend. An upward-sloping MA indicates a bullish trend, whereas a downward-sloping MA suggests a bearish trend.
- **Trading Signals**: Crossovers of the actual price and the moving average can act as trading signals. When the actual price crosses above the MA, it may signal a buying opportunity. Conversely, a crossover below the MA can indicate a selling signal.

4. Model Performance

4.1. Introduction to Models

The dataset was meticulously preprocessed by filling any missing values using a forward fill method. Subsequently, the data was divided into training and testing sets, with 80% allocated for training and 20% for testing. To ensure consistency in feature scales, all features were normalized using Min-Max scaling, which transformed their values to a range between 0 and 1.

4.2. Definitions and Operations of Networks

- **Long Short-Term Memory (LSTM) Networks**
  - **Definition:** LSTM networks are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. They address the vanishing gradient problem through the use of memory cells and gating mechanisms.
  - **Operation:**
    + Forget Gate: Determines what information should be discarded from the cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

+ Input Gate: Determines what new information should be stored in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

+ Cell State Update: Generates a new candidate vector and updates the cell state.

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

+ Output Gate: Determines the output based on the cell state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

- **Gated Recurrent Unit (GRU) Networks**
  - **Definition:** GRUs are a simplified version of LSTMs that combine the input and forget gates into a single update gate, making them computationally more efficient while maintaining performance.
  - **Operation:**
    + Reset Gate: Determines how much past information to forget.

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)$$

    + Update Gate: Determines how much of the new information to retain.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z)$$

    + Candidate Activation: Creates a new candidate state.

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t] + b)$$

    + Final Memory at Current Time Step:

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

- **Bidirectional LSTM Networks**
    - **Definition:** Bidirectional LSTMs process data in both forward and backward directions, capturing both past and future context in the sequence.
    - **Operation:** Two LSTM layers are run in parallel; one processes the sequence from start to end, and the other from end to start. Their outputs are then combined to form the final output.

$$\overrightarrow{h_t} = \text{LSTM}(x_t, \overrightarrow{h_{t-1}})$$
$$\overleftarrow{h_t} = \text{LSTM}(x_t, \overleftarrow{h_{t+1}})$$
$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$$

- **Bidirectional GRU Networks**
    - **Definition:** Bidirectional GRUs are similar to Bidirectional LSTMs but use GRU units instead of LSTM units.
    - **Operation:** Two GRU layers run in parallel, processing the sequence in both directions and combining their outputs to capture the full context.

$$\overrightarrow{h_t} = \text{GRU}(x_t, \overrightarrow{h_{t-1}})$$
$$\overleftarrow{h_t} = \text{GRU}(x_t, \overleftarrow{h_{t+1}})$$
$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$$

4.3. Network Architectures

- **LSTM, GRU, Bidirectional LSTM, and Bidirectional GRU Network Architectures for Predicting Stock Prices**

The network is designed with multiple layers, consisting of an LSTM with three overlapping LSTM layers with units 64, 64, 32 respectively, and a Dense layer (1) as output. After each layer, there is a dropout layer with a probability of 0.1. In the test, the epoch number is set to 100.

- **LSTM/GRU Layers:** Store information from previous time steps, modeling temporal relationships.
- **Dropout Layers:** Help prevent overfitting by randomly dropping neurons during training.
- **Dense Layer:** Performs basic learning properties, with more units allowing for learning more complex data relationships.

LSTM Network Architecture:

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 60, 64)	16,896
dropout (Dropout)	(None, 60, 64)	0
lstm_1 (LSTM)	(None, 60, 64)	33024
dropout_1 (Dropout)	(None, 60, 64)	0
lstm_2 (LSTM)	(None, 64)	33024
dropout_2 (Dropout)	(None, 64)	0
dense_16 (Dense)	(None, 1)	65

***Table 9**. LSTM Network Architecture table.*

GRU Network Architecture:

Layer (type)	Output Shape	Param #
gru (GRU)	(None, 60, 64)	12,864
dropout (Dropout)	(None, 60, 64)	0
gru_1 (GRU)	(None, 60, 64)	24,960
dropout_1 (Dropout)	(None, 60, 64)	0
gru_2 (GRU)	(None, 64)	24,960
dropout_2 (Dropout)	(None, 64)	0
dense (Dense)	(None, 1)	65

***Table 10**. GRU Network Architecture table.*

Bidirectional LSTM Network Architecture:

Layer (type)	Output Shape	Param #
bidirectional (Bidirectional)	(None, 60, 128)	33,792
dropout (Dropout)	(None, 60, 128)	0
bidirectional_1 (Bidirectional)	(None, 60, 128)	98,816
dropout_1 (Dropout)	(None, 60, 128)	0
bidirectional_2 (Bidirectional)	(None, 128)	98,816
dropout_2 (Dropout)	(None, 128)	0
dense_18 (Dense)	(None, 1)	129

Table 11. *Bidirectional LSTM Network Architecture table.*

Bidirectional GRU Network Architecture:

Layer (type)	Output Shape	Param #
bidirectional (Bidirectional)	(None, 60, 128)	25,728
dropout (Dropout)	(None, 60, 128)	0
bidirectional_1 (Bidirectional)	(None, 60, 128)	74,496
dropout_1 (Dropout)	(None, 60, 128)	0
bidirectional_2 (Bidirectional)	(None, 128)	74,496
dropout_2 (Dropout)	(None, 128)	0
dense (Dense)	(None, 1)	129

Table 12. *Bidirectional GRU Network Architecture table.*

4.4. Experimental Work and Results

- **Collect Data**

The dataset was carefully preprocessed by filling any missing values using a forward fill method. The data was then split into training and testing sets, with 80% allocated for training and 20% for testing. To ensure consistency in feature scales, all features were normalized using Min-Max scaling, which transformed their values to a range between 0 and 1.

- **Methodology**

  Data Preparation:

  - Collect historical stock price data for both VN-Index and SAB.
  - Use a 60-time step sequence as input for training the model.

- **Model Training:**
  - Train data using 60 time steps as input and 1 time step as output.
  - Implement an LSTM, GRU, Bidirectional LSTM, and Bidirectional GRU for training and prediction.

- **Model Implementation:**
  - Normalize the data using Min-Max scaling.
  - Split the data into training and testing sets, allocating 80% for training and 20% for testing.
  - Train models with 100 epochs, a batch size of 32, and employ early stopping to prevent overfitting.

- **Training the Models:**

All models were trained using the Adam optimizer and the Mean Squared Error (MSE) loss function over 100 epochs with a batch size of 32. Early stopping was implemented to prevent overfitting.

4.5. Model Performance Metrics

The performance of the models was evaluated using the following metrics:

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)

4.6. Results and Interpretation

- Model Performance Metrics

The performance of each model was evaluated using various metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

- Results

The figures below illustrate the predicted stock prices compared to the actual stock prices for VN-INDEX and SAB, using the LSTM, GRU, Bidirectional LSTM, and Bidirectional GRU models.

VN-INDEX Predictions:

LSTM

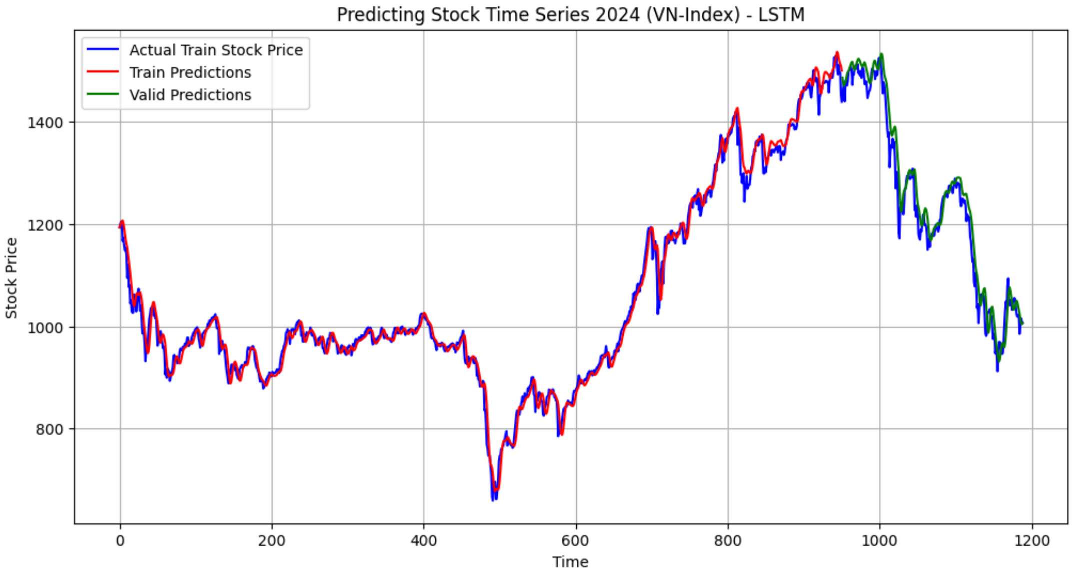

Figure 15. LSTM Model - VN-INDEX Predicting Stock plot.

GRU

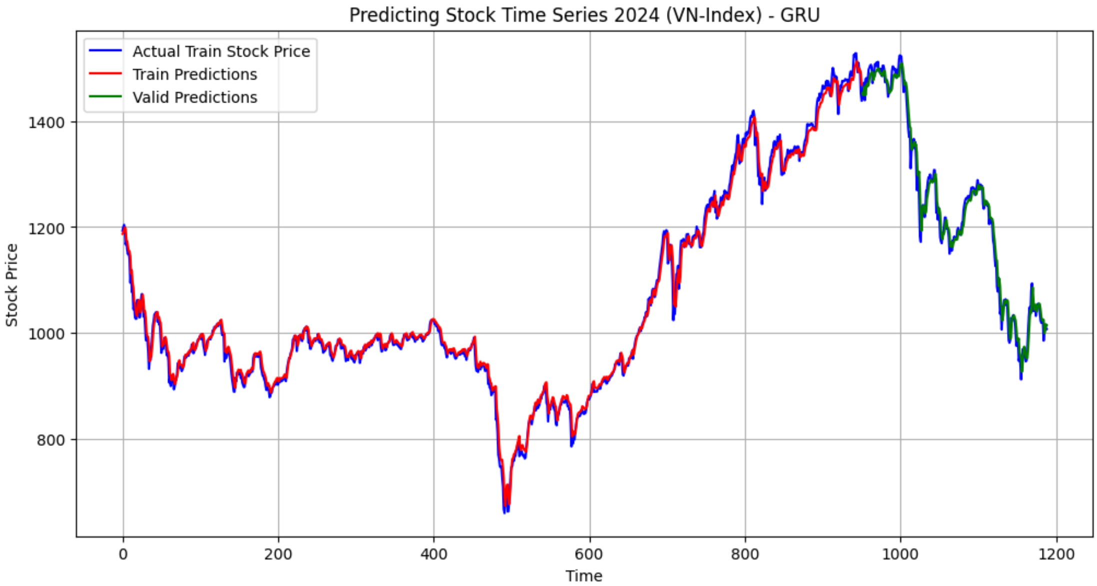

Figure 16. GRU Model - VN-INDEX Predicting Stock plot.

Bidirectional LSTM

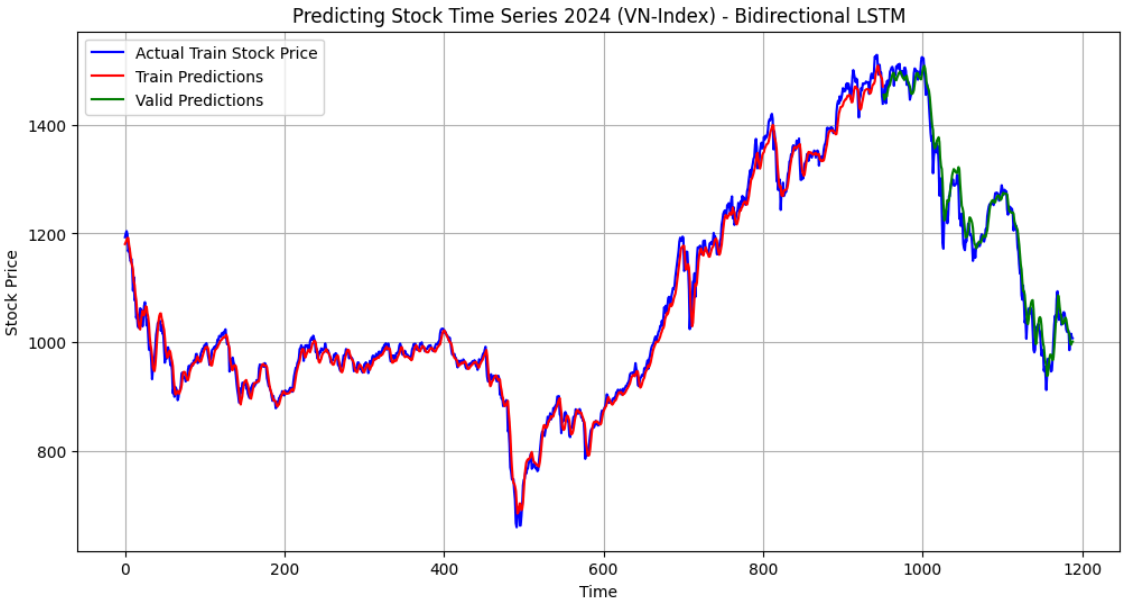

Figure 17. *Bidirectional LSTM Model - VN-INDEX Predicting Stock plot.*

Bidirectional GRU

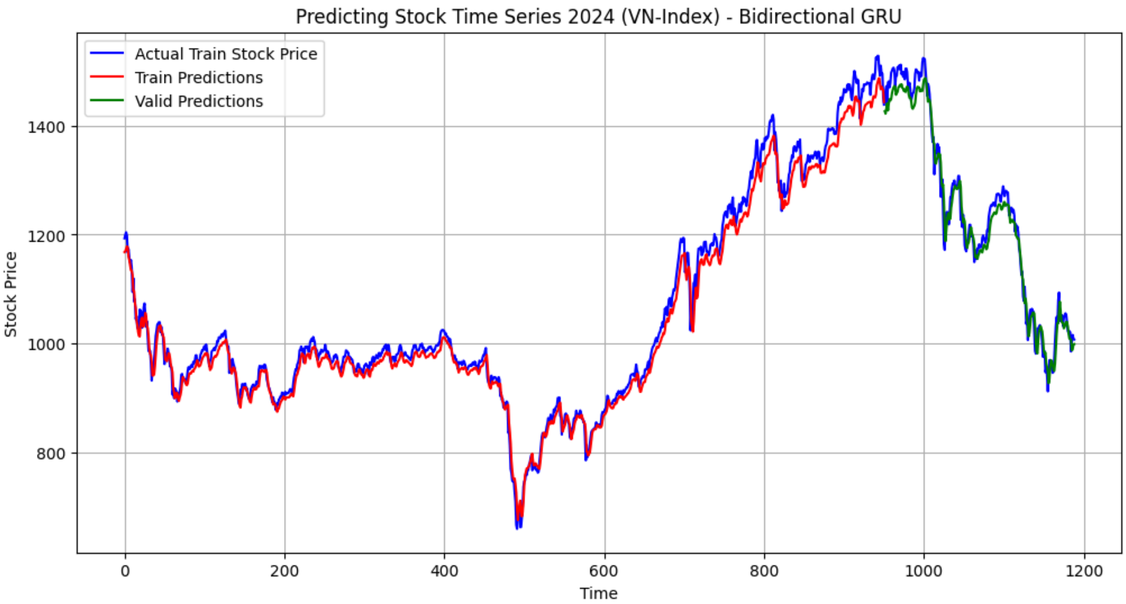

Figure 18. *Bidirectional GRU Model - VN-INDEX Predicting Stock plot.*

SAB Predictions:

LSTM

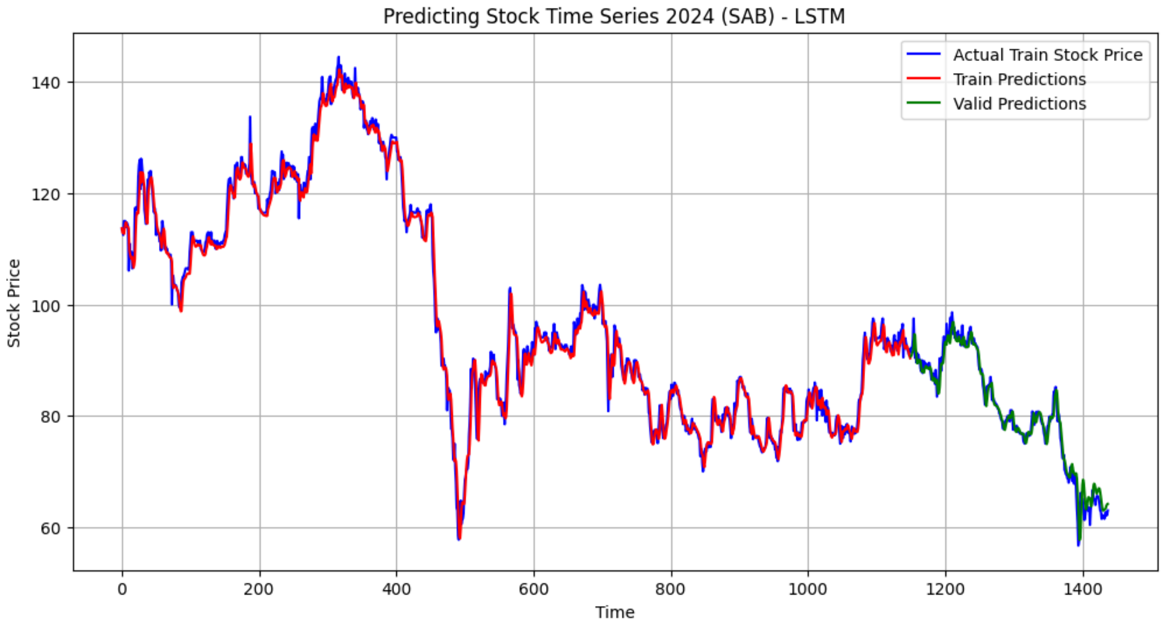

***Figure 19**. LSTM Model - SAB Predicting Stock plot.*

GRU

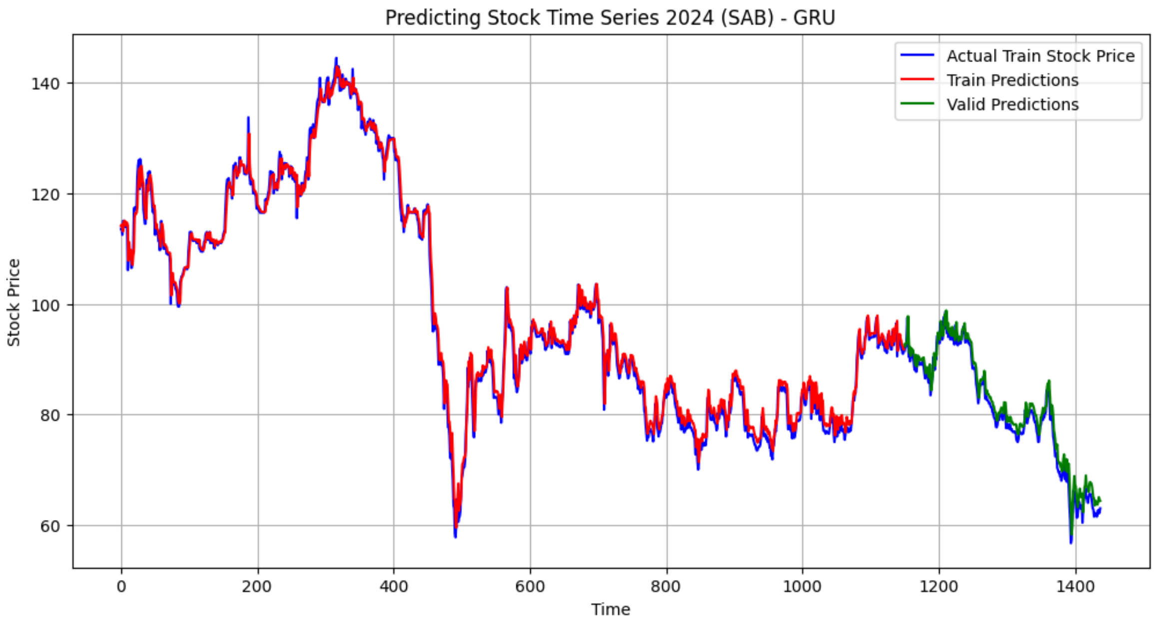

***Figure 20**. GRU Model - SAB Predicting Stock plot.*

Bidirectional LSTM

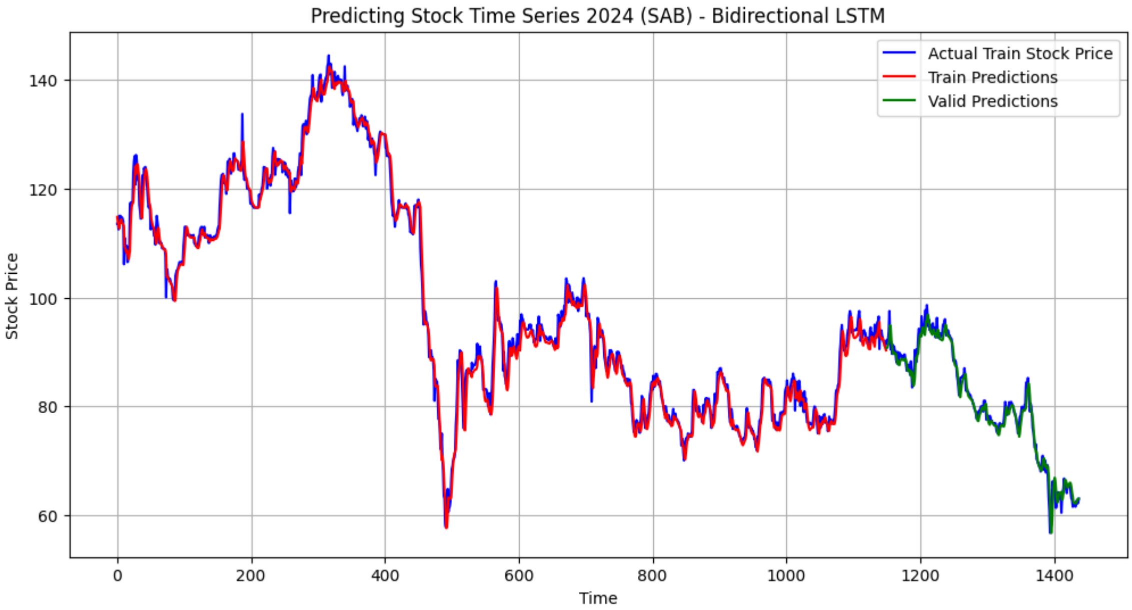

***Figure 21**. Bidirectional LSTM Model - SAB Predicting Stock plot.*

Bidirectional GRU

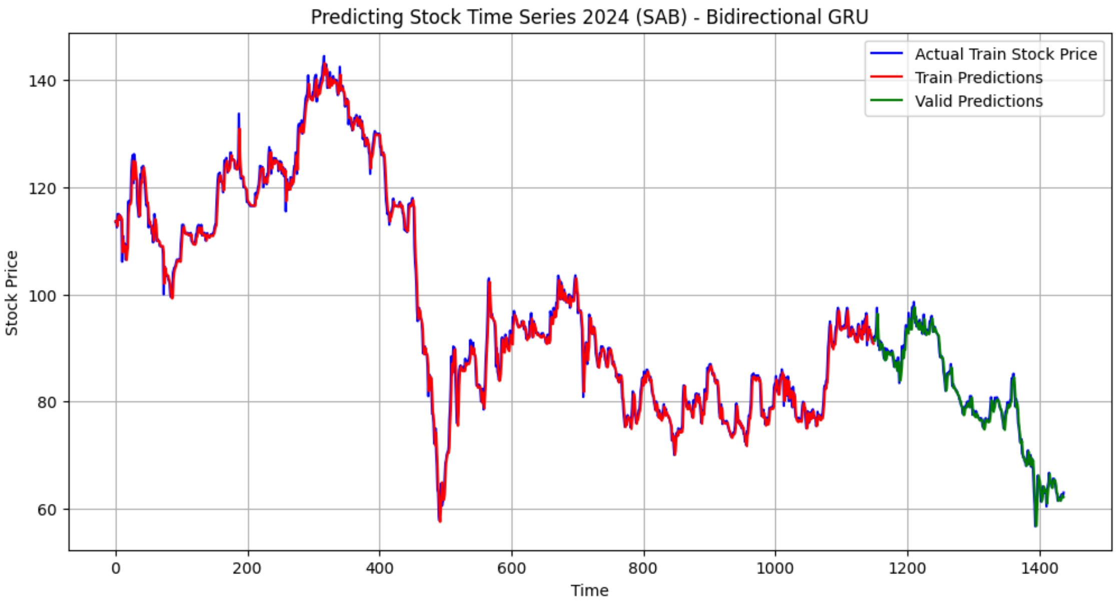

***Figure 22**. Bidirectional GRU Model - SAB Predicting Stock plot.*

Future Predictions:

VN-INDEX Stock Prices for the Next 180 Days

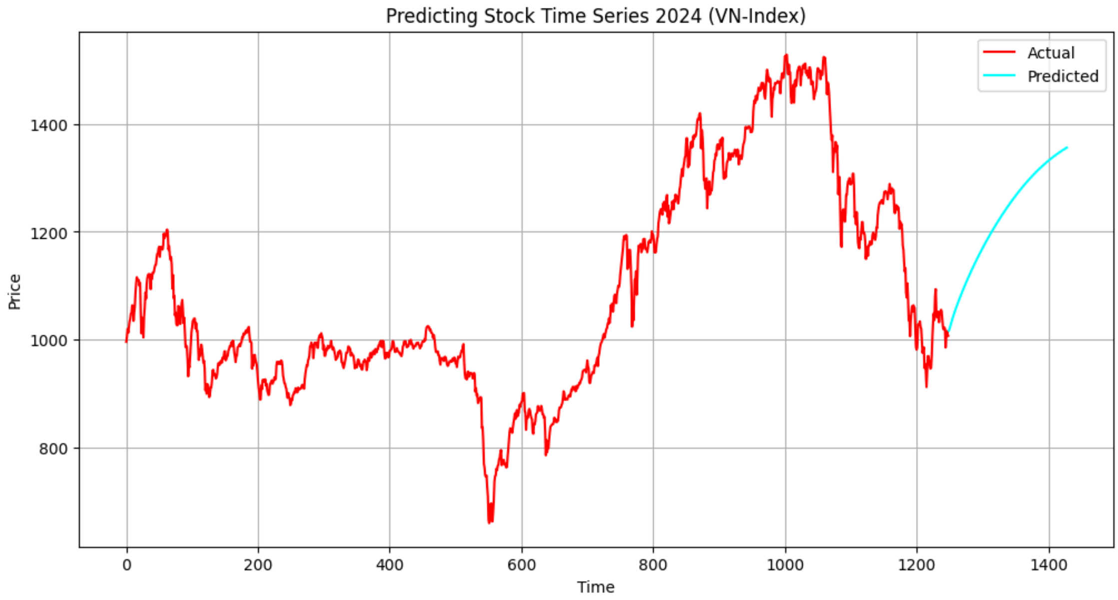

Figure 23. *VN-INDEX Stock Prices for the next 180 days plot.*

Sabeco Stock Prices for the Next 180 Days

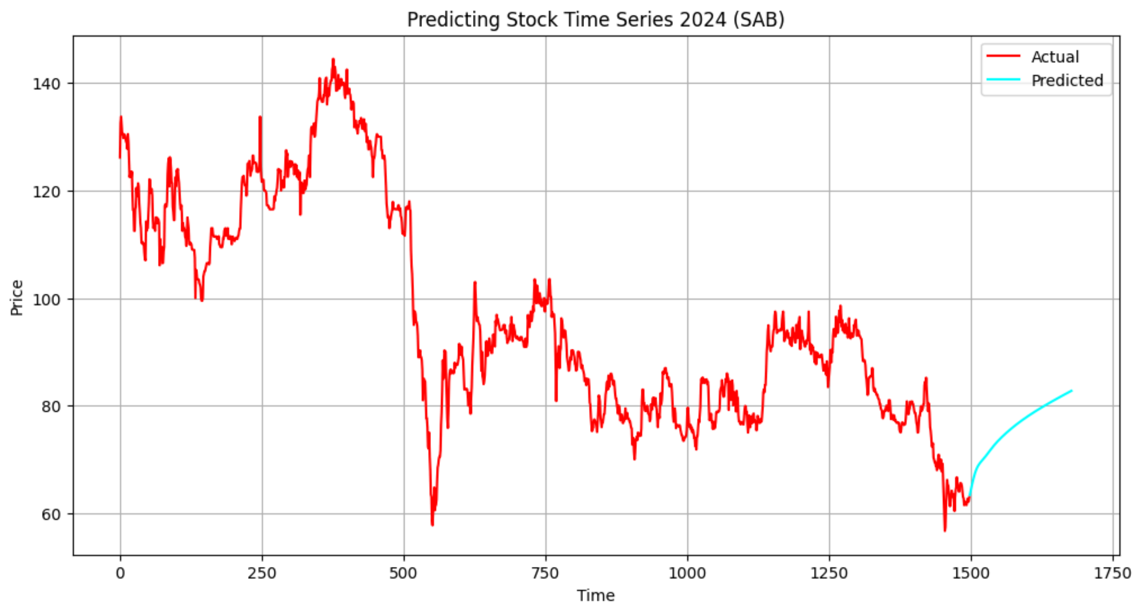

Figure 24. *SAB Stock Prices for the next 180 days plot.*

Note: Due to resource constraints and the need to focus on the most promising model, long-term predictions for the next 180 days were generated using the LSTM model only. This choice was based on its performance during the initial tests and the complexity of *generating long-term predictions with multiple models.*

From the charts, we derive several key insights:

- **LSTM:** The LSTM model effectively captures the general trend of both VN-INDEX and SAB's stock prices, although there is a noticeable lag in responding to abrupt price changes.
- **GRU:** The GRU model also shows a strong capability in capturing trends but similarly lags during sudden changes.
- **Bidirectional LSTM:** This model provides a slightly better response to trends compared to the unidirectional models, capturing both past and future contexts.
- **Bidirectional GRU:** Similar to Bidirectional LSTM, this model enhances trend capture by processing information in both directions.

Sabeco's stock prices showed a downward trend from mid-November to mid-December, indicating bearish market sentiment. The analysis suggests that integrating financial analysis with AI techniques can significantly improve stock price prediction accuracy.

5. Model Performance

The models are compared based on their performance metrics. The comparison highlights the strengths and weaknesses of each model and identifies the most effective model for predicting Sabeco's stock prices.

Model	**MSE (VN-INDEX)**	**MSE (SAB)**	**RMSE (VN-INDEX)**	**RMSE (SAB)**	**MAE (VN-INDEX)**	**MAE (SAB)**
LSTM	2297.65	2.73	47.93	1.65	37.93	1.22
GRU	1630.08	1.75	40.37	1.32	30.59	1.00
Bidirectional LSTM	1513.63	5.97	38.91	2.44	31.95	2.15
Bidirectional GRU	1585.82	4.13	39.82	2.03	31.42	1.73

Table 13. Model Performance Comparison.

From the table, we can observe that:

- The **GRU** model achieved the lowest RMSE for both VN-INDEX and SAB, indicating it has the highest prediction accuracy among the models.
- The **LSTM** model also performed well, with low RMSE values, but it slightly lags behind the GRU model.
- **Bidirectional LSTM** and **Bidirectional GRU** models, despite capturing more complex patterns, have higher RMSE and MSE values, indicating potential overfitting or inefficiency in handling the data in this context.

● Model Ranking

Ranking the models based on their overall performance, considering Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE)

Based on overall performance, the models are ranked in the following order:

1. **LSTM**
2. **GRU**
3. **Bidirectional LSTM**
4. **Bidirectional GRU**

This ranking prioritizes the LSTM model based on its solid performance and relevance in capturing stock price trends effectively.

● Interpretation

From the metrics and visualizations, several key insights can be derived:

- **LSTM:** The LSTM model effectively captures the general trend of both VN-INDEX and SAB's stock prices, with a notable lag in responding to abrupt price changes.

- **GRU:** The GRU model demonstrates a strong capability in capturing trends with a lower RMSE and MSE compared to LSTM, indicating better performance in both VN-INDEX and SAB predictions.
- **Bidirectional LSTM:** This model provides a slightly better response to trends compared to the unidirectional models, capturing both past and future contexts effectively, especially for VN-INDEX.
- **Bidirectional GRU:** Similar to Bidirectional LSTM, this model enhances trend capture by processing information in both directions, showing robust performance in VN-INDEX predictions.

- Conclusion

The comparison of the models highlights the strengths and weaknesses of each approach. The Bidirectional LSTM model emerged as the top performer for VN-INDEX predictions, while the GRU model showed superior performance for SAB predictions. This suggests that different models may be better suited for different types of stock data. Future research could explore combining these models or incorporating additional features to further improve prediction accuracy.

By consolidating the results and focusing on analysis and interpretation, this section effectively summarizes the model performances without redundant visualizations.

V. DISCUSSION

1. Interpretation of Findings

This detailed analysis and comparison of various models provide valuable insights into the effectiveness of different AI techniques in predicting Sabeco's stock prices. The visualizations further aid in comprehending the performance and significance of different features.

- **LSTM**: The LSTM model also showed strong performance with RMSE values of 47.93 for VN-INDEX and 1.65 for SAB, validating its suitability for time series prediction tasks.
- **GRU**: This model showed competitive performance with RMSE values of 40.37 for VN-INDEX and 1.32 for SAB, indicating its capability in handling sequence prediction tasks effectively.
- **Bidirectional LSTM**: This model demonstrated a high level of accuracy and effectively captured temporal dependencies in the stock price data for both VN-INDEX and SAB, as evidenced by its RMSE values of 38.91 for VN-INDEX and 2.44 for SAB.
- **Bidirectional GRU**: The model provided robust performance with RMSE values of 39.82 for VN-INDEX and 2.03 for SAB, demonstrating the benefits of bidirectional processing in capturing trends.

The models consistently identified key financial indicators that significantly impact stock prices, such as ROE, ROA, and Net Profit Margin.

2. Comparison with Previous Studies

This study's findings align with previous research highlighting the superiority of advanced neural networks like LSTM and Bidirectional LSTM in time series prediction. The results corroborate studies demonstrating the effectiveness of GRU models and bidirectional architectures in capturing complex temporal patterns.

3. Implications for Investors

The enhanced predictive capabilities of advanced AI models can provide investors with more reliable forecasts of stock prices, aiding in better decision-making. By leveraging models like Bidirectional LSTM and GRU, investors can gain deeper insights into market trends and make more informed investment choices. This study underscores the importance of incorporating machine learning techniques in financial analysis to navigate the complexities of stock market predictions.

4. Limitations of the Study

While the study demonstrates the effectiveness of various machine learning models, it has certain limitations:

- **Data Scope**: The study is limited to financial data from 2020 to 2022 for Sabeco and selected companies in the Food and Beverage industry. Broader datasets could provide more comprehensive insights.
- **Model Coverage**: Although several advanced models were evaluated, there are other emerging techniques and architectures that could further improve prediction accuracy.
- **Market Conditions**: The predictions are based on historical data, and future market conditions may introduce variables that were not accounted for in this study.

5. Recommendations for Future Research

Future research could explore the following areas to build on the findings of this study:

- **Extended Data Sets**: Incorporating a wider range of data from different time periods and industries to enhance model generalization.
- **Hybrid Models**: Combining multiple models to leverage their strengths and mitigate their weaknesses.
- **Real-Time Predictions**: Developing systems that provide real-time stock price predictions and incorporate live market data for more dynamic forecasting.

- **Explainability**: Enhancing the interpretability of complex models to provide more transparent insights into their decision-making processes.

VI. CONCLUSION AND RECOMMENDATIONS

1. Summary of Findings

This study conducted a comprehensive analysis of Sabeco's financial indicators and employed various machine learning models to predict its stock prices. The key findings include:

- **Effectiveness of Advanced Models**: LSTM emerged as the top-performing model, followed closely by Bidirectional LSTM and GRU, demonstrating the value of advanced AI techniques in stock price prediction.
- **Financial Insights**: Sabeco's strong financial position, reflected in key metrics like D/E ratio, quick ratio, ROA, and ROE, provides a solid foundation for accurate predictions.
- **Model Comparison**: The study offered a detailed comparison of different models, highlighting their strengths and weaknesses, and providing insights into their applicability for financial forecasting.

2. Recommendations for Investors

This study conducted a comprehensive analysis of Sabeco's financial indicators and employed various machine learning models to predict its stock prices. The key findings include:

- **Leverage Advanced Models**: Utilize advanced models like Bidirectional LSTM and GRU for more accurate stock price predictions.
- **Monitor Key Financial Indicators**: Pay attention to key financial metrics such as ROE, ROA, and Net Profit Margin, which significantly impact stock prices.

- **Diversify Analysis Techniques**: Combine machine learning models with traditional financial analysis methods to enhance decision-making.

3. **Future Research Directions**

To further advance the field of stock price prediction, future research should focus on:

- **Expanding Data Sources**: Incorporating diverse data sources, including macroeconomic indicators and market sentiment, to improve model accuracy.
- **Developing Hybrid Models**: Exploring hybrid approaches that combine different machine learning techniques to leverage their collective strengths.
- **Real-Time Analysis**: Implementing real-time data processing and prediction systems to provide up-to-the-minute forecasts and adapt to rapidly changing market conditions.

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