# VIETNAMESE STOCK PRICE PREDICTION USING MACHINE LEARNING ALGORITHMS


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❖ **Abstract-** More and more people are now taking part in the stock market as the result of the economy's expansion. Due to the complexity of predicting stock market trends, inventors can protect their investments and reduce potential losses and make informed decisions regarding buying, selling, or holding stocks by using forecast tools. In this study, we will use various machine learning and deep learning algorithms for predicting stock prices in Vietnam. We compare the effectiveness of ARIMA, ARIMAX, CNN, KNN, GRU, LSTM, BSTS, Linear Regression and HMM models.



❖ **Keywords-** Linear Regression, ARIMA, LSTM, GRU, ARIMAX, KNN, BSTS, CNN, Machine Learning, Deep Learning, stock price


## I. INTRODUCTION

With the increasing popularity of financial markets and the growing complexity of investment decisions, accurate stock price prediction has become a crucial area of research and practical application. Investors, financial institutions, and traders alike seek reliable techniques that can provide insights to forecast stock prices in the future. These methods also can help people to make informed decisions, manage risks, and optimize investment strategies. In the context of Vietnam's stock market, which has been experiencing significant growth and attracting global attention, the ability to predict stock prices holds immense value.

The purpose of this research is to investigate how machine learning algorithms can be used to forecast stock prices in Vietnam. Because of their capacity to find intricate links and patterns in massive datasets. Machine learning models can get useful insights and make forecasts with greater accuracy by utilizing historical stock market data, market indicators, and other pertinent variables.

This paper aims to contribute to the existing literature on stock price prediction by focusing on the Vietnamese market. By employing machine learning algorithms such as Linear Regression, ARIMA, LSTM, GRU, ARIMAX, KNN, BSTS, CNN; and analyzing relevant factors; this research seeks to enhance our understanding of stock price dynamics in Vietnam and provide valuable insights to stakeholders in the financial industry.

## II. RELATED RESEARCH

Several studies have been conducted to explore various algorithms, data preprocessing techniques, feature selection methods, and evaluation metrics in the context of stock price prediction. This section presents a review of the related work conducted in this paper:

P.-F. Pai and C.-S. Lin develop a hybrid model combining autoregressive integrated moving average (ARIMA) and support vector machines (SVM) for stock price forecasting [1]. Aside from that, S. Hochreiter and J. Schmidhuber[2] investigated the effectiveness of long short-term memory (LSTM) neural networks for stock price prediction. They proposed an LSTM-based model that incorporated both historical stock price data and technical indicators as input features. The study demonstrated that LSTM is a powerful architecture for sequential data analysis, addressing the limitations of traditional RNNs. In addition, to forecast stock index, Michael van Gysen et al. employ both linear and non-linear models. Moreover, we use the result of "Predicting prices of stock market using gated recurrent units (GRUs) neural networks"[3] and apply GRU into our research.

## III. MATERIALS

### 1. Data description

We collected three datasets on Investing.com from December 1st, 2017 to June 9, 2023 [4]. The data related to stock price of three large company in Vietnam: Vingroup JSC(VIC), CMC Corp(CMG) and Viet Nam Plastic Corp(VNP) .The dataset has 7 attribute columns including Date, Price, Open, High, Low, Vol and Change%.

### 2. Performance measure

Starting with pre-processing data, we cleaned the dataset by dropping the missing values, changing the data type of attributes, feature selection,…After that, we divided the data into training, testing and validate sets with two ratios: 70%-20%-10% and 60%-20%-20%.In this study, we employ the root means square error (RMSE) ,the MAPE and MAE as three performance measures to evaluate the prediction capability of our models.

## IV. METHODOLOGY

### A. Linear Regression

Linear regression is used to predict the value of a variable based on the value of another variable. The variable need to predict is called the dependent variable. The variable that is used to predict the other variable's value is called the independent variable. Linear regression fits a straight line or surface that minimizes the discrepancies between predicted and actual output values. [5]

A multiple linear regression model has the formula as below: [6]

$$\boldsymbol{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon}$$

Where:

- **Y** is the dependent or predicted variable.
- **X_1,…X_n** are the independent (explanatory) variables.
- **β_0** is the intercept term.
- **β_1,… β_n** are the regression coefficients for the independen variables.
- **ε** is the random error.

### B. ARIMA

The acronym ARIMA represents Autoregressive Integrated Moving Average [9]. The ARIMA model incorporates three key elements from the Box and Jenkins approach: autoregressive (AR) modeling, moving average (MA) modeling, and integration. These components are combined into an ARIMA (p, d, q) model. ARIMA is a time-based quantitative forecasting model that predicts future values of a predictor variable based on the historical trend of that variable.

Where:

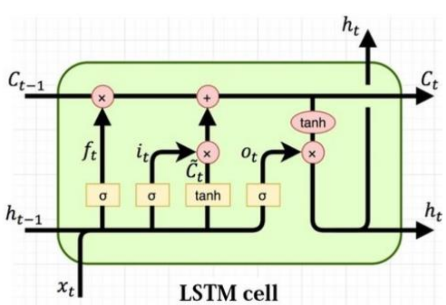
- p defines the AR
- d defines the differential
- q defines the MA.

The ARIMA model consists of three components/parameters: AR, I, and MA. The AR component is represented by "p" in the ARIMA (p, d, q) notation, indicating the weighted linear sum of "p" lagged values. The value of "p" indicates the number of lagged orders considered in the model.

### C. LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is well-suited for processing sequential data such as time series, natural language, and audio. LSTMs are able to learn long-term dependencies in data by using a special structure called a 'memory cell' which can store information over long periods of time. LSTM models are often used for time series prediction tasks, such as forecasting stock prices, weather, or energy consumption. In these tasks, the goal is to use past data to make predictions about future value. [7]

The structure of an LSTM cell is shown in the figure below. It consists of three interacting gates (input, output, and forget gates) and a memory cell, which stores information. The gates control the flow of information into and out of the memory cell, allowing the model to decide which information to keep and which to discard.



[8]

*Figure 1. LSTM Architecture Flow Diagram*

Forget gate: $f1 = \sigma\,(W_f X_t + U_f h_{t-1})$

Input gate: $it = \sigma\,(W_i X_t + U_i h_t - 1)$

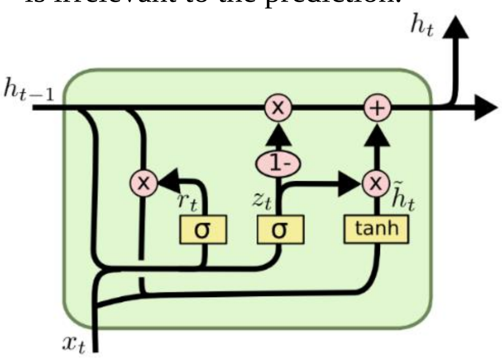
Output gate: $ot = \phi\, h(W_0 X_t + U_0 h_{t-1})$[9]

### D. GRU

A gated recurrent unit (GRU) is a gating mechanism in recurrent neural networks (RNN) similar to a long short-term memory (LSTM) unit but without an output gate. GRU's try to solve the vanishing gradient problem that can come with standard recurrent neural networks. [10]

GRU uses gating mechanisms to selectively update the hidden state of the network at each time step. The gating mechanisms are used to control the flow of information in and out of the network. The GRU has two gating mechanisms, called the reset gate and the update gate.[11]

The update gate controls information that flows into memory, and the reset gate controls the information that flows out of memory. The update gate and reset gate are two vectors that decide which information will get passed on to the output. They can be trained to keep information from the past or remove information that is irrelevant to the prediction.



[12]

*Figure 2. GRU Architecture Flow Diagram*

**Notation:**

$h_t$ : hidden layer vectors.
$x_t$ : input vector.
$b_z$ , $b_r$ , $b_h$ : bias vector.
$W_z$ , $W_r$ , $W_h$ : parameter matrices.
$\sigma$ , $\tanh$ : activation functions.

The equations used to calculate the reset gate, update gate, and hidden state of a GRU are as follows[5]:

- **Reset gate:** $r_t$= sigmoid($W_r$* [$h_{t-1}$, $x_t$])
- **Update gate**: $z_t$= sigmoid($W_z$ * [$h_{t-1}$, $x_t$])
- **Candidate hidden state:** $h\_t^{\sim}$= tanh($W_h$* [$r_t$* $h_{t-1}$, $x_t$])
- **Hidden state:** $h_t$ = (1 – $z_t$) * $h_{t-1}$+ $z_t$* $h\_t^{\sim}$

Where:

$h_{t-1}$ is the previous hidden state, and $h_t$is the current hidden state.

## E. ARIMAX

ARIMAX, an acronym for Auto Regressive Integrated Moving Average with eXogenous inputs, is a popular and efficient model for time series prediction. It extends the well-known ARIMA model by incorporating exogenous variables to improve forecasting accuracy [13].

ARIMA, or Auto-Regressive Integrated Moving Average, models a given time series based on its own prior values, lags, and lagged forecast errors. It is defined by three terms: p, d, q, where p is the order of the Auto-Regressive (AR) term, d is the number of differences needed to make the time series stationary, and q is the order of the Moving Average (MA) term. The AR term relates to the number of lags of the time series to be used as predictors, while the MA term refers to the number of lagged forecast errors that should conform to the ARIMA Model. The series is differentiated (d times) to ensure stationarity, and then the AR and MA terms are combined to form the ARIMA model [13].

The exogenous variable X could be any variable of interest such as a time-varying measurement like the inflation rate or the price of a different index, a categorical variable separating the different days of the week, a Boolean accounting for the special festive periods, or a combination of several different external factors. The only requirement is that this variable should have a potential impact on the time series and its data should be available [18].

In conclusion, ARIMAX is a powerful tool for forecasting time series data, especially when the influence of external factors is significant. It leverages the strengths of the ARIMA model and extends it by incorporating relevant exogenous variables, providing a more comprehensive and accurate forecasting model.

## F. KNN

The K-Nearest Neighbors is a classification algorithm in Machine Learning, which uses similarity or proximity to make classifications or predictions about the grouping of an individual data point. It can be used for either regression or classification problems. [15]

In the KNN algorithm, the "k" represents the number of nearest neighbors used to make predictions. Given a new, unseen data point, KNN identifies the "k" closest neighbors to that point in the training dataset based on a distance metric, commonly Euclidean distance. The prediction is then determined by a majority vote (for classification) or the average of the target values (for regression) of those "k" neighbors.

❖ Euclidean distance:

d = $\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$

Where:

- $(x_1, y_1)$ are the coordinates of one point.
- $(x_2, y_2)$ are the coordinates of the other point.

### G. HMM

The Hidden Markov model (HMM) is a statistical probabilistic model in the field of machine learning BSTS models are a class of additive models for time series data and have an associated state space, which provides a probabilistic model for the serial correlation observed in the time series. The simplest version of STS is the local level model, where y(t) is the sum of our state variable α(t) plus Gaussian Noise, ε(t). All of the time dependency is modeled in the evolution of α(t+1), which is equal to its previous time value α(t) plus Gaussian Noise, η(t) that is independent of all ε(i's). [18]

### H. BSTS

Bayesian Structural Time Series (BSTS) is a statistical method utilized in feature selection, time series forecasting, nowcasting, and inferring causal impact, among other applications. It is particularly useful in analyzing time series data, with applications in analytical marketing, like assessing the impact of different marketing campaigns on key indicators such as web search volumes, product sales, and brand popularity .[17]

The BSTS model comprises three main components: the Kalman filter, the Spike-and-slab method, and Bayesian model averaging. The Kalman filter, a technique for time series decomposition, allows the addition of different state variables like trend, seasonality, and regression. The Spike-and-slab method is responsible for selecting the most important regression predictors. Finally, Bayesian model averaging combines the results and calculates the prediction. The model is adept at inferring causations through counterfactual prediction and observed data. [17]

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### I. CNN

CNN (Convolutional Neural Network) is a neural network architecture used in the field of computer vision and image processing. [19]

The architecture of CNN includes main layers such as convolutional layer, pooling layer and fully connected layer. The convolutional layer is a crucial component in CNN and is used to extract from the input data. The pooling method is often applied after the convolutional layer and retains the most important information in the data. The fully connected layer is typically used at the end of a CNN to connect the extracted data from the convolutional and pooling layers to the desired output. To apply CNN to stock price prediction based on time series data, we can use Convolutional LSTM (Long Short-Term Memory), which combines convolutional layers and LSTM to predict future stock prices. [19]

## V. RESULT

In this evaluation, five distinct models were assessed, to be specific LSTM, ARIMA, ARIMAX, BSTS, CNN, GRU, HMM, KNN, BSTS for the time series examination on 7-2-1, 6-3-1 training, testing and validating.

RMSE and MAPE scores were used to assess model execution. In the table show the forecasting metrics results for examining test data of the dataset. From the outcomes, one can without much of a stretch see that LSTM has better execution compared to different models for all evaluation metrics.

From the conclusions on the model, LSTM is a suitable model for predicting future prices in the next 30 days of 2 stocks VNP, VIC and CMG.

**1. VNP**

| Model | Train - Test | RMSE | MAE | MAPE |
|---|---|---|---|---|
| LN | 7 - 2 | 6705,41 | 5425,25 | 29,64% |
| | 6 - 3 | 11786,6 | 10320,92 | 48,91% |
| | 5 - 3 | 14498,9 | 12740,07 | 65,84% |
| ARIMA | 7 - 2 | 6876,22 | 5779,99 | 40,28% |
| | 6 - 3 | 51021,0 | 41517,24 | 265,28% |
| | 5 - 3 | 11955,5 | 9781,76 | 46,40% |
| ARIMAX | 7 - 2 | 6876,22 | 5779,99 | 40,28% |
| | 6 - 3 | 51021,03 | 41517,24 | 265,28% |

| | | | | |
|---|---|---|---|---|
| | 5 - 3 | 11056,52 | 8945,18 | 42,02% |
| KNN | 7 - 2 | 8850,73 | 7335,81 | 51,46% |
| | 6 - 3 | 7727,18 | 6071,46 | 27,75% |
| | 5 - 3 | 11931,82 | 9748,82 | 46,14% |
| GRU | 7 - 2 | 573,88 | 417,48 | 3,04% |
| | 6 - 3 | 831,14 | 616,07 | 3,34% |
| | 5 - 3 | 895,35 | 633,28 | 3,10% |
| LSTM | 7 - 2 | 2131,14 | 1889,26 | 13.35% |
| | 6 - 3 | 1945,55 | 1627,70 | 8.27% |
| | 5 - 3 | 22206,3 | 18787,05 | 80,8% |
| HMM | 7 - 2 | 34760.7 | 32913,55 | 202.81% |
| | 6 - 3 | 77020.8 | 58149,82 | 79.61% |
| | 5 - 3 | 29135.7 | 22147.42 | 197.16 |
| CNN | 7 - 2 | 669.88 | 6713.19 | 3.507% |
| | 6 - 3 | 986.97 | 5613.39 | 6.74% |
| | 5 - 3 | 1900,75 | 1469.0 | 7.10% |
| BSTS | 7 - 2 | 19930,3 | 16922,93 | 115,59% |
| | 6 - 3 | 7845,07 | 6850,81 | 39,26% |
| | 5-3-2 | 5840,25 | 4254,59 | 19,13% |

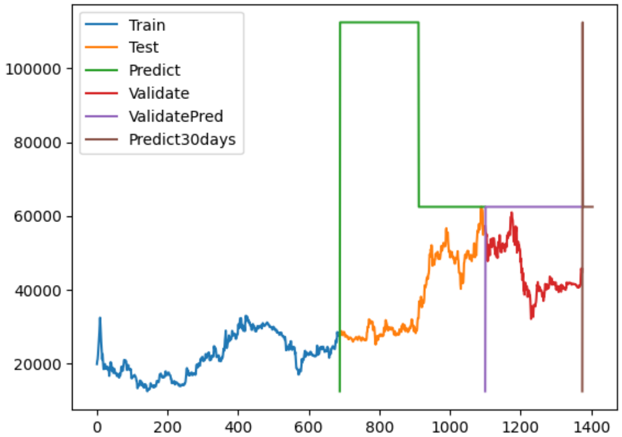
**2. VIC**

| Model | Train - Test | RMSE | MAE | MAPE |
|---|---|---|---|---|
| LN | 7 - 2 | 24021,55 | 20138,55 | 29,77% |
| | 6 - 3 | 18183,89 | 14649,26 | 19,72% |
| | 5 - 3 | 10569,41 | 8269,173 | 9,015% |
| ARIMA | 7 - 2 | 20405,17 | 17076 | 25,19% |
| | 6 - 3 | 20869,99 | 16640,29 | 22,94% |
| | 5 - 3 | 16746,81 | 13764,44 | 13,67% |
| ARIMAX | 7 - 2 | 25357,31 | 20865,25 | 31,01% |
| | 6 - 3 | 30506,71 | 24537,27 | 34,076% |
| | 5 - 3 | 13513,97 | 10990,92 | 11,182% |
| KNN | 7 - 2 | 17248,02 | 14849,72 | 21,442% |
| | 6 - 3 | 19148,90 | 15284,17 | 20,754% |
| | 5 - 3 | 15479,63 | 12576,0 | 12,488% |
| GRU | 7 - 2 | 1532,9772 | 1197,8723 | 1,8067% |
| | 6 - 3 | 1764,900 | 1268,03 | 1,667% |
| | 5 - 3 | 2070,084 | 1422,337 | 1,463% |
| LSTM | 7 - 2 | 2266,729 | 1690.993 | 2,682% |
| | 6 - 3 | 2714,184 | 2028.074 | 2,814% |
| | 5 - 3 | 3451.51 | 2523.806 | 2.611% |
| HMM | 7 - 2 | 70034.18 | 51489.78 | 67.89% |
| | 6 - 3 | 82080.45 | 75333.62 | 93.07% |
| | 5 - 3 | 75683.26 | 67899.86 | 74.97% |
| CNN | 7 - 2 | 1688,249 | 1218.26 | 1,908% |
| | 6 - 3 | 2169,72 | 1521.784 | 2,022% |
| | 5 - 3 | 2849.11 | 2003.98 | 2.033% |

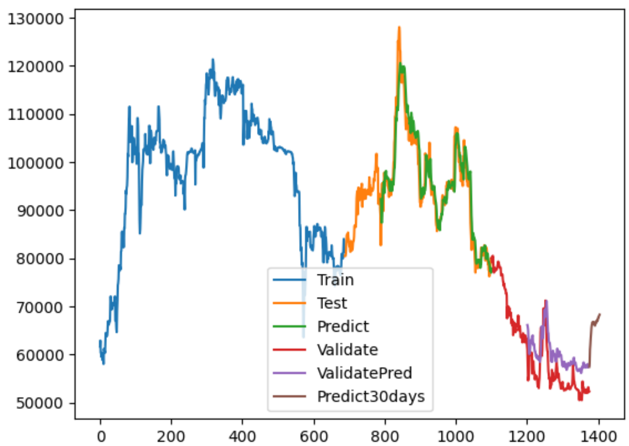
| | | | | |
|---|---|---|---|---|
| BSTS | 7 - 2 | 13993,51 | 12651,13 | 15,91% |
| | 6 - 3 | 33229,34 | 26505,61 | 36,64% |
| | 5 - 3 | 37085,04 | 33821,52 | 35,35% |

### 3. CMG

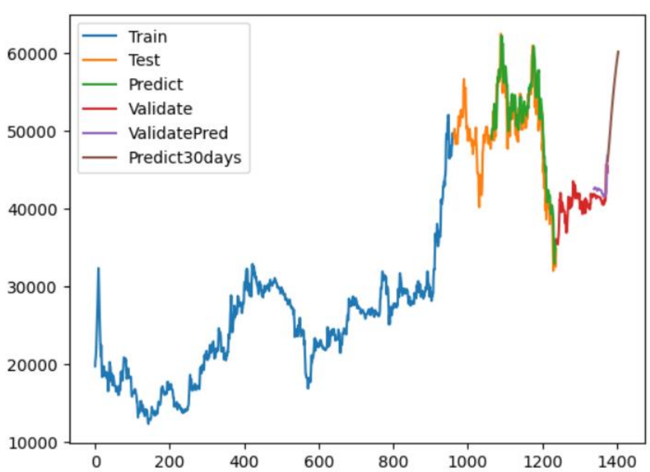
| Model | Train - Test | RMSE | MAE | MAPE |
|---|---|---|---|---|
| LN | 7 - 2 | 14916,18 | 13911,55 | 26,99% |
| | 6 - 3 | 15015,53 | 12698,94 | 25,39% |
| | 5 - 3 | 11340,21 | 7995,76 | 17,21% |
| ARIMA | 7 - 2 | 5695,18 | 4210,186 | 8,96% |
| | 6 - 3 | 18200,60 | 15589,32 | 31,26% |
| | 5 - 3 | 14725,74 | 10346,39 | 22,00% |
| ARIMAX | 7 - 2 | 7600,8420 | 5100,34 | 11,66% |
| | 6 - 3 | 15745,33 | 13349,2 | 26,69% |
| | 5 - 3 | 12299,91 | 8553,70 | 18,18% |
| KNN | 7 - 2 | 5679,22 | 4173,48 | 8,928% |
| | 6 - 3 | 17185,65 | 14775,81 | 29,78% |
| | 5 - 3 | 14530,00 | 10176,97 | 21,61% |
| GRU | 7 - 2 | 1709,65 | 1279,17 | 2,601% |
| | 6 - 3 | 1544,72 | 1186,30 | 2,402% |
| | 5 - 3 | 1217,34 | 859,7465 | 2,053% |
| LSTM | 7 - 2 | 1991,8957 | 1555.4053 | 3,202% |
| | 6 - 3 | 2754,2221 | 2359.4824 | 4,64% |
| | 5 - 3 | 1348.894 | 972.1159 | 2.341% |
| HMM | 7 - 2 | 15847.72 | 14421.007 | 36.39% |
| | 6 - 3 | 50440.31 | 42715.53 | 106.7% |
| | 5 - 3 | 1957442996.41 | 1881544441.9805 | 99.99% |
| CNN | 7 - 2 | 2305,0413 | 1813.5836 | 3,576% |
| | 6 - 3 | 3433,91 | 2848.66 | 5,842% |
| | 5 - 3 | 2719.63 | 1949.53 | 4.350% |
| BSTS | 7 - 2 | 9299,79 | 7701,06 | 16,11% |
| | 6 - 3 | 7619,66 | 6277,13 | 14,67% |
| | 5 - 3 | 12476,19 | 9022,77 | 19,73% |




Predictive results of the HMM model for CMG with the rate of 5-3-2 (%)

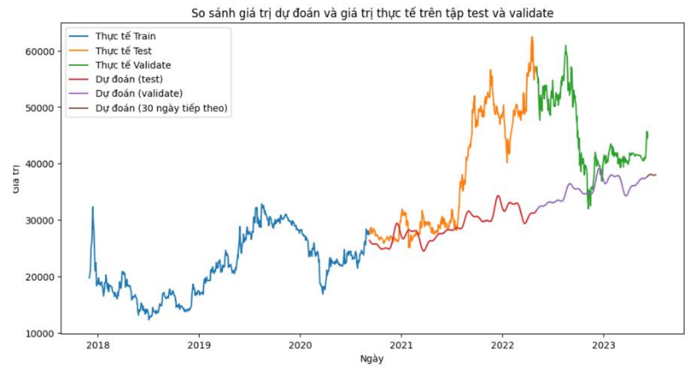



Predictive results of the CNN model for VIC with the rate of 5-3-2 (%)

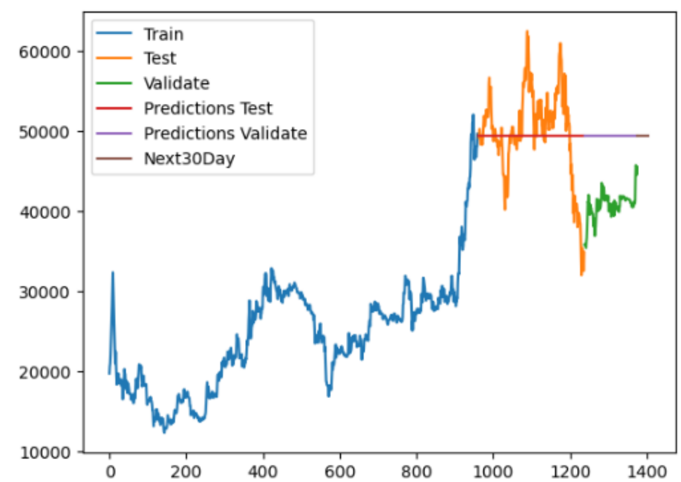



Predictive results of the LSTM model for CMG with the rate of 7-2-1 (%)

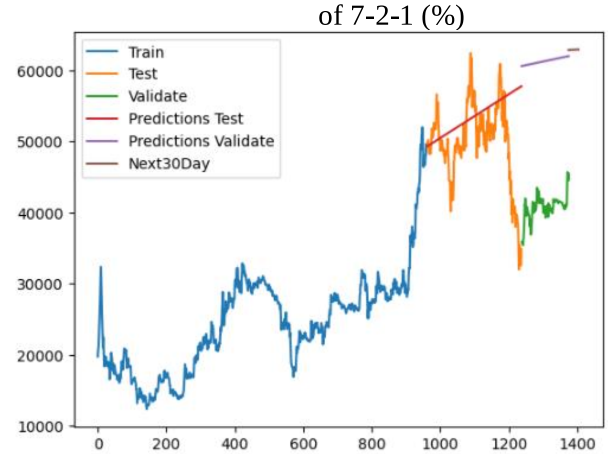

Predictive results of the Linear Regression model for CMG with the rate of 7-2-1(%)



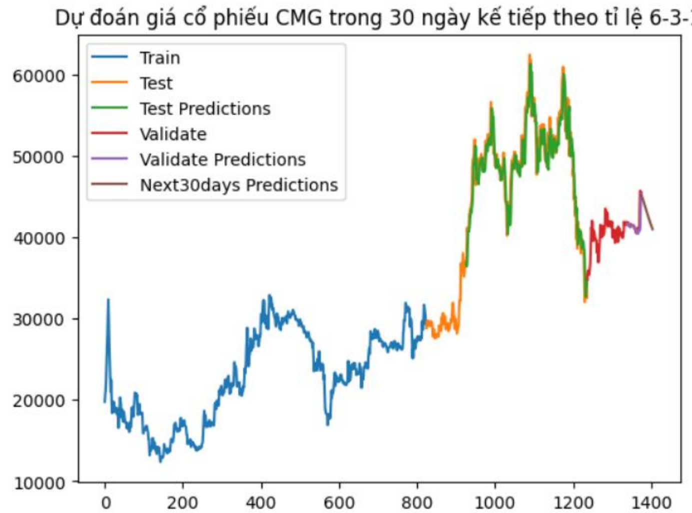

Predictive results of the BSTS model for CMG with the rate of 5-3-2 (%)



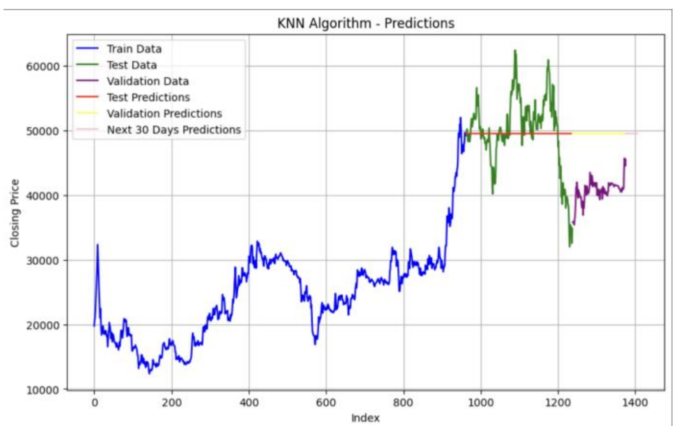

Predictive results of the ARIMA model for CMG with the rate of 7-2-1 (%)



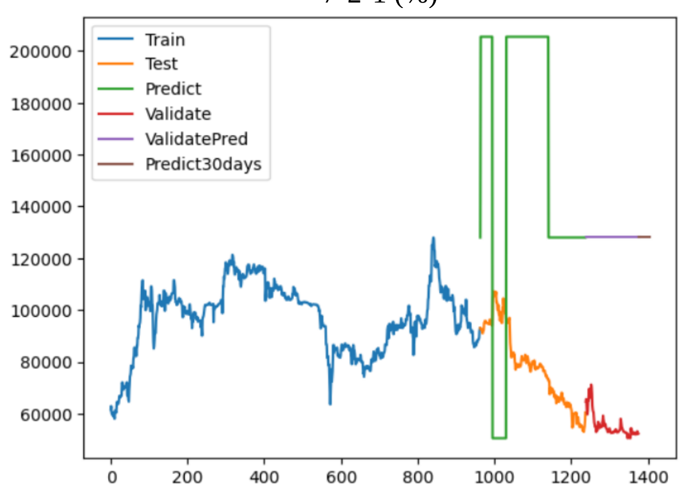

Predictive results of the ARIMAX model for CMG with the rate of 7-2-1 (%)



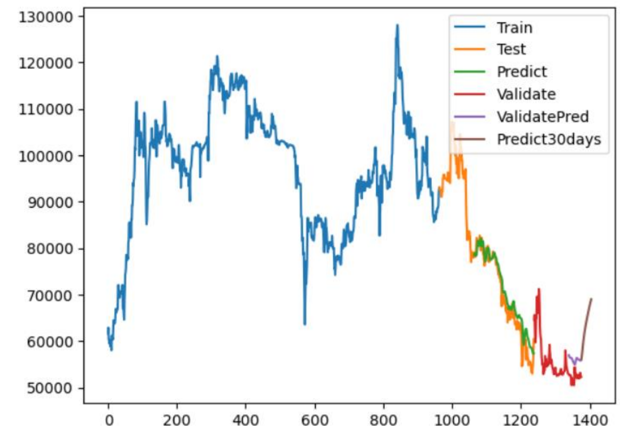
Predictive results of the GRU model for CMG with the rate of 6-3-1 (%)



Predictive results of the KNN model for CMG with the rate of 7-2-1 (%)

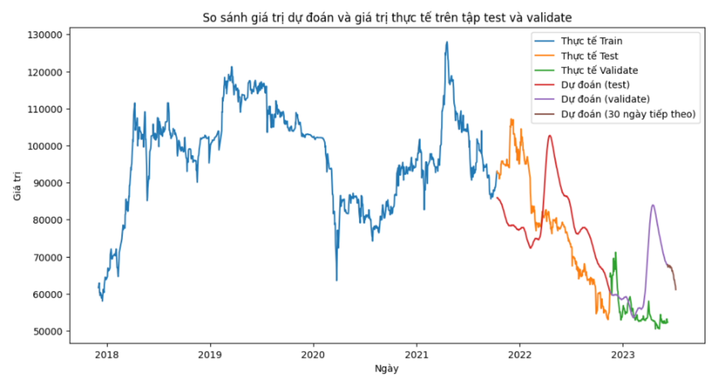


Predictive results of the HMM model for VIC with the rate of 7-2-1 (%)

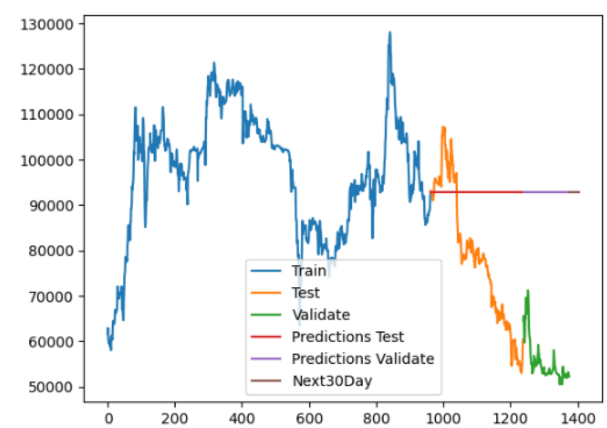


Predictive results of the LSTM model for VIC with the rate of 7-2-1 (%)

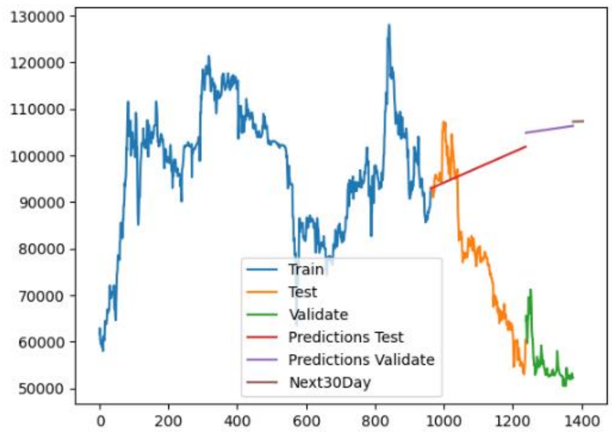
Predictive results of the Linear Regression model for VIC with the rate of 6-3-1 (%)



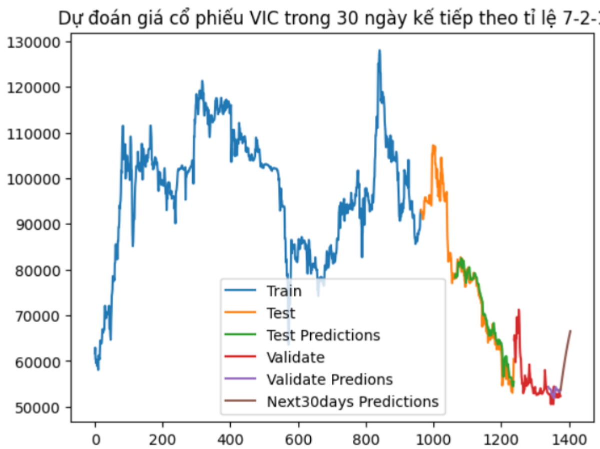
Predictive results of the BSTS model for VIC with the rate of 7-2-1 (%)



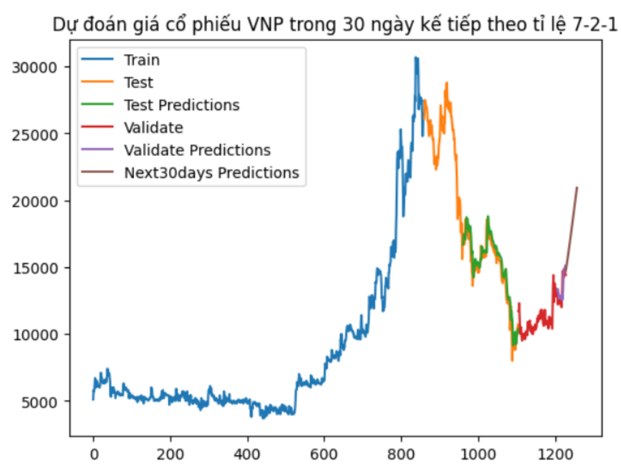
Predictive results of the ARIMA model for VIC with the rate of 7-2-1 (%)




Predictive results of the ARIMAX model for VIC with the rate of 7-2-1 (%)



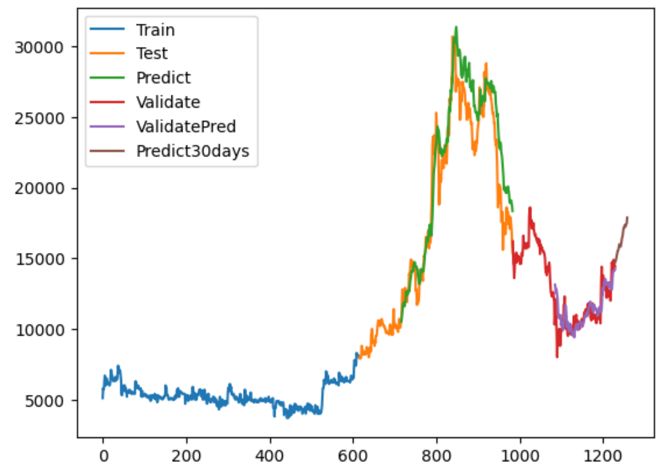

Predictive results of the GRU model for VIC with the rate of 7-2-1 (%)



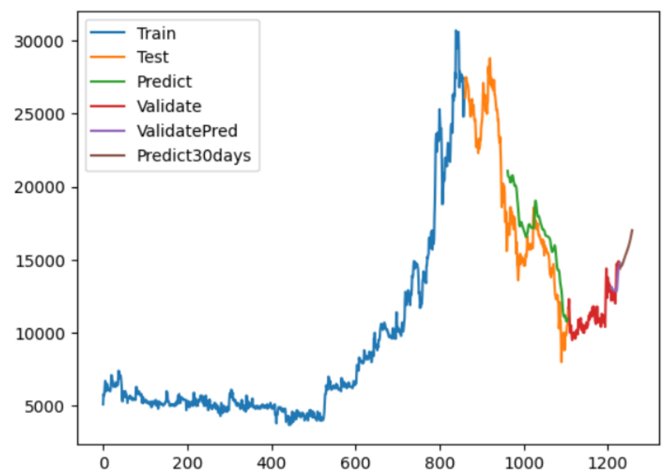

Predictive results of the GRU model for VNP with the rate of 7-2-1 (%)

## VI. CONCLUSION

The results of this study demonstrate that out of the five models tested (Linear, ARIMA, ARIMAX, LSTM, KNN, CNN, BSTS, HMM, GRU), the most




Predictive results of the CNN model for VNP with the rate of 5-3-2 (%)




Predictive results of the LSTM model for VNP with the rate of 7-2-1 (%)

suitable for predicting the future price of VIC, VNP and CMG stocks in the resulting time series was LSTM, GRU, CNN model. The other models, including the Linear, ARIMA, ARIMAX, KNN, BSTS, HMM did not perform as well. This study highlights the importance of considering a variety of modeling approaches in financial analysis, and the potential value of using LSTM, GRU, CNN model for predicting stock prices in the future. Further research could be conducted to verify the results of this study and to investigate the performance of the other models on different types stock price prediction tasks.

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