



FORECASTING STOCK PRICES IN VIETNAM USING MACHINE LEARNING AND DEEP LEARNING MODELS

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ABSTRACT The stock market has assumed a significant position within investment portfolios, as evidenced by the recent surge in investor participation within Vietnam's market. However, navigating the inherent volatility of stock prices requires experience and robust analytical tools. This paper seeks to empower investors by employing various forecasting models such as Linear Regression (LR), Auto Regressive Integrated Moving Average (ARIMA), recurrent neural network (RNN), Gated Recurrent Units (GRU), Long short term memory (LSTM), Fast Fourier Transform (FFT), XGBOOST, Fully Convolutional Networks (FCNs) to analyze price trends within three prominent bank stocks: ACB, BIDV, VCB traded on Hochiminh Stock Exchange (HOSE) over a five-year period (2019-2024). By evaluating the effectiveness of these models using RMSE, MAPE, and MSLE techniques. This paper aims to equip investors for informed stock selection within their portfolios, ultimately contributing to more accurate decision-making.

INDEX TERMS Time Series Analysis, Machine Learning, Financial Forecasting, Vietnamese Stock Market, GRU, RNN, ARIMA, LSTM, FFT, XGBoost, FCN, Linear Regression.

I. INTRODUCTION

The Vietnamese stock market has witnessed a record-high level of participation in recent years, reflecting the growing attention and interest it has garnered. This trend is a positive indicator of the market's potential and the overall recovery of the economy in the post-2023 period. However, the stock market also inherently carries short-term risks that investors must navigate. Among the various sectors, the banking industry has traditionally occupied a high proportion and serves as a crucial pillar of the economy. The purpose of this paper is to support investors in making accurate decisions regarding three bank stocks (ACB, BID, VCB) listed on the Hochiminh Stock Exchange (HOSE).

To achieve this goal, the study will apply various models, including Linear Linear Regression (LR), Auto Regressive Integrated Moving Average (ARIMA), recurrent neural network (RNN), Gated Recurrent Units (GRU), Long short term memory (LSTM), Fast Fourier Transform (FFT), XGBOOST, Fully Convolutional Networks (FCNs) to the stock price data from 2019 to 2024 to forecast the trends. Techniques such as RMSE, MAPE, and MSLE will be utilized to evaluate the effectiveness of these models.

II. RELATED WORKS

Over the past several years, a significant volume of research has concentrated on forecasting stock prices by leveraging various machine learning and statistical techniques. Maqsood et al. have used linear regression and 2 models for stock exchange forecasting [1]. Meanwhile, URAS combined linear regression and neural network models to forecast Bitcoin closing prices, showing that linear regression had faster execution speed and could accurately predict Bitcoin price fluctuations [2].

Manish Dadhich studied and applied the ARIMA model for short-term forecasting of BSE and NSE stock prices. After carrying out his research, Manish Dadhich demonstrated the strength of the ARIMA model in predicting daily closing prices of time series data [3]. In Anusha Garlapati's research, she also used ARIMA to forecast stock prices and concluded that ARIMA is a good model for predicting stock prices [4].

Yongqiong Zhu [5] applied an RNN model to predict the stock prices of Apple. The training dataset spanned 10 years with 65% allocated for training and the remaining 3% for testing. With 50 epochs, Adam optimization, and Mean Squared Error (MSE) as the loss function, the model achieved highly favorable outcomes. It attained a predictive accuracy exceeding 95%, with a reported loss value of 0.1%. In 2015, Xiao Ding [6] also proposed a deep learning method for

event-driven stock market prediction.

Shejul et al. [7] compared the performance of the Gated Recurrent Unit (GRU) and Bidirectional Long Short-Term Memory (BiLSTM) models in predicting stock prices. Experimental results indicate that both models accurately forecast future stock prices, with the BiLSTM model outperforming the GRU model. Despite this, the GRU model demonstrates nearly double the speed of the BiLSTM model due to its simpler architecture. Overall, both models offer precise predictions and can effectively anticipate future stock market trends.

C. Fjellström (2022) [8] explored an LSTM ensemble for stock price prediction in the paper "Long Short-Term Memory Neural Network for Financial Time Series." The work demonstrates superior performance over traditional portfolios, offering insights into LSTM's potential for financial forecasting and strategies for enhancing model accuracy and reducing market risk. S. Mehtab, J. Sen (2020) [9] proposed a deep learning approach for stock price prediction by employing Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Their work contributes to the field by exploring the effectiveness of this combined deep learning architecture in forecasting the NIFTY 50 index prices. They further emphasize the importance of data pre-processing and model evaluation, providing a methodological blueprint for financial market analysis using deep learning techniques.

Chen et al. [10] used an Fast Fourier Transform algorithm to deal with historical training data for forecasting stock prices, achieving a more highly accurate. Experimental analysis is performed on datasets covering a seven-year period of both the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and the Dow-Jones Industrial Average (DJIA).

A. Qingwen Jin et al. [11] established predictive models using the Best Track TC dataset and the XGBOOST algorithm to anticipate Tropical Cyclone (TC) intensity in the Western North Pacific (WNP). Across six scenarios, the model achieved high accuracy with MAE < 4.50 m/s, CC > 0.89, and NRMSE < 10.00%. The XGBOOST model exhibited superior performance compared to traditional Back-Propagation Neural Network (BPNN) models for the same predictors and independent prediction samples. A. O. A. A. Tianqi Chen and Carlos Guestrin (2016) [12] introduced XGBoost, a scalable tree boosting system. The paper describes the architecture of XGBoost and its core algorithms, presenting improvements to enhance performance and accuracy across a variety of machine learning tasks.

Fully Convolutional Networks (FCNs) have been studied and applied in various fields related to image data processing and semantic segmentation. According to Shima Nabiee's research on stock trend prediction, FCNs have also been proven to be a powerful and flexible tool, enabling the analysis and prediction of stock price trends based on raw data [13].

III. MATERIALS

A. DATASET

The analysis will focus on the historical stock prices of three banks in Vietnam: the Asia Commercial Joint Stock Bank (ACB), the Bank for Investment and Development of Vietnam (BIDV), and the Joint Stock Commercial Bank for Foreign Trade of Vietnam (VCB). The data spans from January 3, 2019, to January 3, 2024, and includes information such as date, price, opening price, highest and lowest prices, volume, and price change. However, the primary aim is to forecast closing prices, so only the "Price" column (VND) will be used for analysis.

B. DESCRIPTIVE STATISTICS

TABLE 1. ACB, BIDV, VCB's Descriptive Statistics

	ACB	BID	VCB
Count	1247	1252	1252
Mean	19.712	35.993	74.810
Standard Deviation	6.205	6.574	12.664
Min	8.763	23.420	43.925
25%	11.963	31.226	65.274
50%	22.000	34.823	75.871
75%	24.980	41.600	84.525
Max	30.360	53.900	106.500
Variance	49.100	28.667	106.500
Skewness	-0.345	0.299	-0.132
Kurtosis	-1.457	-0.821	-0.530

1) ACB stock price visualization

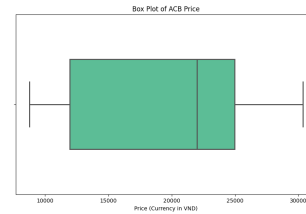


FIGURE 1. ACB stock price's boxplot



FIGURE 2. ACB stock price's time

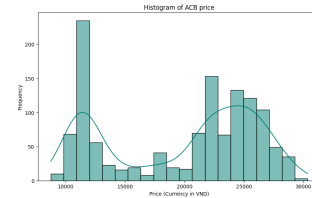


FIGURE 3. ACB stock price's histogram

ACB's price distribution appears left-skewed, as evidenced by the pronounced peak in the histogram at the lower end of the price range. Interestingly, ACB's box plot appears relatively compact, with the median closer to the higher end of the price range

2) BID stock price visualization

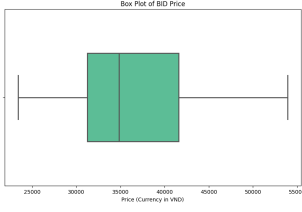


FIGURE 4. BID stock price's boxplot

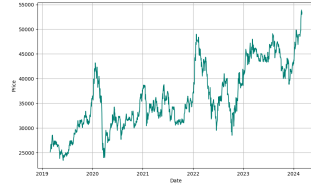


FIGURE 5. BID stock price's time

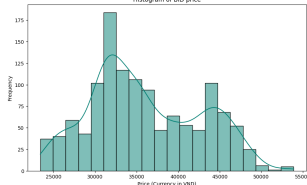


FIGURE 6. BID stock price's histogram

The value of BID shares mainly fluctuates between 33,000 VND and 43,000 VND, and the highest current value that BID shares have reached is 54,000 VND. Additionally, the current trend regarding the value of BID shares is on the rise.

3) VCB stock price visualization

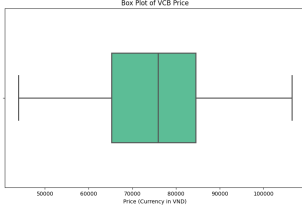


FIGURE 7. VCB stock price's boxplot

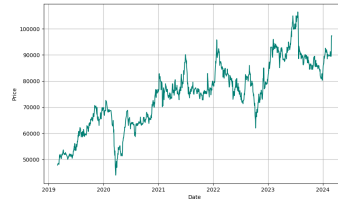


FIGURE 8. VCB stock price's time

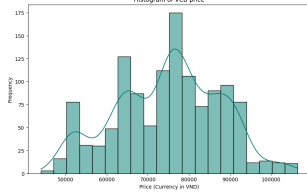


FIGURE 9. VCB stock price's histogram

Based on VCB's Boxplot, it can be seen that most of the data is concentrated in Q2 to Q3 with length 8654 approximately 75871 to 84525. The highest concentration on the chart at the price of about 76,000 VND with a frequency of nearly 175 times may be a sign of investors' special interest in VCB stock price. Besides, the price also fluctuates frequently around 70,000 VND. The data chart of price fluctuations over the years shows that stock prices tend to gradually increase, although prices also decrease to the lowest (43925) in early 2020 and the highest (106500) in mid-2023.

IV. METHODOLOGY

A. ARIMA

Auto Regressive Integrated Moving Average (ARIMA) is a model that describes time series based on observed values, which can be used to forecast future values. Applying ARIMA models to any time series showing patterns with no random white noise and non-seasonality. The model was introduced by Box and Jenkins in 1970. To generate short-term forecasts, ARIMA models have shown efficient capabilities, outperforming complex structural models. The future value of a variable in the ARIMA model is a combination of linearity to the past values and errors, expressed as follows [14]:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q}$$

Where:

- Y_t is the actual value at time t .
- ε_t is the random error at time t .
- ϕ_i and θ_j are the coefficients.
- p and q are integers, often referred to as autoregressive and moving average parameters, respectively.

B. FAST FOURIER TRANSFORM

The Fast Fourier Transform (commonly abbreviated as FFT) is a fast algorithm for computing the discrete Fourier transform (DFT) of a sequence [14] by using the factor $N/2 \log N$ where N is the number of points, therefore, the FFT is a way to convert the time series from time domain to frequency domain [15] with equation [16]:

$$F[n] = \sum_{k=0}^{N-1} f[k] \cdot e^{-i \frac{2\pi}{N} kn}$$

where:

- $F[n]$ is the Discrete Fourier Transform of the sequence.
- $f[k]$ is the k -th element of the input sequence.
- N is the total number of elements in the input sequence.
- n is the index of the frequency component in the output sequence $F[n]$.
- k is the index of the element in the input sequence $f[k]$.

C. LINEAR REGRESSION

Linear regression is a statistical technique used to model the relationship between a dependent variable, Y , and one or more independent variables, X . The goal is to find the best-fitting straight line (or hyperplane in higher dimensions) that describes the relationship between the variables. When there are multiple independent variables, the linear regression is called multivariable linear regression, with equation has the form [17]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon$$

Where:

- Y is the dependent variable.
- X_1, X_2, \dots, X_k are the independent variables.

- β_0 is the intercept term.
- β_1, \dots, β_k are the regression coefficients for the independent variables.
- ε is the error term.

D. XGBOOST

XGBoost is a highly efficient and scalable implementation of gradient boosting, a powerful machine learning technique. XGBoost operates by constructing a series of decision trees in an additive manner. Each tree is built sequentially, with each one correcting the errors of the previous trees. The model's objective is to minimize the loss function. Key advantages of XGBoost include its ability to handle large datasets through parallelized computing, effective handling of missing data values, and flexible parameter tuning. These features, along with its state-of-the-art algorithm for supervised learning problems, known for its high accuracy, which rivals deep learning models [18]. Unlike deep learning that typically requires numerical raw data, XGBoost can handle tabular datasets of any size and type, including categorical data often found in business models.

Explanation of the mathematics behind XGBoost:

Ensemble Model: XGBoost combines predictions from multiple decision trees (f_k) to create a final prediction ($F(x)$) [18]:

$$y_i = \phi(x_i) = \sum_{k=1}^K f_k(x_i), \quad f_k \in \mathcal{F},$$

Where: $F = f(x) = w_q(x) \mid q: \mathbb{R}^m \rightarrow T, w \in \mathbb{R}^T$

Objective Function: It minimizes a loss function (L) that measures prediction error, with a regularization term (Ω) to prevent overfitting: [19]

$$\text{obj}(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

Where, first term is the loss function and the second is the regularization parameter

E. GRU

The Gated Recurrent Unit, just like the LSTM, is a Recurrent Neural Network. It, however, has a less complicated structure compared to LSTM. It lacks an output gate but has an update z and a reset gate r . These gates are vectors which decide what information should be passed to the output. The Reset gate defines how to combine the new input with the previous memory. The definition of how much of the last memory to keep is done by the Update [12]. The GRU has the following equations: [20]

Update gate:

$$z_t = \sigma(W_z h_{t-1} + U_z x_t) \quad (1)$$

Reset gate:

$$r_t = \sigma(W_r h_{t-1} + U_r x_t) \quad (2)$$

Cell state:

$$c_t = \tanh(W_c(h_{t-1} * r_t) + U_c x_t) \quad (3)$$

New state:

$$h_t = (z_t * c_t) + ((1 - z_t) * h_{t-1}) \quad (4)$$

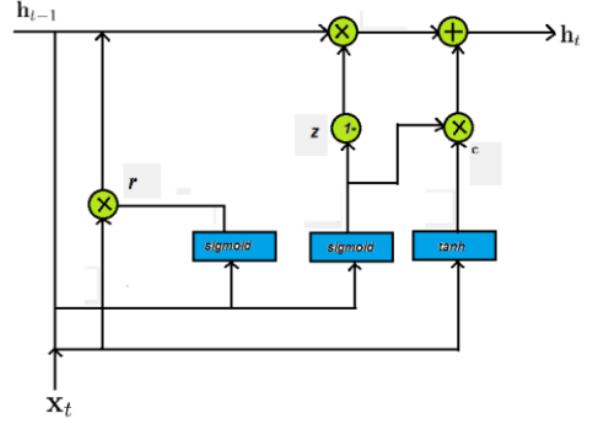


FIGURE 10. Fully Convolutional Neural Network architecture

F. FULLY CONVOLUTIONAL NEURAL NETWORK(FCN)

Fully Convolutional Neural Networks (FCNs) were introduced by Wang et al. (2017b) for univariate time series classification, validated on 44 UCR/UEA datasets. FCNs use convolutional layers without local pooling, maintaining the time series length throughout. A key feature is replacing the final fully connected layer with a Global Average Pooling (GAP) layer, reducing parameters and enabling Class Activation Mapping (CAM) to identify crucial input segments. FCNs lack pooling and regularization, benefiting from parameter invariance across varying time series lengths due to GAP, supporting transfer learning for model adaptation from one dataset to another. [21]

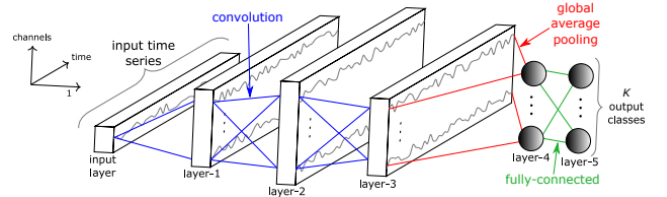


FIGURE 11. Fully Convolutional Neural Network architecture

G. RECURRENT NEURAL NETWORK (RNN)

A recurrent neural network (RNN) is a type of artificial neural network which uses sequential data or time series data [22]. A recurrent neural network (RNN) is an extension of a conventional feedforward neural network, which is able to handle a variable-length sequence input. The RNN handles the variable-length sequence by having a recurrent hidden state whose activation at each time is dependent on that of the

previous time [23]. For each timestep t , the activation $a^{<t>}$ and the output $y^{<t>}$ are expressed as follows:

$$a^{<t>} = g_1 (W_{aa} a^{<t-1>} + W_{ax} x^{<t>} + b_a)$$

and

$$y^{<t>} = g_2 (W_{ya} a^{<t>} + b_y)$$

where W_{ax} , W_{aa} , W_{ya} , b_a , b_y are coefficients that are shared temporally and g_1, g_2 are activation functions [24].

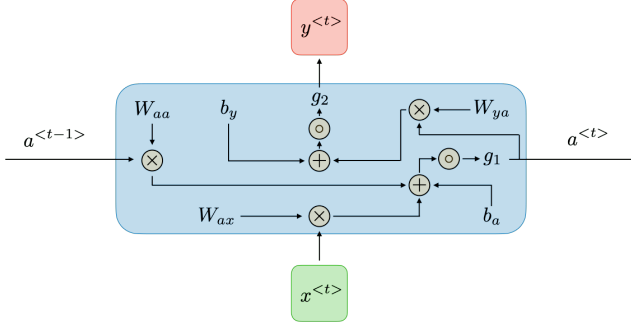


FIGURE 12. Architecture of a Traditional RNN

H. LONG SHORT TERM MEMORY (LSTM)

The Long Short-Term Memory (LSTM) model is a recurrent neural network designed to handle sequential data like time series. Unlike standard RNNs, LSTMs employ memory cells and gating mechanisms to selectively retain and discard information over long sequences. This allows LSTMs to effectively capture long-range dependencies within the sequential data.

At the core of an LSTM are the memory cells regulated by gates - input gate (controls inflow), forget gate (controls clearing), and output gate (controls outflow). This gating architecture enables LSTMs to learn and leverage long-term patterns and relationships present in sequences. By addressing long-range temporal dependencies, LSTMs excel at sequence prediction tasks, making them well-suited for applications such as time series forecasting.

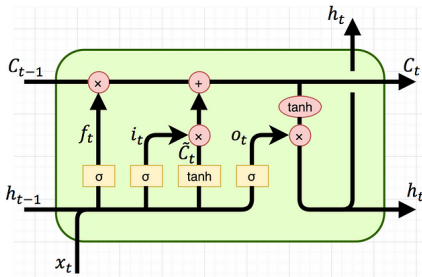


FIGURE 13. LSTM model

Input gate (i_t):

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

Forget gate (f_t):

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

Output gate (o_t):

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

Memory cell (C_t):

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

Hidden state (h_t):

$$h_t = o_t * \tanh(C_t)$$

- i_t, f_t, o_t are the values of the gates at time t .
- W_i, W_f, W_o, W_c are weight matrices.
- b_i, b_f, b_o, b_c are bias vectors.
- h_{t-1} is the hidden state from the previous layer.
- x_t is the input at time t .
- C_t is the memory cell state at time t .
- h_t is the hidden state at time t .

V. RESULT

A. EVALUATION METHODS

Mean Percentage Absolute Error (MAPE): is the average percentage error in a set of predicted values.

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n |y_i - \hat{y}_i| = 1$$

Root Mean Squared Error (RMSE): is the square root of average value of squared error in a set of predicted values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}}$$

Mean Absolute Error (MAE): is the average absolute differences between the expected and actual values.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Where:

- n is the number of observations in the dataset.
- y_i is the true value.
- \hat{y}_i is the predicted value.

B. ACB DATASET

Dataset's Evaluation				
Model	Proportion	RMSE	MAPE (%)	MAE
ARIMA	7:3	3932.5798	13.7514	3308.4751
	8:2	1542.0814	4.8217	1224.8404
	9:1	1238.2448	3.8899	997.3810
GRU	7:3	394.5391	1.007	244.3960
	8:2	476.5528	1.2615	297.4063
	9:1	765.6026	1.5120	411.5345
FCN	7:3	761.2610	0.0160	665.6353
	8:2	791.9841	0.0234	593.1706
	9:1	810.7567	0.0259	596.3067
RNN	7:3	448.0029	1.1568	281.8691
	8:2	470.8093	1.4700	293.8402
	9:1	810.3059	1.4771	512.4873
LSTM	7:3	531.4864	1.4123	363.7865
	8:2	493.5754	1.2753	329.8735
	9:1	575.0604	1.6582	426.0182
FFT	7:3	12402.8913	50.2753	11653.0983
	8:2	4641.5937	18.8262	4368.4796
	9:1	5794.8085	13.1265	4777.7704
XGBOOST	7:3	404.4547	1.1835	288.2362
	8:2	431.8621	1.5538	337.4326
	9:1	797.5681	2.2187	616.6294
LR	7:3	9134.5335	6.7563	1721.6769
	8:2	3512.4499	11.5962	3100.1106
	9:1	1797.1567	5.5612	1449.3393

TABLE 2. ACB Dataset's Evaluation

Based on the table, we conclude that the GRU model with a 7:3 proportion is the best choice for forecasting ACB's stock prices over the next 30 days, as it achieves the low values in RMSE, MAPE, MAE.

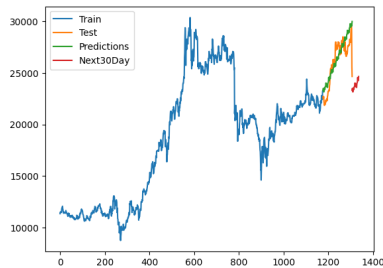


FIGURE 14. ARIMA model's result with 9:1 splitting proportion

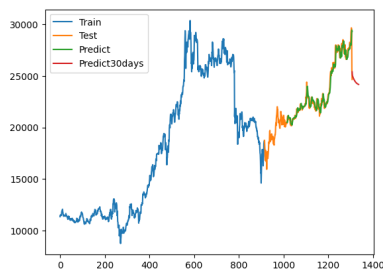


FIGURE 15. GRU model's result with 7:3 splitting proportion

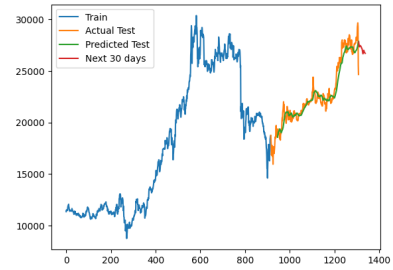


FIGURE 16. FCN model's result with 7:3 splitting proportion

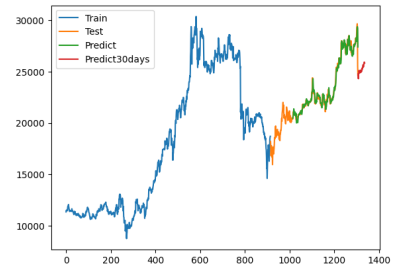


FIGURE 17. RNN model's result with 7:3 splitting proportion

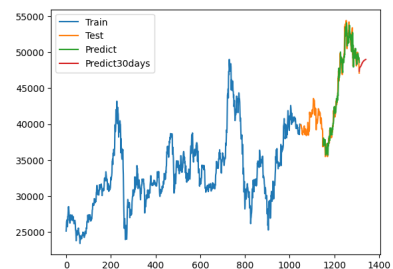


FIGURE 18. LSTM model's result with 8:2 splitting proportion



FIGURE 19. FFT model's result with 7:3 splitting proportion

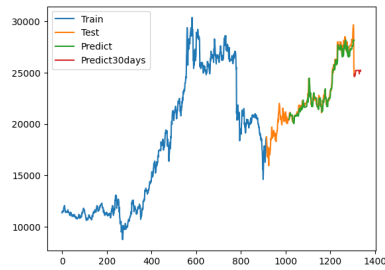


FIGURE 20. XGBoost model's result with 7:3 splitting proportion

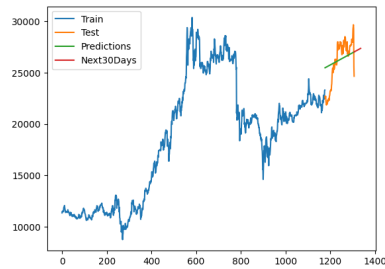


FIGURE 21. Linear Regression model's result with 9:1 splitting proportion

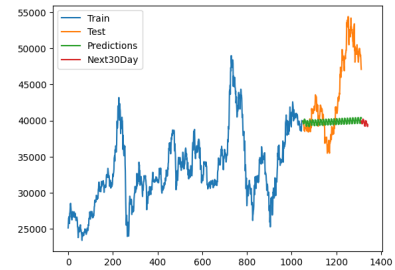


FIGURE 22. ARIMA model's result with 8:2 splitting proportion

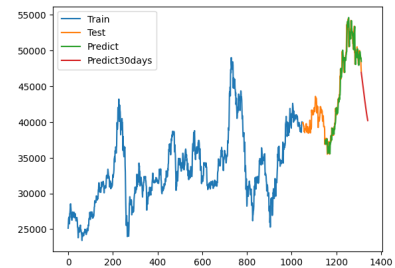


FIGURE 23. GRU model's result with 8:2 splitting proportion

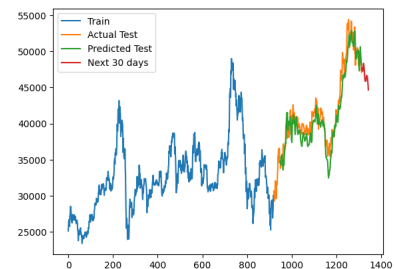


FIGURE 24. FCN model's result with 7:3 splitting proportion

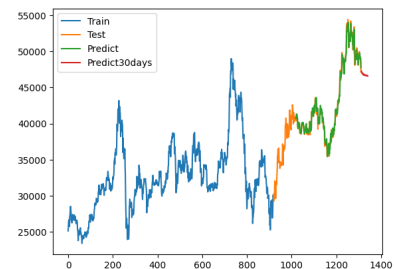


FIGURE 25. RNN model's result with 7:3 splitting proportion

C. BID DATASET

Dataset's Evaluation				
Model	Proportion	RMSE	MAPE (%)	MAE
ARIMA	7:3	9563.7477	19.8847	8620.5906
	8:2	6464.7779	10.0109	4764.1887
	9:1	6158.2991	10.6520	5292.1888
GRU	7:3	811.9859	1.3382	586.6200
	8:2	804.1871	1.2751	584.2526
	9:1	1047.6395	1.4999	744.9879
FCN	7:3	1636.2305	0.0317	1336.0777
	8:2	2481.7959	0.0432	2005.2779
	9:1	2552.3799	0.0446	2247.3583
RNN	7:3	730.3118	1.2270	533.1443
	8:2	831.5655	1.3253	603.7621
	9:1	920.7904	1.2527	617.9939
LSTM	7:3	531.4864	1.4123	339.2725
	8:2	493.5754	1.2753	329.8735
	9:1	577.0604	1.6582	426.0182
FFT	7:3	4894.1684	11.6059	5783.9707
	8:2	6459.4307	12.6873	5674.0699
	9:1	8002.1502	12.4200	6248.1023
XGBOOST	7:3	2908.0631	3.8156	4318.2261
	8:2	3206.6953	3.9514	3670.8829
	9:1	3752.4153	7.2912	3620.9575
LR	7:3	5967.7684	11.6453	4496.2716
	8:2	6678.0104	12.9205	5097.8035
	9:1	8699.7701	19.1198	7686.7608

TABLE 3. BID Dataset's Evaluation

Based on the evaluation table, the LSTM model with an 8:2 training/testing ratio provides the best prediction results for BID stock prices, with the lowest RMSE (493.5754), MAPE (1.2753), and MAE (329.8735). GRU is also a strong choice with similar performance at the same ratio. Overall, LSTM stands out as the top choice for predicting BID stock prices.

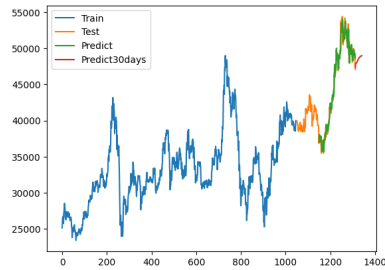


FIGURE 26. LSTM model's result with 8:2 splitting proportion

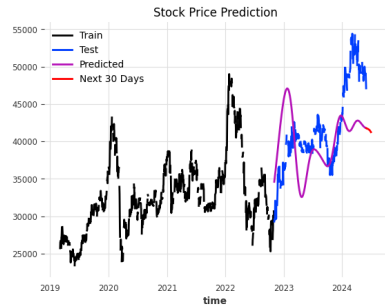


FIGURE 27. FFT model's result with 7:3 splitting proportion

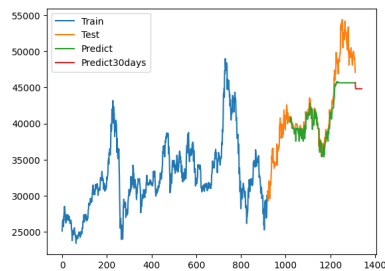


FIGURE 28. XGBoost model's result with 7:3 splitting proportion

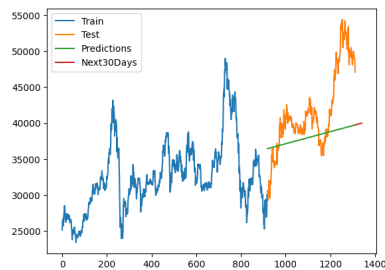


FIGURE 29. Linear Regression model's result with 7:3 splitting proportion

D. VCB DATASET

Dataset's Evaluation				
Model	Proportion	RMSE	MAPE (%)	MAE
ARIMA	7:3	39861.8637	41.9820	36312.4125
	8:2	16889.0992	15.3808	13728.8500
	9:1	3827.0147	3.5494	3130.8613
GRU	7:3	1224.6726	1.0457	912.9100
	8:2	1314.5240	1.1061	989.5174
	9:1	829.2120	0.7164	656.1504
FCN	7:3	2192.3873	0.0202	1712.1799
	8:2	3943.3529	0.039	3509.7156
	9:1	2773.4293	0.0234	2163.6424
RNN	7:3	1697.2557	1.5721	1348.6940
	8:2	1537.9391	1.3413	1185.1081
	9:1	872.8985	0.7490	682.9690
LSTM	7:3	1902.6655	1.8272	1648.573
	8:2	2788.466	2.8693	2580.269
	9:1	1135.6407	0.9596	851.0078
FFT	7:3	5304.4333	4.7513	4075.0324
	8:2	10602.9959	10.4838	9349.2730
	9:1	10551.3341	9.4645	8695.5248
XGBOOST	7:3	3682.6546	3.308	2924.0263
	8:2	4647.9822	4.4902	3.990
	9:1	1698.2616	1.5916	1462.3939
LR	7:3	6987.9849	7.1427	5818.5129
	8:2	9168.4296	10.5427	8439.4780
	9:1	6673.7497	6.9101	5853.9128

TABLE 4. VCB Dataset's Evaluation

Based on the table, we conclude that the GRU model with a 7:3 proportion is the best choice for forecasting VCB's stock prices over the next 30 days, as it achieves the low values in RMSE(829.2120), MAPE(0.7164), MAE(656.1504)

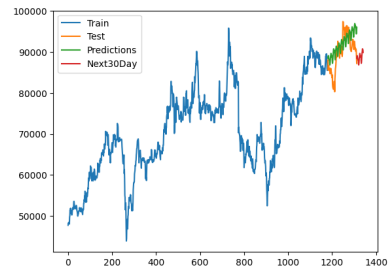


FIGURE 30. ARIMA model's result with 9:1 splitting proportion

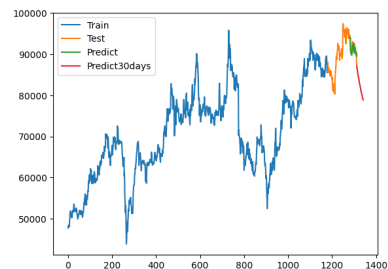


FIGURE 31. GRU model's result with 9:1 splitting proportion

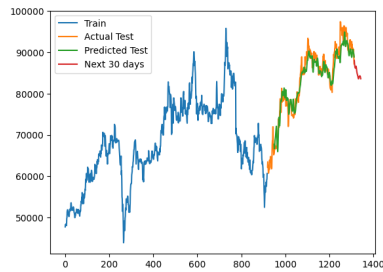


FIGURE 32. FCN model's result with 7:3 splitting proportion

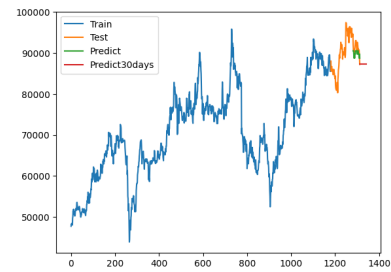


FIGURE 36. XGBoost model's result with 9:1 splitting proportion

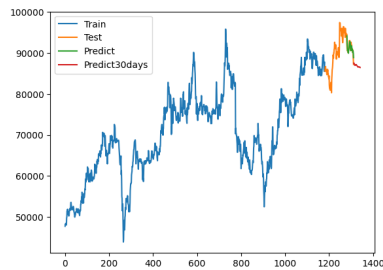


FIGURE 33. RNN model's result with 9:1 splitting proportion

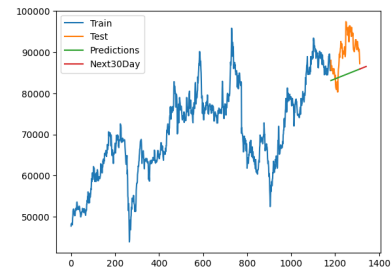


FIGURE 37. LR model's result with 9:1 splitting proportion

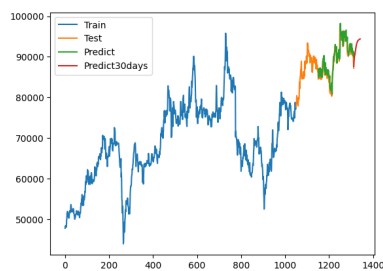


FIGURE 34. LSTM model's result with 9:1 splitting proportion

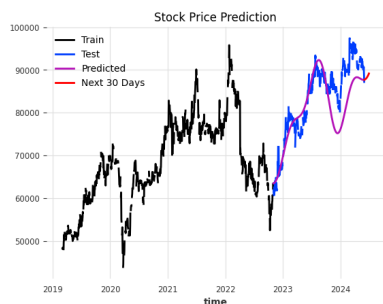


FIGURE 35. FFT model's result with 7:3 splitting proportion

VI. CONCLUSION

Based on the summary table of the accuracy of 8 models (ARIMA, GRU, FCN, RNN, LSTM, FFT, XGBoost, and Linear Regression) for 3 datasets (ACB, BID, and VCB) with 3 train-test ratios (7:3, 8:2, and 9:1), we can draw some notable conclusions:

GRU and RNN demonstrate impressive performance across all three datasets and all train-test ratios. Their RMSE, MAPE, and MAE scores are significantly lower compared to the ARIMA, FFT, and Linear Regression models. GRU is also a strong choice with similar performance when the train-test ratio is 8:2. XGBoost also shows good performance, especially with train-test ratios of 7:3 and 8:2, outperforming traditional models.

LSTM, with a train-test ratio of 8:2, gives the best prediction results for BID stock prices, with the lowest RMSE, MAPE, and MAE, but it is not as stable as GRU and RNN. Its results are generally average compared to other models, but overall, LSTM stands out and is the top choice for predicting BID stock prices. FCN shows positive results with ACB and BID but is not stable with VCB.

VII. ORIENTATION

The report can be expanded and improved by enhancing evaluation methods such as perform sensitivity analysis to better understand the influence of each input factor on the forecasting results. Secondly, develop Real-Time Forecasting Systems like create a real-time forecasting system to continuously provide investment recommendations to investors. These development directions will help improve the accuracy and applicability of forecasting models, better supporting investors in making informed decisions.

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