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Stock Market Prediction: ARIMA-LSTM-PROPHET Approach - Statistic Model

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-Abstract

Time series modelling and forecasting – a method that predicts future values by analyzing past values – plays an important role in many practical fields. Stock Market prediction bring us these advantages which are the basic factors for most researchers in the field . More and more valuable market information is publicly available online. In this paper, we analyze the stock market as BIDV, MaSan Group Corp, HoaSen Group from May 12, 2017 to May 12, 2022 with 3 models such as ARIMA[1], LSTM[2], Prophet[3]] and statistical methods like Linear Regression[4] and Non-Linear Regression[5] to choose and build the most suitable model according to the closed price. The first data about 10-30% are used as the training set, while the remaining data are used as the testing set. A detailed explanation of model selection and forecasting accuracy is presented.

Keywords: Long short-term memory(LSTM),Autoregressive integrated moving average(ARIMA),Linear Regression, Non-Linear Regression,Prophet,statistical methods, models, Stock Market prediction

I. INTRODUCTION

When its comes to demand forecasting, stock market prediction is considered a field of predictive analytics that attempts to understand and predict customer needs in order to optimize supply decisions along a company's supply chain and business management. Price and demand forecasting involves quantitative methods such as using data and especially historical sales data as well as statistical techniques from test markets. Accordingly, demand forecasting can be used in production planning, inventory management and sometimes in assessing future capacity requirements or in making decisions about whether should enter a new market or not. Market forecasting can be considered as the process of creating estimates about the economic situation in general and the market in particular in the future, serving business decisions or policy making government, and accordingly, a variety of forecasting methods are used to estimate indicators that reflect complex economic situations, require large amounts of data, and are expensive.

The prediction of market offers huge chances for profit and is a major motivation for research. This leads to a picture of the importance of mining techniques to automatically extract meaningful information for stock market analysis. To work towards a good outcome, it is important to provide reliable forecasts to investors. The aim of this paper is to predict the stock market (BIDV, MASAN ,HSG) from May 12, 2017 to May 12, 2022.These model(ARIMA, LSTM, Prophet) are selected because of the capability to correct the local trend in data, where the pattern in the previous period can be used to forecast the future. Thus, these model also supports the modeling of one perspective as a function of time. Due to the seasonal trend of time series used, these models are selected for development.

Market forecasting is necessary for marketing this is all decisions in the field of marketing are based on market forecasts, in case the market forecast is more accurate, the more likely it will be make correct decisions.

Thus, a 15-day ahead forecast of Close Price seems to be a good balance and allows us to closely link my analysis to there cent literature.

II. RELATED WORK

The Stock market prediction has been an important exertion in business and finance for many years. Correct prediction of stock market is very important for the investors to determine that if it would be better to buy any specific stock or not. There have been a significant number of studies and analysis done by many enthusiasts who applied previously established prediction models to acquire more accuracy

In the report “Stock Market Price Forecasting Using the Arima Model” of Tamerlan Mashadihasanli [6]. The author has researched and investigated the application of an autoregressive integrated moving average (ARIMA) to forecast the monthly stock market price index in Istanbul in the period from 2009-M01 to 2021-M03. Compared with all other projection models, the study shows that the ARIMA(3,1,5) model is the most suitable model to predict the stock market price index. The forecast is made using the developed ARIMA (3,1,5) model and the results show that the predicted values are very similar to the actual values, which helps to reduce the forecast error.

“Stock Price Prediction using ARIMA Model” of Aravind Ganesan, Adarsh Kannan[7].This report has been predicted by the ARIMA model of the stock prices of ICICI Bank and Reliance Industries and implemented with various packages in python. The specific instances of ICICI Bank and Reliance Industries have been used for verifying the hypothesis. The only drawback of this analysis is that ARIMA model holds higher accuracy for short-term prediction. Stock prices depend upon not only economic factors, but they relate to various physical, psychological, rational and other important parameters. In this research work, the stock prices are predicted using the Auto Regressive Integrated Moving Average (ARIMA) Model. Stock price predictive models have been developed and run-on published stock data acquired from Yahoo Finance. The experimental results lead to the conclusion that ARIMA Model can be used to predict stock prices for a short period of time with reasonable accuracy.

“Stock Market Analysis Using Linear Regression” of Taran Rishi[8]. After calculating the residual, the p-value, determine the variance, know the result of the R2 value of 1,0000. This shows that the entire change in the closing price of a stock can be explained by the change in the opening price, high price, low price and volume of the stock. Therefore, opening, high, low and volume are important variables in predicting closing prices. Open, high, and low are statistically significant variables while volume is not statistically significant in this model. To eliminate multicollinearity, the author removed high and low variables. The reduced model has an R2 value of 0.9997. This implies that 99.97% of the change in a stock's closing price can be explained by the change in the stock's opening price and volume. Both open and volume are statistically significant variables in this model

Jui-Sheng Chou and Thi-Kha Nguyen [9]. “Forward forecast of stock price using sliding-window metaheuristic-optimized machine-learning regression”. The future prices of stock has been calculated by using the Time series forecasting.The efficacy of stock price predicts affecting the nonlinearity of the time series in a dynamic environment. The purpose of predicting the stock prices of Taiwan construction companies, this paper suggests uses metaheuristic optimization as an intelligent time series prediction system. Patterns are difficult to capture by traditional models, the proposed model is a predictive technique for highly nonlinear time series. Investors used stock price statistics and stock indices as well as news on stocks for the purpose ofpredicbbting market movement. Hence they showed their effects on stock prices or historical shifts in prices and analyzed their movements for the future. This work incorporates market knowledge and stock prices in a single model in order to achieve greater precision in stock forecasts.

“Using LSTM in Stock prediction and Quantitative Trading” of Zhichao Zou, Zihao Qu[10]. This article establishes a forecasting framework for predicting stock prices. The author uses combination of price, volume, and company statistics as input. The owner of the report proposes, develops, trains and tested four models: ARIMA, LSTM, Stacked-LSTM and Attention-LSTM models, and built Long-Only and Long-Short trading strategies according to the author's model prediction.Attention-LSTM shows superior results compared to other models due to the ability to assign different weights to input features thus automatically selecting the most suitable features. Therefore, Attention-LSTM capable of capturing long-term dependence in time series and is more suitable in predicting financial time series. Author's superior trading profit from Attention-LSTM further confirmed experimental results. Furthermore, the author has shown that although the more complex model structure of LSTM stacked on single LSTM model, LSTM stacked no better model performance on the single LSTM model due to the possibility of overfitting. A direction of future work will are dealing with volatility of stock time series. A difficulty in predicting the stock market arises from its non-permanent behavior.

“Stock Price Prediction using Facebook Prophet” of Sumedh Kaninde , Manish Mahajan , Aditya Janghale and Bharti Joshi[11]. The conclusion show that the system is designed for predictions of the future prices of stocks for next 5 years using Facebook Prophet that can be used for better investments. This makes it easy to determine which stock to choose for investment based on the predictions giving the highest percentage of returns in a given period of time.The prediction accuracy can be increased by using several other features of Facebook Prophet and also make the application interactive and easy to use. In future, the stock market prediction system can be further increased by utilising a larger dataset than one being used presently. This will help to rise the accuracy of prediction models

III. MATERIALS AND METHODS

A. Data Collection

This research was carried out Stock market in four years(12/05/2017-12/05/2022). The data was using ARIMA, LSTM, Prophet model to predict. The collected data will need to go through cleaning to ensure that the findings are not skewered by errors such as missing values. The dataset of the daily opening price, highest price, lowest price, and closing price of Market Stock is formatted in .CSV file and does not require much cleaning as there were no missing or unreliable entries of data. The most of them needs to be done in order to determine which parameters would best lead to a higher accuracy in predicting the price direction of Market Stock. We get the data set through investing.com website with three datasets about companies SHB,BID,MSN. This website provides a full range of market-related information according to each trend over the years with the highest possible accuracy. The information here has been compiled according to the following components: highest, lowest, difference, average, % change and these data have alternating changes over many amplitudes of days in each year. These fluctuations give different results in an uptrend or downtrend. The orderly opening and closing time of the market ensures investors have the best time to prepare within the specified time frame. Based on past data, we filter the data set by components to predict the future: Date, Open, High, Low, Close, Volume (12/05/2017-12/05/2022).

Date	Open	High	Low	Close	Volume
5/12/2017	42600	42750	42500	42600	430230
5/15/2017	42500	42700	42300	42600	212110
5/16/2017	42500	44500	42500	43850	572240
5/17/2017	43850	44250	43200	43500	410490
5/18/2017	43000	44000	43000	43500	377570
5/19/2017	43500	43750	43000	43000	191520
5/22/2017	43300	44500	43050	44100	403650
5/23/2017	44600	45100	43700	44100	591860
5/24/2017	44500	44500	43500	43500	607770
5/25/2017	43500	43800	42500	43000	962430
5/26/2017	42600	43800	42600	42800	241540

Fig1. Data file MSN. csv

Date	Open	High	Low	Close	Volume
5/12/2017	12608	12830	12534	12571	4070000
5/15/2017	12534	12571	12385	12534	3890000
5/16/2017	12608	12645	12385	12534	4470000
5/17/2017	12460	12534	12348	12385	2880000
5/18/2017	12385	12645	12348	12460	4110000
5/19/2017	12497	12756	12422	12756	6780000
5/22/2017	12905	13646	12905	13646	19750000
5/23/2017	13646	14202	13461	13757	12710000
5/24/2017	13683	14351	13572	14277	12100000
5/25/2017	14277	14610	14091	14165	10770000
5/26/2017	14091	14462	14091	14462	8380000

Fig2. Data file BID. csv

Date	Open	High	Low	Close	Volume
5/12/2017	16300	16383	16218	16300	4690000
5/15/2017	16432	16432	16251	16284	3850000
5/16/2017	16251	16267	15839	15839	7580000
5/17/2017	15806	16070	15708	15938	1470000
5/18/2017	15905	15987	15740	15905	3480000
5/19/2017	15955	15971	15757	15955	3060000
5/22/2017	16053	16432	16037	16366	7700000
5/23/2017	16564	16663	16416	16465	5010000
5/24/2017	16531	16992	16432	16959	9140000
5/25/2017	17124	17124	16663	16695	7310000

Fig3. Data file HSG. Csv

B. Feature Extraction

We have compiled some features based on the database after sifting through. We found the two most important components to giving accurate parameters are Date and Close. The library matplotlib.pyplot helps us to calculate the columns in the histogram with the Axes object. These features are correlated with the Close of data files(20,5).

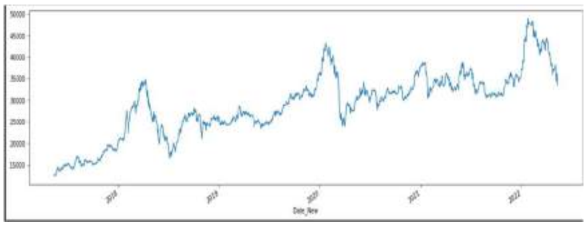

Fig4. Histogram of BID

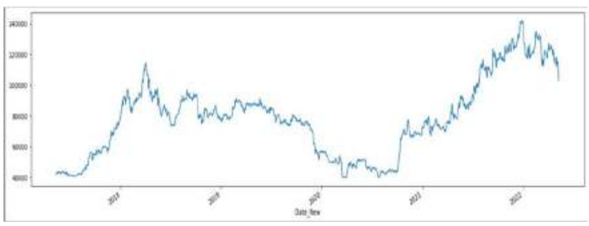

Fig5. Histogram of MSN

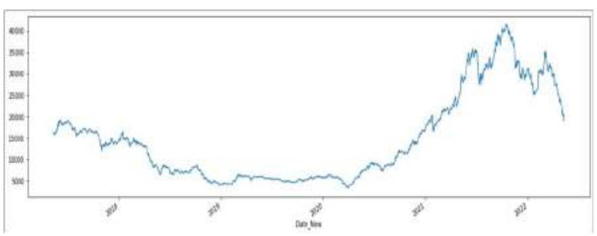

Fig6. Histogram of HSG

The histograms show the data grouped from 12/05/2017 to12/05/2022 and each bin has a width of one year. The histograms of the Close data peaks on 2022. The value of each histograms achieving the highest Close price are **HSG**: 41542 **BID**: 49000, **MSN**: 142286.

After statistical significance of the dataset, we continue to use those two components to predict the next days. The turn models that we use for prediction are: Linear Regression ,Non-Linear Regression, ARIMA, LSTM, Prophet

C. Modelling

- **Regression Analysis**
- ***Linear Regression***

Linear regression is a way to model the relationship between two variables. You might also recognize the equation as the slope formula. The equation has the form

$$Y = a + bX$$

- **Where**
  - Y is the dependent variable (that's the variable that goes on the Y axis)
  - X is the independent variable (i.e. it is plotted on the X axis)
  - b is the slope of the line and a is the y-intercept.
- ***Non-Linear Regression***

Nonlinear regression is a mathematical model that fits an equation to certain data using a generated line. As is the case with a linear regression that uses a straight-line equation (such as Ỵ= c + m x), nonlinear regression shows association using a curve, making it nonlinear in the parameter.

A simple nonlinear regression model is expressed as follows:

$$Y = f(X,\beta) + \epsilon$$

- **Where:**
  - X is a vector of P predictors
  - β is a vector of k parameters
  - F (-) is the known regression function
  - ϵ is the error term
- ***ARIMA model***

The ARIMA model is a statistical tool that provides complementary approaches for predicting future values in time series to obtain meaningful insights with random errors. Although exponential smoothing approaches are constructed for the trend and seasonality captured in the data, the ARIMA model describes autoregressive moving average linear model types in statistical predictions . However, there is a significant stumbling block in the adoption of the ARIMA prediction model: the order selection procedure is often considered subjective and is difficult to implement . The performance with seasonal series data renders the use of the standard ARIMA model ineffective . The model has the disadvantage of not being able to handle seasonal data, which is frustrating. Thus, the Inventions ARIMA model was upgraded to the SARIMA model to maintain the time series when it uses both seasonal and non-seasonal data for processing univariate time series data . The main components of the ARIMA model are autoregression (AR), integration (I), and the moving average (MA), and the model defines the data as stationary, non-stationary, and seasonal processes with the order (p, d, q), where p refers to the autoregressive lag observations included in the model, d is the difference order or the number of times that the raw observations are differenced, and q is the MA lag or the size of the MA window . The seasonal ARIMA (p, d, q) ∗ $(P, D, Q)_s$ are the non-negative integers for handling seasonality, X_t is the observed value at time t, and s is the number of periods per season. Equation (1) represents the general form of the SARIMA prediction model

$$\mathbf{\Phi_p(G)\phi_p(G^s)\,(1-G)^d\,(1-G^s)^D\,X_t = \gamma_q(G)\,w_Q(G^s)\,e_t} \quad (1)$$

Where the coefficients $\phi_p(G)$ and $\gamma_q(G)$ are the orders of the non-seasonal AR and nonseasonal MA components characteristic polynomials, and the polynomials $\phi_p(G^s)$ and $w_Q(G^s)$ are the seasonal autoregressive (SAR) and seasonal moving average (SMA) polynomials, respectively. The non-seasonal and seasonal time series are $(1-G)$ and $(1-G^s)$, respectively, which are the differencing components.

In addition, d and D are the non-seasonal ARIMA model's ordinary differenced terms and the SARIMA model's seasonal differenced terms, respectively; et is the prediction error; s is the duration of the seasonal pattern and G is the backshift operator coefficient.

- RA : $\phi_p(G) = 1 - \phi_1 G - \phi_2 G^2 - \phi_3 G^3 - \ldots - \phi_p G^p$ (2)
- MA : $\gamma_q(G) = 1 - \gamma_1 G - \gamma_2 G^2 - \gamma_3 G^3 - \ldots - \gamma_q G^q$ (3)
- SRA : $\phi_p(G^s) = 1 - \phi_1 G^s - \phi_2 G^{2s} - \phi_3 G^{3s} - \ldots - \phi_p G^{ps}$ (4)
- SMA : $w_Q(G^s) = 1 - w_1 G^s - w_2 G^{2s} - w_3 G^{3s} - \ldots - w_Q^{GQs}$ (5)

- ***LSTM model***

LSTM is a popular deep learning technique in RNN for time series prediction. LSTM is used for both classification and regression problems. The key component of LSTM architecture is the cell state which runs through the chain, with only linear interaction, keeping information flow unchanged. The gate mechanism of LSTM deletes or modifies the information of the cell state. It is a way to pass the information selectively that consists of the sigmoid layer, hyperbolic tangent layer, and the point-wise multiplication operation.

For given input sequence $\{x_1,x_2,\ldots,x_n\}$, $x_t \in R^{k\times 1}$ is the input sequence at time t. The memory cell c_t updates the information using three gates: input gate i_t, forget gate f_t, and change gate $\tilde{c_t}$. The hidden state h_t is updated using output gate o_t and the memory cell c_t. At time t, the respective gates and layers compute the following functions:

- Input gate: $i_t = \sigma(W_i x_t + W_{hi} h_{t-1} + b_i)$,
- Forget gate: $f_t = \sigma(W_f x_t + W_{hf} h_{t-1} + b_f)$,
- Output gate: $o_t = \sigma(W_0 x_t + W_{ho} h_{t-1} + b_0)$,
- $\tilde{c_t} = \tanh(W_c x_t + W_{ho} h_{t-1} + b_c)$,
- $c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{c_t}$,
- $h_t = o_t \otimes \tanh(c_t)$
- **where**
  - σ
  - tanh represent the sigmoid and hyperbolic tangent functions respectively the operator is the element-wise product
  - $W \in R^{dxd}$ are weight matrices
  - $B \in R^{dx1}$and are bias vectors.
  - n,k,d are sequence length, the number of features, and the hidden size respectively

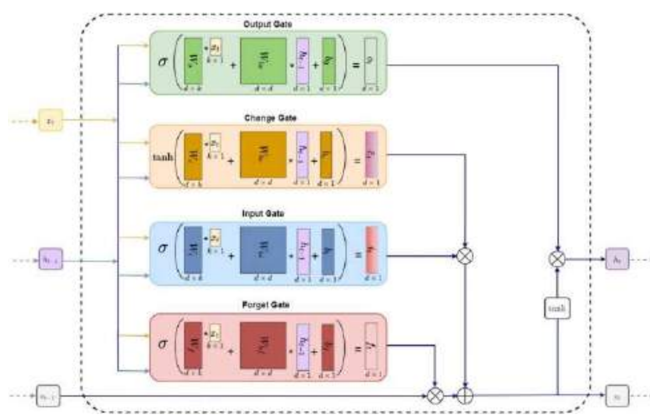

Fig7. Long short-term memory (LSTM) architecture

- ***Prophet model***

Prophet is an open source data algorithm released by the Core Data Science team of Facebook based on the Sklearn model. It is used for many applications with high accuracy and fast processing speed. Prophet can handle cluttered data with ease, adapting to outliers without manual handling, data loss, and sudden changes in time series. Prophet also supports the ability to refine the prediction,, using various parameters to improve the prediction

The core of Prophet is the sum of three functions of time plus an error term:

- growth g(t)
- seasonality s(t)
- holiday h(t)
- error e(t)

$$y(t) = g(t) + s(t) + h(t) + e(t)$$

- **Splitting data**

At the same time, we split the data sets into 70% training data - 30% testing data, 80% training data - 20% testing data and 90%training data – 10% testing data.

IV. RESULT

Table evaluation of models with the closing price of each dataset and single models

According to the survey of each model for the datasets, we have selected 5 models LR, NLR, ARIMA, LSTM, PROPHET to evaluate through specific numbers tested and trained from the training sets, test with parameters like 90%-10%,80%-20%,70%-30%. We use two mathematical formulas that are RMSE and MAPE to compare the difference of these train and test sets and draw conclusions according to the most correctness in the predictive models.

- **Table 1.** Evaluation of models with the closing price of BID.

Model		RMSE	MAPE
		Closing	Closing
LR	10-0	3886.46	10.87%
NLR	10-0	3344.52	8.89%
ARIMA	9-1	6874.04	15.26%
	8-2	5662.56	12.11%
	7-3	6959.50	17.97%
LTSM	9-1	4576.49	9.86%
	8-2	3194.66	6.43%
	7-3	**2891.12**	**6.08%**
PROPHET	9-1	5299.0	9%
	8-2	6275.0	11.7%
	7-3	7012.0	14.0%

- **Table 2.** Evaluation of models with the closing price of HSG.

Model		RMSE	MAPE
		Closing	Closing
LR	10-0	8373.30	78.95%
NLR	10-0	1816.56	9.92%
ARIMA	9-1	9760.23	23.27%
	8-2	11742.39	20.18%
	7-3	16953.03	121.91%
LTSM	9-1	2123.96	6.25%
	8-2	7818.05	20.05%
	7-3	**2577.46**	**7.85%**
PROPHET	9-1	16587.0	55.5%
	8-2	7174.0	19.55%
	7-3	12941.0	38.4%

- **Table 3.** Evaluation of models with the closing price of MSN.

Model		RMSE	MAPE
		Closing	**Closing**
LR	10-0	**22096.29**	**27.82%**
NLR	10-0	**7202.54**	**7.99%**
ARIMA	9-1	7851.95	4.87%
	8-2	32523.34	33.99%
	7-3	37249.37	41.96%
LTSM	9-1	7097.91	4.79%
	8-2	10200.19	7.41%
	7-3	**7444.14**	**5.47%**
PROPHET	9-1	11671.0	7.45%
	8-2	27724.0	21.26%
	7-3	45117.0	36.37%

From the results in Tables 1,2,3, we are able to easily see that the LSTM has better performance than other models for all the evaluation indicators. The RMSE values in the models in Tables 1,2,3, show that the RMSE index of the LSTM with the train-test (ratio 70% and 30%) set has the lowest number. With only 6.98%,7.85%,5.47% for MAPE, we find that LSTM is the most suitable model to predict for the future market. The LSTM has the lowest error in the original mean squared error data compared to single models. At the same time, the LSTM is the most stable of all the models we have shown.

- **Histogram forecasting of single models**
  - **BID**

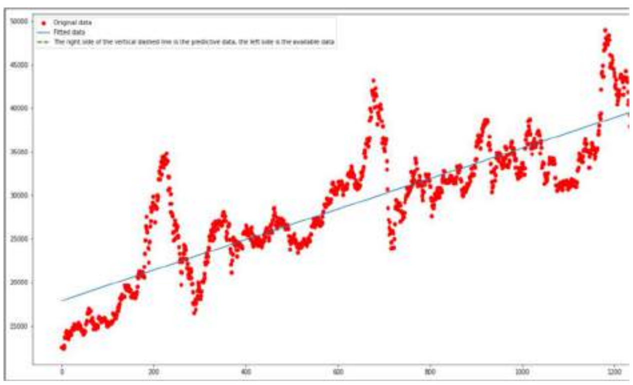

Fig8.Histogram forecasting of Linear Regression

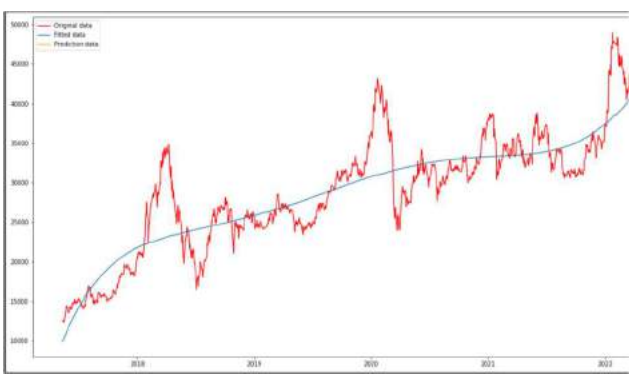

Fig9.Histogram forecasting of Non-Linear Regression

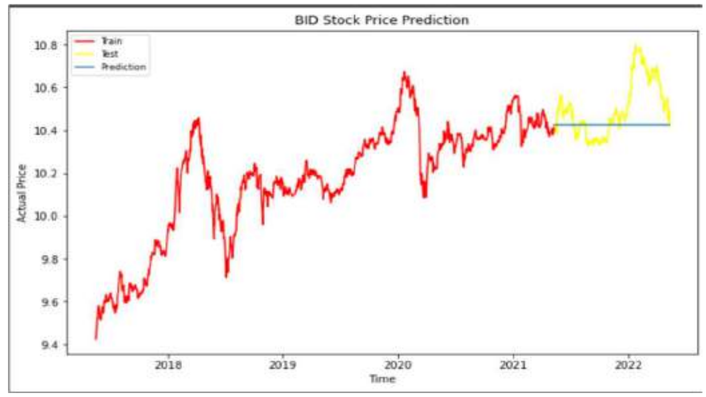

Fig10.Histogram forecasting of ARIMA models (8-2)

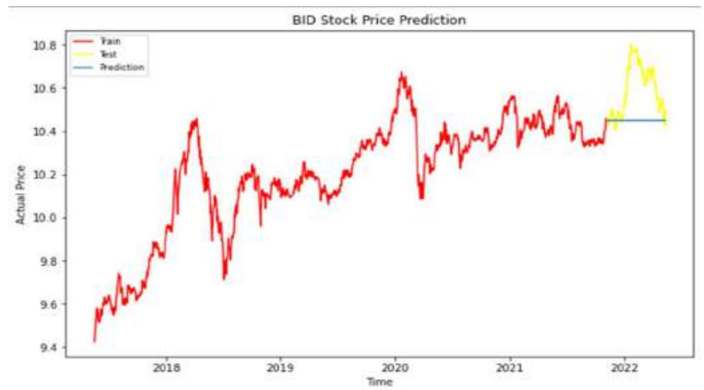

Fig11.Histogram forecasting of ARIMA models (9-1)

Fig12.Histogram forecasting of ARIMA models (7-3)

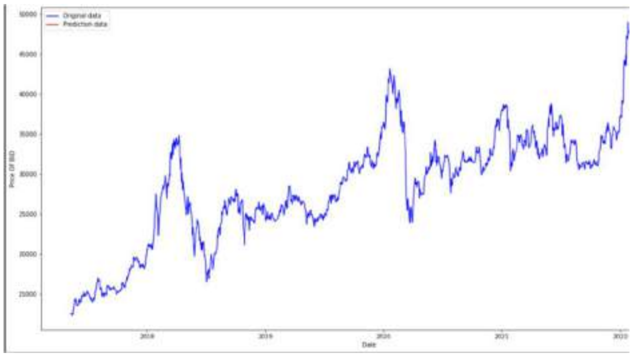

Fig13.Histogram forecasting of LSTM models (7-3)

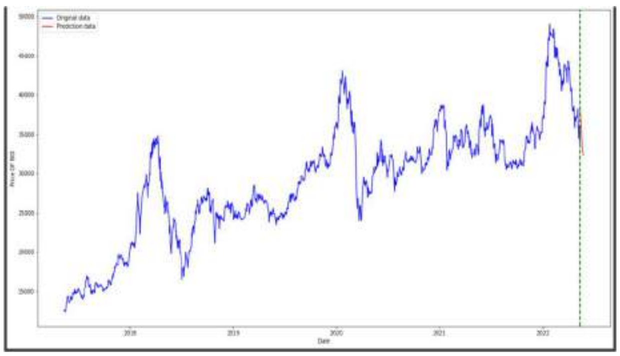

Fig14.Histogram forecasting of LSTM models (8-2)

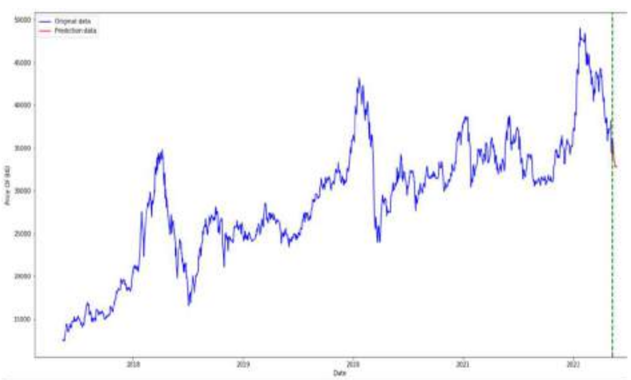

Fig15.Histogram forecasting of LSTM models (9-1)

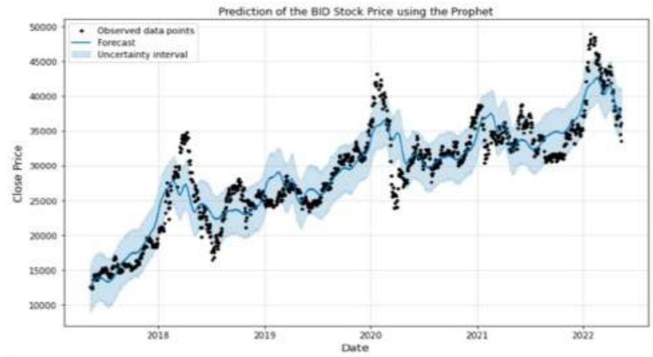

Fig16.Histogram forecasting of PROPHET model

- MSN

Fig17. Histogram forecasting of Linear Regression

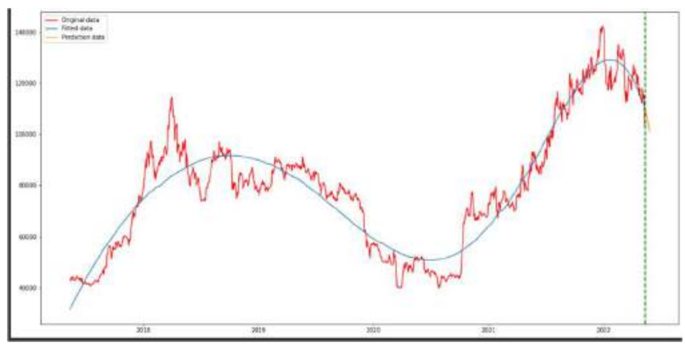

Fig18. Histogram forecasting of Non-Linear Regression

Fig19.Histogram forecasting of ARIMA models (8-2)

Fig20.Histogram forecasting of ARIMA models (9-1)

Fig21.Histogram forecasting of ARIMA models (7-3)

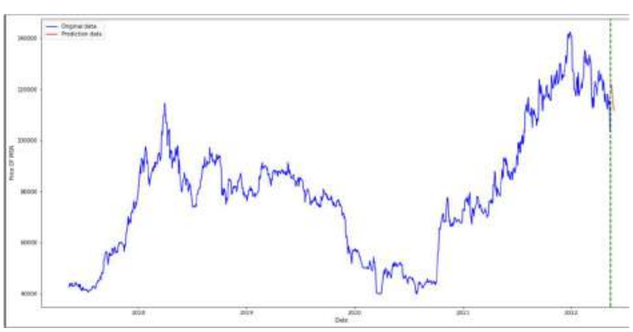

Fig22.Histogram forecasting of LSTM models (9-1)

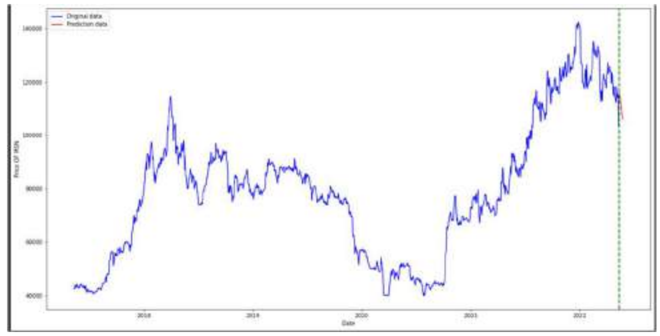

Fig23.Histogram forecasting of LSTM models (8-2)

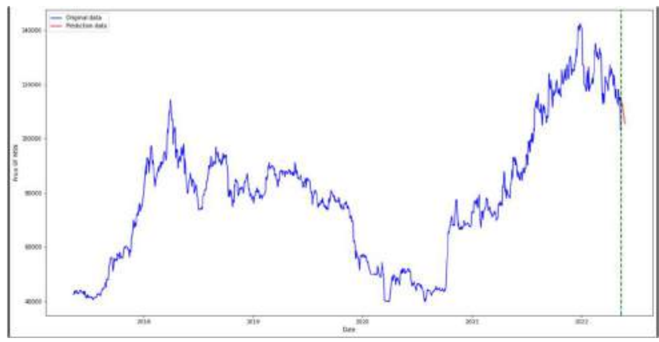

Fig24.Histogram forecasting of LSTM models (7-3)

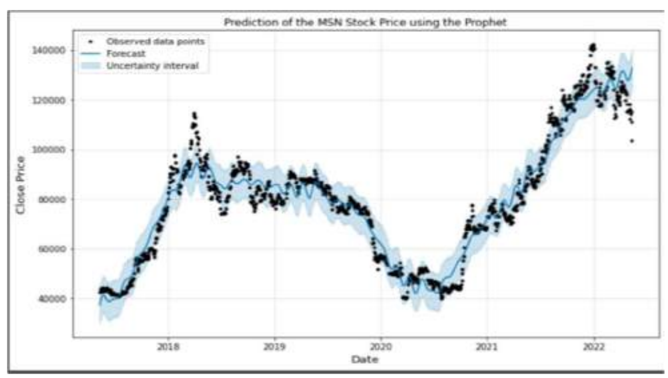

Fig25.Histogram forecasting of PROPHET models

- HSG

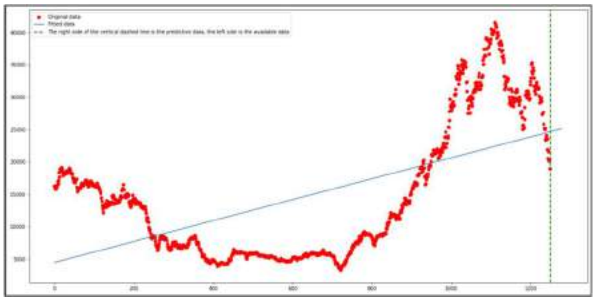

Fig26.Histogram forecasting of Linear Regression

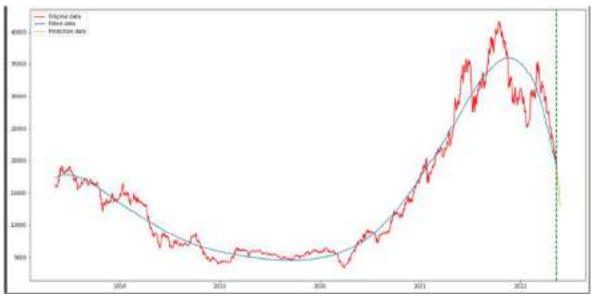

Fig27.Histogram forecasting of Non-Linear Regression

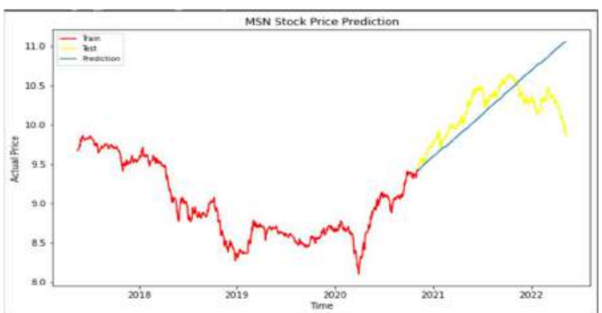

Fig28.Histogram forecasting of ARIMA models (7-3)

Fig29.Histogram forecasting of ARIMA models (8-2)

Fig30.Histogram forecasting of ARIMA models (9-1)

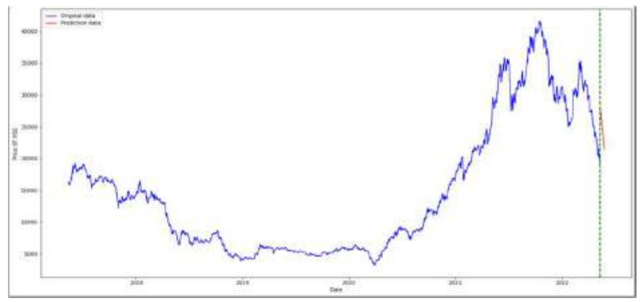

Fig31.Histogram forecasting of LSTM models (7-3)

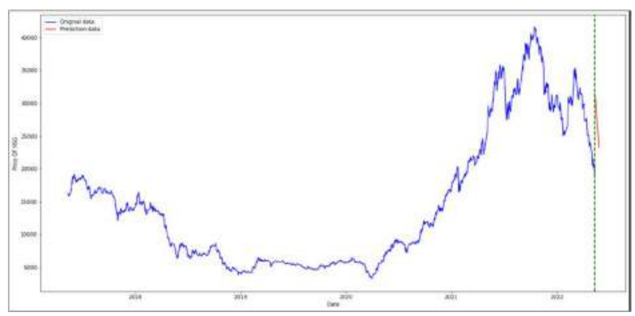

Fig32.Histogram forecasting of LSTM models (8-2)

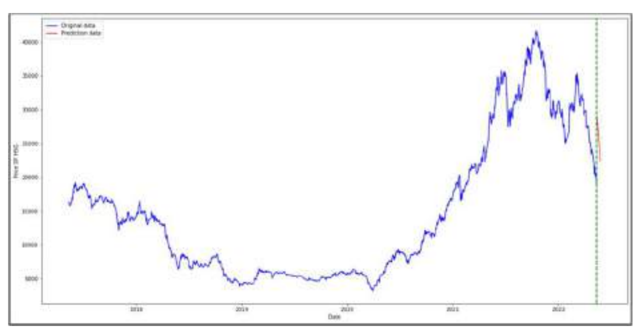

Fig33.Histogram forecasting of LSTM models (9-1)

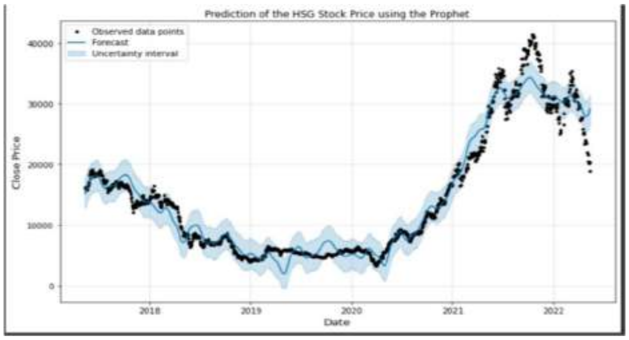

Fig34.Histogram forecasting of PROPHET model

V. DISCUSSION

In this research paper, the assumptions we have made on the stock market, which are currently experiencing a lot of great fluctuations in terms of economy, commodities, etc., we have tried to find the most suitable models for the stock market. for investors to understand the market in the future. We choose models with safety indicators that economically guarantee not to suffer too much loss. With only five models LNR, NLNR, LSTM, ARIMA, PROPHET divided into many train test sets with ratio 90% and 10%,80% and 20%,70% and 30% with the same time period from 12-5 -2017 to 12-5-2022, the LSTM model did very well, far surpassing the rest of the model indexes in terms of RMSE, MAPE score. Besides, even though the LSTM model has the most suitable index for making predictions, we realize that the ARIMA,PROPHET models are very desirable and in the future the models will develop and be recognized by analysts. accumulate .

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