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Predicting Stock Prices Using Deep Learning Algorithms: A Case of Food-Processing Industry

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Prediction of stock prices has been a focal point of the financial body of knowledge for decades now. The complexity of stock price prediction involves various factors, including market trends, economic indicators, company performance, news sentiment, and more. Accordingly, stock prices are said to follow the 'random walk hypothesis'. This systemic factor should be coupled with the limited human cognitive abilities to envisage the dynamics of financial markets. Novel machine learning algorithms have been advocated as potentially supreme replacement for the 'human-centric' stock prediction approaches. Hitherto, a myriad of machine learning algorithms has been effectively used for this purpose – ARIMA (Auto-Regressive Integrated Moving Average), XGBoost (Random Forest and Gradient Boosting Algorithms), CNN (Convolutional Neural Networks) or LSTM (Long Short-Term Memory). The aim of this paper is to test the predictive capacity of LSTM on a sample of large global food industry companies. The prices of shares of five companies were observed, namely: PEP (PepsiCo), TSN (Tyson Foods), NSRGY (Nestle), JBSAY (JBS S.A.), KHC (The Kraft Heinz Company), in the period from 01.01.2015. until 1.11.2022. Based on the data from this time range, a stock price forecast for Nov 2nd, 2022, was made. The results indicate very precise prediction since the difference between predicted and real stock price is insignificant.

Keywords: *stock price, machine learning, long-short term memory, food-processing industry*

Introduction

Prediction of stock prices has been a "holy grail" of financial management for many decades now. Accurate prediction of changes in price can reduce the risk and improve returns (Lu et al. 2020). The complexity of stock price prediction involves various factors, including market trends, economic indicators, company performance, news sentiment, and more (Shaban and Al-Zubi 2014). Accordingly, stock prices are said to follow the 'random walk hypothesis' and their price prediction is hard, if not impossible. This systemic factor should also be coupled with the limited human cognitive abilities to envisage the dynamics of financial markets.

Nowadays, machine learning has been applied to stock price prediction by utilizing historical stock market data to train models that can forecast future stock prices. These algorithms have been advocated as potentially supreme replacement

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for the 'human-centric' stock prediction approaches. Hitherto, a myriad of machine learning algorithms has been effectively used for this purpose – ARIMA (Auto-Regressive Integrated Moving Average), XGBoost (Random Forest and Gradient Boosting Algorithms), CNN (Convolutional Neural Networks) or LSTM (Long Short-Term Memory). The latest one is particularly suitable for capturing patterns in time series data, making them suitable for stock price prediction. LSTM networks consist of memory cells that store state information over time using memory and output units that regulate and control the flow of information through them. These networks use three types of gates - forget, input and output. Since LSTM networks can assign different weights to input variables it automatically selects the most relevant variables. Hence the ability of LSTM to capture the long-term dependence of time series and the ability to forecast financial time series. However, the disadvantage of the LSTM algorithm is that it takes a long time to train and requires a large sample of data.

Having this in mind, the aim of this paper is to test the predictive capacity of LSTM on a sample of large global food industry companies. The prices of shares of five companies were observed: PEP (PepsiCo), TSN (Tyson Foods), NSRGY (Nestle), JBSAY (JBS S.A.), KHC (The Kraft Heinz Company), in the period from 01.01.2015. until 1.11.2022. Based on the data from this time range, a stock price forecast for Nov 2nd, 2022, was made.

To the best of authors' knowledge, a study of this kind has never been conducted before. LSTM has been widely used for stock price predictions (see Selvin et al. 2017, Jin et al. 2020, Mehtab et al. 2021). However, the food processing industry has not been analyzed as a case study. Scarce evidence can only be found for the pet food industry (see Ahnaf et al. 2021).

The remainder of the study is organized as follows. Section 2 provides a theoretical background of the study, putting the general emphasis on the predictability of stock prices. Section 3 explains the LSTM as a general approach used in this study to predict the stock prices on the selected group of companies from the food processing industry. Section 4 elaborates on the main findings and results of the study. Section 5 contextualizes the findings by explaining the implications, contributions, limitations and further recommendations. The last part of this section is reserved for the concluding remarks.

Theoretical Background

In this section, we explain the theoretical concept behind the predictability of any class of investments through the Random Walk Hypothesis. After that, we consider how deep learning (a class of machine learning algorithms) can be used to forecast stock prices.

Random Walk Hypothesis

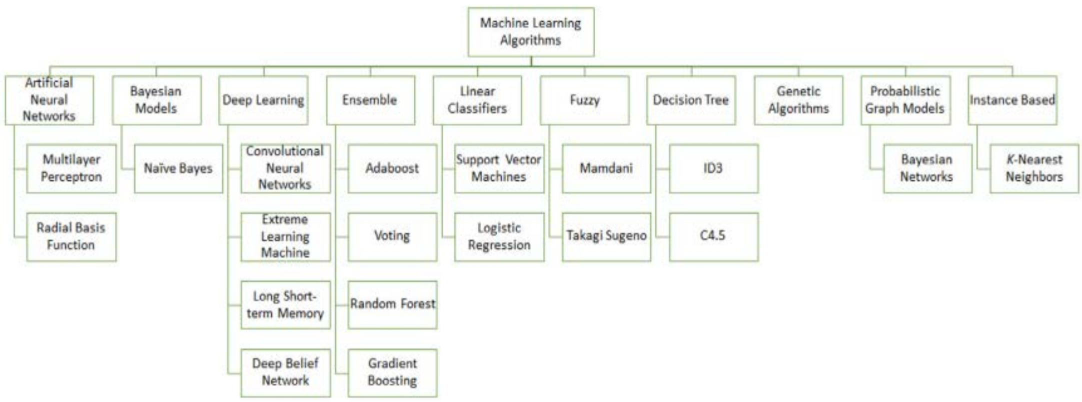
The financial industry has always been interested in successfully forecasting financial time series. Numerous studies have been published on machine learning models with relatively reliable performances. Meanwhile the widespread adoption of automated electronic trading systems along with the increasing demand for higher returns continues to compel researchers and practitioners to work on the implementation of better models.

Nonetheless, financial theory has not unanimously reached the conclusion that stock prices can be predicted. The fundamental theory called the Random Walk Hypothesis claims that stock prices evolve around the random walk, and thus it is impossible to predict their future value. Thus, theory has roots in the influential Fama's (1997) work. In specific, stock prices are influenced by a multitude of factors, including economic indicators, company performance, geopolitical events, investor sentiment, news, and more. These factors interact in complex ways, leading to a high degree of randomness in stock price movements.

Even though this theory indicates that stock price movements cannot be accurately foreseeable, scholarly knowledge has been developing around the best-fit methods to explain the future. This particularly holds true for statistical, pattern recognition, machine learning, and sentiment analysis approaches, alongside some hybrid techniques. There is no unequivocal voice among scholars and practitioners about the best approach, since some authors advocate statistical (see Islam and Nguyen 2020) whereas other advocate for machine learning approaches (see Singh et al. 2017, Nõu et al. 2023).

The focal point of this paper is machine learning approaches. The systematic overview of the machine learning techniques for predicting stock prices is given in Figure 1.

Figure 1. *Systematic Overview of Machine Learning Techniques for Predicting Stock Price Movements*



Source: Bustos and Pomares-Quimbaya 2020.

The use of machine learning for economic prediction has first been recorded by White (1988). New publications and implementations continue to add to the finance and computational intelligence literature. In the last few years, deep learning has strongly emerged as the best performing class of machine learning predictors in various implementation areas. Time series forecasting is no exception as such, in recent years an increasing number of forecasts based on various deep learning techniques have been introduced at appropriate conferences and journals.

Deep Learning Methods for Stock Price Prediction

Deep learning architectures such as deep neural networks and RNNs are used in speech recognition, natural language processing and bioinformatics. However, the complex task of training a model can be described by a hierarchical structure, and when simple tasks are stacked on top of each other, they get a deep structure with many layers. For this reason, this approach is called deep learning. Recurrent Neural Networks (RNNs) and LSTMs are examples of deep learning models (see Bustos and Pomeras-Quimbaya 2020).

There are many reasons why deep learning is important to the field of finance. First, the availability of large data sets that are collected more quickly than in other fields. Second, certain financial applications depend on the speed and emergence of efficient machine learning hardware to achieve a level of responsiveness that is critical to the viability of a trading algorithm. Third, a large part of finance involves recognizing patterns of data usage, where different inputs are modeled to predict outputs. For example, stock market forecasting can be based on many variables (stock price data flow, interest rates, volatility, etc.). Another case is in consumer banking, where customers are characterized by a myriad of variables to determine which products to offer them or to calculate the likelihood of retention. It can be noted that pattern recognition in big data is analogous to the ImageNet problem. Thus, DL architectures that can learn to recognize an image can be used to learn to recognize stock market signatures that predict the direction of index movement. What DL discovers in the data, which cannot be discovered by standard economic methods, are "non-linearities" (see Culkin and Das 2017).

The main challenge for further research in this area is to simultaneously consider numerous factors in modeling financial data. In the search for factors that explain expected stock returns, a few potential candidates have been found using economic methods, such as accounting data, macroeconomic data, and news. Stock price forecasts that consider several predetermined factors can lead to inaccurate forecasting, because they maintain partial information or an ineffective combination of factors. Therefore, currently one of the most important tasks in finance is to develop a method that effectively integrates various factors into the forecasting process. Several recent studies have begun to use deep learning (see Lee and Yoo 2019).

Forecasting the stock market is significant in finance and is receiving more and more attention, since if the right market movement is successfully predicted, investors can be successfully guided. Researchers have proposed many models using different fundamentals, technical and time series forecasting techniques to make the forecasts competitive (see Abhyankar et al. 1997).

Event studies, introduced by Fama (1997), provide useful evidence of how stock prices react to information. Many studies focus on returns in a short period (a few days) around a clearly defined event date. The advantage of this approach is that as daily expected yields are close to zero, models for expected vegetable yields do not have a large impact on inferences about abnormal yields. The assumption of studies that focus on short return periods is that any lag in price response to an event is short-lived. Some authors challenge this assumption, arguing instead that stock prices adjust slowly to information, so to examine market inefficiency one needs to examine returns over longer time periods.

Investors make decisions based on a variety of factors, including the consumer price index, the price-to-earnings ratio, and other news-reported events. To aid in their modern decisions, many automatic ways to automatically analyze that information have been proposed in the last decade (see Akita et al. 2016).

Statistical models such as autoregressive moving average models (ARIMA) and linear regression have been used to predict share prices. The best ARIMA model has done a satisfactory job in predicting the share price of Nokia and Zenit Bank. Also, the emergence of machine learning has led researchers to focus on various techniques such as artificial neural networks and genetic algorithms for time series forecasting (see Shah et al. 2018).

Long-Short Term Memory (LSTM) for Stock Price Movement Prediction

Neural networks with complex interconnections make up biological learning systems. As fundamental components, neurons receive real-valued input vectors and produce output values that correspond to those input values. In the typical neural network typology, the feedforward neural network is one of the most popular forms. These networks are organized into layers that include output, input, and—most importantly—one or more hidden layers. Because their primary purpose is statistical categorization, feedforward neural networks must work within the limitations of a consistent input-to-output mapping.

For modeling prediction tasks, a so-called dynamic classifier is required. We can extend feedforward neural networks for dynamic classification. To achieve this feature, it is necessary to feed signals from previous time steps back into the network. These networks with feedback loops are called Recurrent Neural Networks (RNNs). RNNs are limited to looking back approximately ten-time steps due to the recurrent signal, which can vanish or explode. This is resolved with Long Short-Term Memory (LSTM-RNN) recurrent neural networks. LSTM networks are to some extent biologically plausible and capable of learning over 1000-time steps, depending on the network (see Sangiorgio and Dercole 2020).

Unlike non-recurrent (non-reversible) neural networks, RNNs have recurrent connections between nodes and layers that can process input sequences of arbitrary lengths. However, training simplified RNNs can be a challenging task. Algorithms mostly manually update weights based on gradients, leading to the gradient vanishing or exploding problems. It has been proven that these issues are overcome by the development of 'Long Short-Term Memory' (LSTM).

LSTM is a special type of RNN that possesses internal memory and multiplicative gates. Different configurations of LSTM cells have been described since the introduction of LSTM in 1997 (see Hochreiter and Schmidhuber 1997).

LSTM networks overcome the gradient vanishing or exploding problem by intelligently forgetting past irrelevant information. Such networks have proven suitable for modeling sequential data, such as textual data or time series.

LSTM networks consist of memory cells that store information about the state over time using memory and output units that regulate and control the flow of information through them. These networks use three types of gates - forget, input, and output gates. Forget gates serve as tools to discard irrelevant information from the past, retaining only relevant information for the current pass. Input gates control the information acting as input for the current network state. Old information from the forget gate and new information from the input gate are effectively aggregated into the cell state vector. The final output from the network at the current layer is produced by the output gate. This output can be seen as the predicted value that the model has calculated for the observed pass (see Mehtab et al. 2021).

Methods

In this section, we explain the rationale behind (1) the selection of LSTM for stock price movement predictions, (2) selection of five food-processing companies, and (3) selection of technical analysis related attributes used as inputs in the analysis.

Sample – Industry and Companies

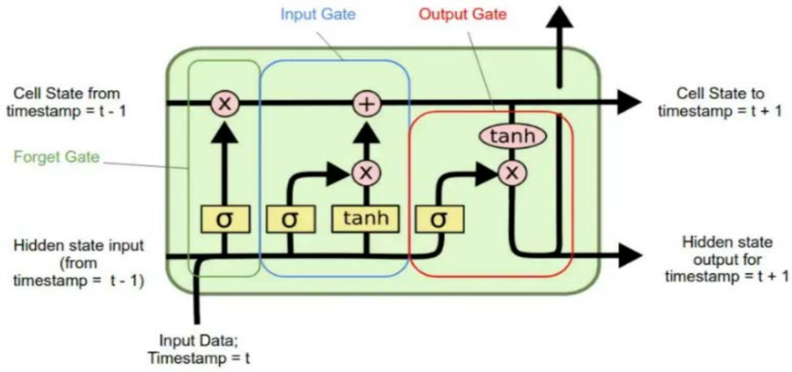
Industries that satisfy basic human needs, such as the food processing industry, are in high demand ever since the economic crisis induced by the pandemics of COVID-19 (see Clapp and Moseley 2020). Not only that the global food consumption grows at a staggering rate with a projection that the world will surpass 3000 kcal per capita per day (see Vasileska and Rechkoska 2012), but the consumer demands have been shifting toward the higher quality – health and wellness – products (see Nunes et al. 2020). Accordingly, the food-processing industry is expected to grow over the next decades, making this industry attractive for long-term investments.

The market power in the agrifood industry has been highly concentrated. Some authors even emphasize the negative effects of 'common ownership' – largest firms across a single sector sharing the same owners (see Clapp 2019). It should be mentioned that the 25 world's largest companies generated $1.5 trillion in revenue in 2022 (see Sorvino 2022). For this study, we selected five out of these 25 companies: PEP (PepsiCo), TSN (Tyson Foods), NSRGY (Nestle), JBSAY (JBS S.A.), and KHC (The Kraft Heinz Company) as a sample for our analysis.

Experimental Environment – Units of Observations and Attributes

Hidden state input from timestamp t-1: h_{t-1} = [1, 2, 3], input data timestamp t: x_t = [4, 5, 6]. Assumption is that each LSTM layer contains three LSTM units. Each unit build identically is given in Figure 2, but each learn different thing.

Figure 2. *Internal Mechanisms of Each Layer*



Source: Colah 2015.

Which means that have three *Cell state*, and entry matrix of *Forget gate* have dimension 3x6.

$$W_f = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & -1 \\ 5 & 6 & 7 & 8 & 9 & 10 \\ 3 & 4 & 5 & 6 & 7 & 8 \end{bmatrix} \quad b_f = [1, 2, 3]$$

Forget gate targets are calculated per function (1), where b_t is the Bayes vector.

$$f_t = \sigma\left(W_t\left[h_{t-1}, x_t\right] + b_t\right) \tag{1}$$

After considering everything, multiplying the inputs to the Forget gate yields the matrix (2).

$$W_f\left[h_{t-1}, x_t\right] + b_f = \begin{bmatrix} -6 \\ 175 \\ 133 \end{bmatrix} + \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} -5 \\ 177 \\ 136 \end{bmatrix} \tag{2}$$

By inserting everything that was previously obtainted into the equation (1), the output from the *Forget gate* given below (3) is obtained.

$$f_t = \sigma(W_f\left[h_{t-1}, x_t\right] + b_f) = \sigma \begin{bmatrix} -5 \\ 177 \\ 136 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \tag{3}$$

The *Cell state* is calculated using the formula (4) provided below.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{4}$$

The first component of formula (4) is the result of *Forget gate* and *Cell state* at the previous moment. Taking into account the value obtained for the *Forget gate*, let C_{t-1} = [5,5,5]. The Cell state formula's value can be found below (5).

$$C_t = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 5 & 5 & 5 \end{bmatrix} + i_t \cdot \tilde{C}_t = \begin{bmatrix} 0 & 5 & 5 \end{bmatrix} + i_t \cdot \tilde{C}_t \tag{5}$$

The next step is to decide which information to store in the *Cell state*. Value i_t indicates which state is being updated and its size. Assume that:

$$W_i = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 & 2 & 2 \\ 3 & 3 & 3 & 3 & 3 & 3 \end{bmatrix} \qquad b_i = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}$$

And put it in formula for i_t the value given below has been obtained:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) = \sigma(\begin{bmatrix} 22 \\ 42 \\ 64 \end{bmatrix}) = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

In a similar manner, assume that:

$$W_c = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 & 2 & 2 \\ -3 & -3 & -3 & -3 & -3 & -3 \end{bmatrix} \qquad b_C = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}$$

Inputting everything into the formula for $\widetilde{C}_t$ result in:

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) = tanh(\begin{bmatrix} 22 \\ 42 \\ -62 \end{bmatrix}) = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}$$

When formula (5) is filled with everything that has previously been acquired:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 5 \\ 5 \\ 5 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 6 \\ 4 \end{bmatrix}$$

The output decision will be based on a filtered *Cell state*. First, a sigmoid layer is run to determine which state to display. Then the state of the cell is passed through the tangent hyperbolic (so that the values are between -1 and 1), and multiplied by the output of the Ssigmoind gate so that only the selected parts are printed.

$$tang(C_t) = tang(\begin{bmatrix}1 & 6 & 4\end{bmatrix}) = \begin{bmatrix}0.76 & 0.9999 & 0.9999\end{bmatrix}$$

Suppose that:

$$o_t = \begin{bmatrix}0 & 0.5 & 1\end{bmatrix}$$

When everything put into formula: $h_t = o_t * tang(C_t)$, we get:

$$h_t = \begin{bmatrix}0 & 0.495 & 0.99\end{bmatrix}$$

Empirical Model

LSTM was used to create a model for stock price prediction. Prior to creating an empirical model, the data was pre-processed. First, we conducted the normalization of data using min-max scaler (see Saboor et al. 2020) where the data took value from 0 to 1. Afterwards, the data was split into two parts: (1) train and (2) test. Since the neural network is expected to be 3-dimensional (output, time steps and features), the function reshape was used. Number of rows (units of observation) was 1.417.

The model was made using 'Tensorflow' in Python as one of the most popular libraries for deep learning (see Pang et al. 2020). The model was sequential with 50 neurons in the first, and the additional 50 neurons in the second layer. Also, we added two dense (output) layers, one with 10 and the other with a single neuron.

Model Compiling

For the compilation, the Adam optimizer was used (see Kingma and Ba 2014). This optimization algorithm is used instead of the procedure of the stochastic gradient descent as it can iteratively update the weight of parameters (see Dogo et al. 2018).

To check how well the model is trained, we used mean square error as a loss function. The use of mean square error has already been recorded in LSTM-based financial predictions (see Wu et al. 2018).

Model Training

Two parameters were important for the model training: (1) Batch size – explaining how many observations the model will take into account prior to updating the weights, and (2) Epochs – how many observations will the model take into account during the test phase prior to end the testing (Ranjan 2020). The values for the different parameters '*Batch_size*' are given in Table 1.

Table 1. *Batch Size and Predicted Value for the Sampled Companies*

Company	**Batch_size=32**	**Batch_size=64**	**Batch_size=128**
PEP	180.1373	178.4878	173.6704
TSN	67.1967	66.5833	65.9999
NSRGY	107.3569	107.5837	106.9103
JBSAY	9.72186	9.5016	9.5032
KHC	36.7604	36.1036	36.1207

Results

Pre-Analysis

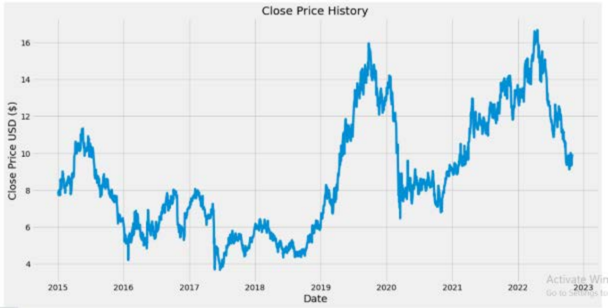
Prior to forecasting stock price of five selected companies, their time series were first decomposed. Actual price movements are given in Figure 3.

Figure 3. *Actual Price Movements*

[PEP] Dickey-Fuler Test results
Test statistics: -0.495
p-value: 0.893
#Lags used: 9.000
Number of observations: 1,958
Critical Value (1%): -3.434
Critical Value (5%): -2.863
Critical Value (10%): -2.567

[TSN] Dickey-Fuler Test results
Test statistics: -1.223
p-value: 0.663
#Lags used: 8.000
Number of observations: 1,953
Critical Value (1%): -3.434
Critical Value (5%): -2.863
Critical Value (10%): -2.568

[NSRGY] Dickey-Fuler Test results
Test statistics: -0.495
p-value: 0.893
#Lags used: 8.000
Number of observations: 1,958
Critical Value (1%): -3.434
Critical Value (5%): -2.863
Critical Value (10%): -2.568



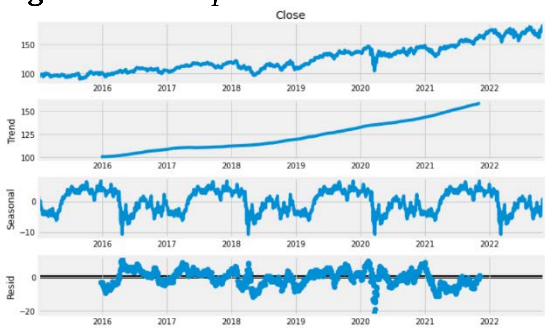
[JBSAY] Dickey-Fuler Test results
Test statistics: -1.713
p-value: 0.424
#Lags used: 1.000
Number of observations: 1,970
Critical Value (1%): -3.434
Critical Value (5%): -2.863
Critical Value (10%): -2.566

[KHC] Dickey-Fuler Test results
Test statistics: -0.906
p-value: 0.786
#Lags used: 1.000
Number of observations: 1,844
Critical Value (1%): -3.434
Critical Value (5%): -2.863
Critical Value (10%): -2.566

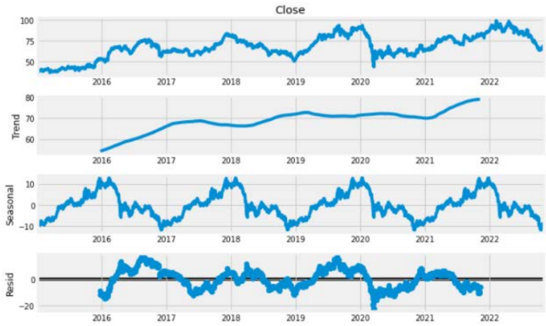
Source: authors' calculations.

Actual price movements were first decomposed. Decomposition of the time series was made with regards to the trend, cyclicity, and irregular movements (Qi and Zhang 2008), since these factors affect the stock price volatility (Castillo-Ponce et al. 2012). The results for all the observed companies are given in Figure 4.

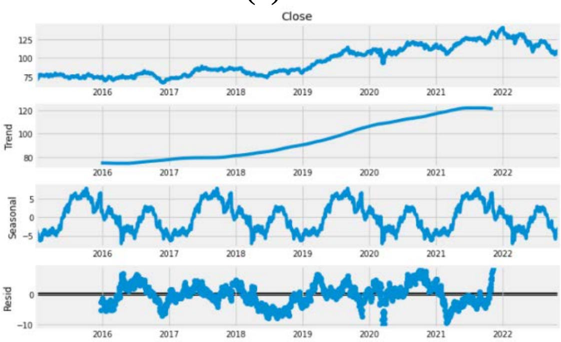
Figure 4. *Decomposed Values*



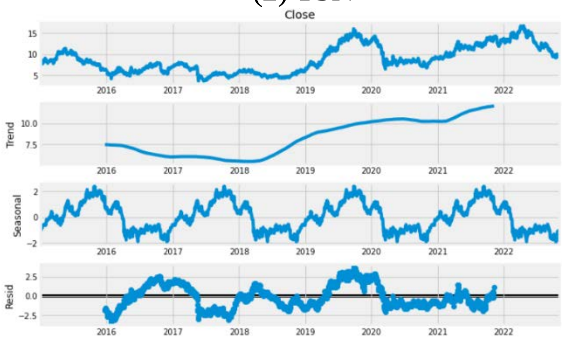
(1) PEP



(2) TSN



(3) NSRGY



(4) JBSAY

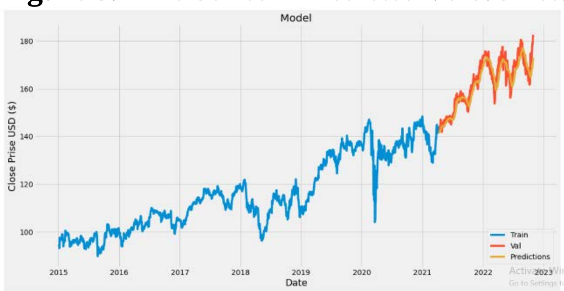
(5) KHC

Source: authors' calculations.

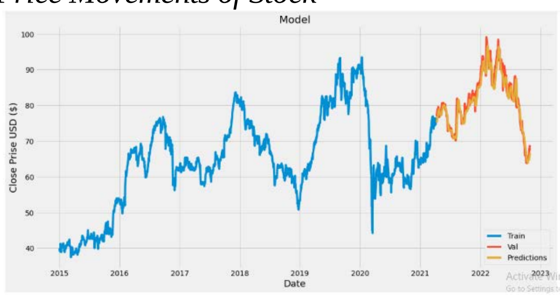
Main Analysis

After running the model on the observed set of companies, the predicted stock prices were close to the actual prices of stocks. For the given value of parameter batch_size=64 and epochs=10, the graphical display of movements in actual and predicted stock prices is given in Figure 5.

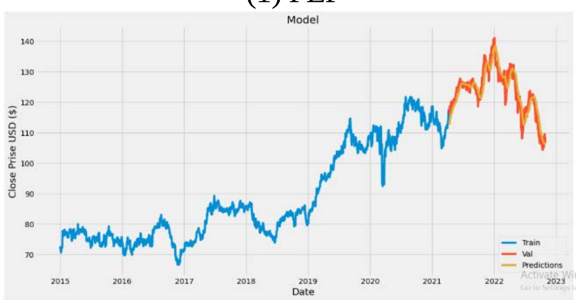
Figure 5. *Time Series – Predicted Versus Actual Price Movements of Stock*



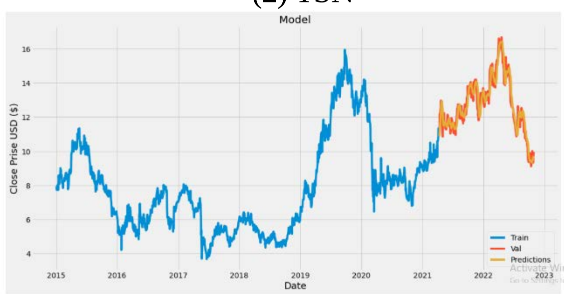
(1) PEP



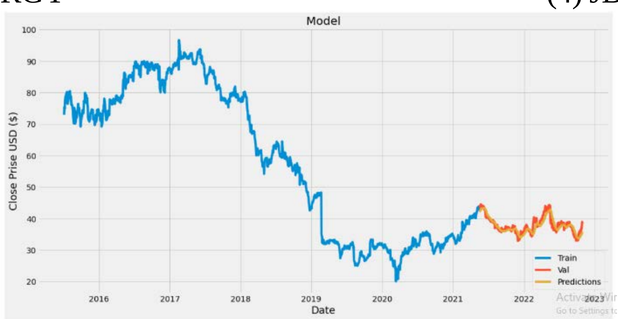
(2) TSN



(3) NSRGY



(4) JBSAY



Source: authors' calculations.

The model had a solid prediction result since the difference in average predicted and actual value is close (see Table 2).

Table 2. *Predicted Versus Actual Average Value of Stock Prices*

Company	Predicted value	Actual value
PEP	178.4878	178.2400
TSN	66.5833	67.4400
NSRGY	107.5837	108.07
JBSAY	9.5016	9.43
KHC	36.1036	38.1199

Discussion and Conclusions

Our study analyzed the predictability of stock prices of five global food-processing companies (PepsiCo, Tyson Foods, Nestle, JBS USA, The Kraft Heinz Company). For the prediction, we used the LSTM, a class of deep-learning models. The time series of five technical attributes were used in seven consecutive years to train the model. The LSTM algorithm showed very good results.

Because of its ability to assign different weights to input variables, the model automatically selects the most relevant variables. Hence, the ability of LSTM to capture the long-term dependence of time series and the ability to forecast financial time series (see Zou and Qu 2020). However, the disadvantage of the LSTM algorithm is that it takes a long time to train and requires a large sample of data (see Qian and Chen 2019).

Our findings can be valuable for investors, brokers and other stock market players. This approach is particularly important for investors who use algorithmic approaches to trading strategies.

Normally, predicting stock prices accurately is challenging due to the inherent volatility and randomness in financial markets. Machine learning models might not always provide precise predictions, and they should be used cautiously, considering various other factors that can influence stock prices. Accordingly, our study has a myriad of limitations. First, we observed only five global food-processing companies. This industry is well known for low-risk and low-returns (see Mukherjee et al. 2023). Hence, the predictability of stock prices is partially simplified.

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