Forecasting the nexus and impact of Covid-19 news sentiment on NYSE, Gold, and WTI oil prices indexes using the neural network approach

[1]Aneeza Ismail, [2]Javid Iqbal, [3]Muhammad Ramzan

[1]Department of Management Sciences, COMSATS University Islamabad, (aneezakhan2010@hotmail.com
[2]Department of Management Sciences, COMSATS University Islamabad, ijavid100@gmail.com; javidiqbal@comsats.edu.pk
[3]Hailey College of Commerce, Punjab University, Lahore,(ramzan.hcc@pu.edu.pk

ABSTRACT

The study aims to determine the impact of news sentiment during Covid-19 and the interconnectivity of NYSE, Gold prices, and WTI oil prices. For this purpose, we use hourly data of news sentiment and commodity prices hourly data from February 10, 2020, hours 1000 to March 06, 2020 hours, 1600 hours, with the help of a multilayer artificial neural network. Further, We use the connection weight approach to observe the relative importance of input variables that help predict output variables. The results suggest that all the indexes are interconnected, where the increase/decrease of any index impacts the other commodity index. Further, the news index remains the second highest predictor for gold price and WTI oil price indexes. In addition, the news index also seems to be an essential predictor of these commodities. This understanding is crucial for making informed investment decisions in the dynamic and interconnected realm of commodities trading. The study also underscores the importance for investors, policymakers, and analysts to carefully monitor news developments, as such vigilance can contribute to forecasting the trajectory of commodity prices.

Keywords: *NYSE, WTI Oil, Gold, Covid-19, Neural Network, Connection Weight*

INTRODUCTION:

The recent outbreak of COVID-19 in China since December 2019 has caused several adverse impacts in terms of losses of human lives and rising economic costs. The threat of coronavirus not only affected the Chinese economy but also adversely impacted the world. The worst affected countries were the US, China, Iran, and EU countries. The shocks of COVID-19 were not only felt in the world stock markets and commodities markets, i.e., oil prices hit the lowest level after 1990 and gold prices at the highest level in history.

Global uncertainty due to Covid-19 changes the dynamics of gold and oil prices. Gold and oil are strategic resources that are used in different economic activities. Since the outbreak of Covid-19, oil prices faced a severe fall, specifically in April 2020. The crude oil prices of the USA fell to negative values, reducing from 18$ to -38$ per barrel for the first time in history[1]. Oil is one of the common sources of energy and is also used as a predictor of commodity price fluctuations (Lardic & Mignon, 2008). Gold is usually used for financial purposes as collateral against foreign currencies and as part of international banks' reserves(Wen et al., 2017). Therefore, gold is considered an important choice for investors among all

[1] 1 https://www.theguardian.com/world/2020/apr/20/oil-prices-sink-to-20-year-low-as-un-sounds-alarm-on-tocovid-19-relief-fund

precious commodities (Gangopadhyay et al., 2016). Forecasting gold prices with high accuracy plays a significant role in commodity markets (Kristjanpoller & Minutolo, 2015).

Over the last few decades, there has been significant research in advanced machine learning methods for more accurate predictions. Machine learning is one of the most important domains of computational intelligence, focusing on the model that provides better-hidden insight into data. Researchers have used these machine-learning methods, including artificial Neural Networks (Iqbal et al., 2023), Support Vector Machines (Gong et al., 2019), Bayesian Networks (Li, 2010), and similar machine-learning techniques. The ANN is the most widely used machine learning method due to its accuracy and better prediction, including the area in commodity price forecasting (Hamid & Iqbal, 2004; Khashei & Bijari, 2010; Lineesh et al., 2010; Ramyar & Kianfar, 2019). Most of the studies highlight the importance of neural network-based machine learning models giving better forecasting results as compared to the conventional econometric models (Gogas et al., 2018; Iqbal et al., 2023; Jardin, 2017; Ristolainen, 2018). The advantage of applying artificial neural networks is that they can accurately estimate nonlinear functions(Ali & Yang, 2010). These developments in machine learning and soft computing enhanced the modeling of nonlinear, dynamic, and complex systems (Lek et al., 1996).

There is no prior research that has endeavored to forecast the correlation between COVID-19-related news articles and their impact on the New York Stock Exchange (NYSE), gold prices, and WTI oil prices through the utilization of artificial neural networks. Furthermore, existing studies do not elucidate the interconnectedness among commodity prices, specifically how fluctuations in one commodity may reverberate and influence others. This facet remains unexplored within the current corpus of literature.

Our study provides two significant contributions to the existing literature. Firstly, we try to predict the relationship between news articles related to COVID-19 on the NYSE, gold prices, and WTI oil prices with the help of artificial neural networks, which have not been addressed in previous studies. Secondly, the neural network models are considered black boxes because the relationship between input and output variables is either unknown or provides little insight. Therefore, we apply the Connection Weight Approach (CWA) suggested by Olden and Jackson (2002). The approach provides the relative importance of each input variable and demonstrates the directional relationship among commodities.

The results of ANN and CWA suggest a significantly negative relationship between the COVID-19 News index and gold prices; as COVID news increases, gold prices also tend to decrease. Similarly, the COVID-19 News index has a negative relationship with the NYSE index. The NYSE index also shows a downward trend with the plummeting negative News related to COVID-19. The news index shows a negative and most important predictor within the network in the respective model, where the gold price was taken as the output index. Accordingly, there is a negative relationship between the Covid-19 news index and WTI oil price, which suggests that as the negative COVID-19 news spreads, oil prices show a downward trend.

The findings of this study offer valuable insights for investors, enabling them to discern that changes in the index of one commodity may exert an influence on another commodity. This comprehension is essential for formulating well-informed investment decisions within the dynamic and interlinked domain of commodity trading.

The remainder of this paper is organized as follows: section 2 presents the methodology and data. Section 3 describes the empirical results. The conclusion is presented in section 4.

METHODOLOGY

Data

The study links NYSE, WTI oil, and gold commodity prices to the COVID-19 news index (Negative Sentiment). We use hourly data ranging from February 10, 2020 hours 1000 to March 06, 2020 hours 1600 hours) for analysis. We downloaded the news articles from Yahoo Finance and developed the News index during the sample period using Term Frequency-Inverse Document Frequency (TF-IDF). This technique was proposed by Salton and McGill (1986) and is widely used to develop sentiment indexes. The method reduces frequent word weights and scales up the rare words. We use the Loughran and McDonald (2011) financial dictionary, which is more appropriate in the financial context.

Predictive Modeling Using Neural Network

Researchers have argued that Artificial Neural Networks (NN), referred to as neural networks, have better predictive powers than other conventional econometric models (Ecer, 2013; Enke & Thawornwong, 2005; Patuelli, Reggiani, Nijkamp, & Blien, 2006; Tam, 1991; Yi & Prybutok, 1996). Other researchers have suggested that ANN can perform classification tasks and solve regression problems (Bishop, 1995). Similarly, it has in explaining some real-work problems, particularly in the areas of forecasting (Wilson & Sharda, 1994). The ANN inherently performs representation learning, allowing them to automatically discover hierarchical representations of the input data and continually improve their performance over time as they are exposed to more data, making them suitable for applications where continuous learning and adaptation are essential. In the specific context of our study, incorporating the news index alongside other commodity prices introduces a layer of complexity in the relationships to be discerned, further justifying the aptness of neural network models for such scenarios.

The architecture of the neural network

The architecture of ANN includes input nodes (input variables), neurons in multiple layers along with their connection weights, and output node (output variable). The starting point to decide the number of hidden neurons in the hidden layer is the total inputs and output divided by two (Panchal, Ganatra, Kosta, & Panchal, 2011). However, fine-tuning of hyperparameters through experimentation by increasing or decreasing the neurons and hidden layers can reveal the sensitivity of the model to different configurations. A well-tuned neural network is more likely to exhibit robust performance. Moreover, conducting sensitivity analysis, which involves assessing variations in input data or model parameters affect the model's predictions. Understanding the sensitivity of the neural network to changes in the dataset or architecture contributes to its robustness assessment. Techniques like regularization and dropout are employed to prevent overfitting, enhancing the model's ability to generalize to new data.

In a neural network, all the input variables pass through neurons along with their weights assigned to them. Each input variable interacts with each neuron in the hidden layer to train the network model, as shown in Figure 1.

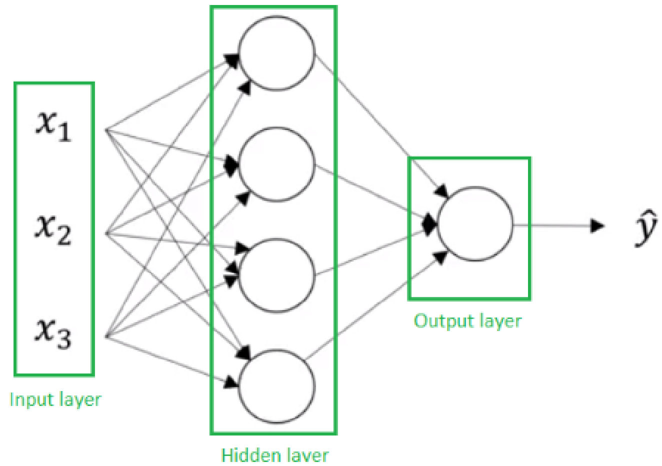


Figure 1: Architecture of Neural Network

The dataset is divided into two subsets, i.e., the training dataset used for training the network and the test dataset on which the trained network is used for prediction. This trained model is used to predict the output variables.

This is calculated using the following equation.

$$(\hat{y}) = f\left(w_o + \sum_{i=1}^{n} w_i x_1 + w_i x_2 + w_i x_3\right) \qquad (1)$$

Where $(\hat{y})$ the output calculated by the network, w_o denotes the intercept or bias, w_i are the weights assigned to each input variable, and $x_1, x_2, and\ x_3$ are the input variables of the News index, WTI oil, Gold prices, and NYSE. As mentioned earlier, we used the Tews index as input variables in the network, whereas other variables were used as output variables simultaneously.

For activation of the network to calculate weights corresponding to the output variable's predicted values, we employed the hyperbolic tangent (tanh) function, shown in the following equation 2.

$$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1 \qquad (2)$$

The function of training a network is an iterative process where the number of neurons in multiple hidden layers is increased or decreased so that the weights of networks can be adjusted to minimize prediction error after selecting the number of neurons in each hidden layer. This training process continues until a high-accuracy network level is achieved.

Evaluating the models' performance using appropriate metrics, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Sum of Squared Error (SSE) provide quantitative insights into how well the neural network is capturing patterns in the commodity price data. Consistent and satisfactory performance across these metrics indicates a robust model. These statistical measures indicate that the lower the values of these statistics, the higher the prediction. The formulas to measure the accuracies are mentioned below.

$$MSE = \frac{1}{n} \sum_{i}^{n} (y_i - \hat{y}_i)^2 \qquad (3)$$

Where y_i is the actual value of each output, $\hat{y}_i$ is the output predicted by the neural network. The difference between both reflects prediction accuracy: the less the value, the greater the accuracy of neural network models.

$$RMSE = \sqrt{MSE} \quad (4)$$

The MSE is the squared deviation of actual value from predicted values. We also take the squared root of MSE to normalize the error value. Finally, we also show the accuracy with the help of SSE, as shown in formula 5.

$$SSE = \sum_{i=1}^{n}(y_i - f(x_i))^2 \quad (5)$$

Where y_i is the ith value of the variable to be predicted, $f(x_i)$ predicted value of y_i and n is the upper limit of summation.

Variable Importance in Neural Network

Machine learning models are believed to be "black box" because they do not explain which input variables help predict output variables. This makes it difficult to interpret the contribution of each within the network. In this context, we used connection weights (CW) proposed by Olden and Jackson (2002) to identify the relative importance of variables within the network. It also explains the directional relationship between input and out variables. The algorithm calculates the raw input-output connection weights among each neuron and sums them across all hidden neurons, calculated in the following equation.

$$I_j = \sum_{H=1}^{k} W_k \,.\, W_{kj} \qquad (3)$$

Where I_j shows the importance of each input variable to determine the output variable. In document W_k, W is the weight assigned to each input variable in hidden neuron $_k$ in document $_j$. Hence, the Olden algorithm approach helps explain the network model in terms of magnitude and relative sign ((Olden, Joy, & Death, 2004).

RESULTS

Descriptive statistics

Table 1 presents the descriptive statistics of the News index, NYSE Index, Gold price index, and WTI oil price index. The News index has a mean of 52, which is not far from the median and ranges between 21 and 96, showing low to high negative News. It shows that at some point, the negative news sentiment is low and vice versa. The standard deviation seems to be little high. In addition, the index seems to be symmetrical with no high Kurtosis. The NYSE index has a mean of 13595.35, which is still not far away from the median. Minimum difference between mean and median shows that data is not skewed. On the other hand, the range of this index between 12058.17 to 14137.66. Though, its standard deviation is little high with a value of 624.49. The gold price index value ranges between 1563.94 and 1659.52, with a mean value of 1604.75. Finally, the WTI oil price has a mean of 50.6, with 44.46 being the lowest and 54.14 being the highest. All these indexes show that there is no big anamoly or large variation in the dataset.

Table 1: Descriptive statistics

Variable	N	Mean	Median	Min	Max	Std Dev	Skewness	Kurtosis
News Index	126	52.03	50	21	96	15.36	0.45	0.11
NYSE Index	126	13595.35	13980.07	12058.17	14137.66	624.49	-0.89	-0.67
Gold Price	126	1604.75	1601.67	1563.94	1659.52	31.85	0.24	-1.53
WTI Oil Price	126	50.6	51.16	44.46	54.14	2.52	-0.76	-0.05

Correlation Matrix

The correlation matrix provides insights into the relationships between the variables. The strength of the correlation is determined by the absolute value of the correlation coefficient, with 1 indicating a perfect correlation and 0 indicating no correlation.

Table 2 provides the correlation matrix that displays the pairwise correlations between four variables: the NYSE Index, WTI Oil Price, Gold Price, and News Index. The correlation coefficient between the NYSE index and WTI oil price is 0.8446, which indicates a strong positive correlation between both indexes. The correlation coefficient between NYSE and Gold price indexes is approximately -0.2788, suggesting a moderate correlation between them. In contrast, the NYSE index and WTI oil price indicate a weak negative correlation.

Table 2: Correlation Matrix

	NYSE Index	WTI Oil Price	Gold Price	News Index
NYSE Index	1			
WTI Oil Price	0.8446	1		
Gold Price	-0.2788	0.0512	1	
News Index	-0.1716	-0.2820	-0.5995	1

Upon scrutinizing the correlation between the News Index and various commodities indexes, it is evident that a range of correlations exists, covering from -0.5995 to -0.1716. Notably, the News Index demonstrates a negative association with all the commodities indexes. This consistent negative relationship suggests a pattern of movement wherein an increase in the News Index is associated with a tendency for a decrease in the respective commodities indexes.

Predictive modeling using Neural Network

The study's objective is to predict the impact of COVID-19 news on different index and their interconnectedness. We trained 27 networks, 9 for each model, from simple networks to two hidden layer networks. The NYSE, Gold, and WTI oil prices were taken as output variables in each model to observe the prediction accuracy. News index is taken as an input variable in all the models and its impact on these indexes, resulting in 27 networks. The high MSE, RMSE, and SSE mean square values are the main criteria used to check the accuracy of the models. We use the News index as the primary input variable and other commodities as the output variable. We simultaneously combine the News index, gold price, and WTI oil price as input variables and the NYSE index as output variables.

Table 3: Prediction of NYSE, Gold price, and WTI oil indexes using the News index.

Fit Stats	**NYSE Index**			**Gold Price Index**			**WTI Oil Price**		
Single Layer Neural Network									
	Neuron 1 (1)	**Neuron 2 (2)**	**Neuron 4 (3)**	**Neuron 1 (1)**	**Neuron 2 (2)**	**Neuron 4 (3)**	**Neuron 1 (1)**	**Neuron 2 (2)**	**Neuron 4 (3)**
MSE	0.5472	0.5472	0.7085	0.3445	0.4719	0.8724	0.1585	0.1735	0.1835
RMSE	0.7397	0.7397	0.8417	0.5869	0.6869	0.9340	0.3981	0.4165	0.4284
SSE	20.7933	36.0819	26.9228	10.3356	14.1582	26.1722	5.8628	6.4207	6.7885
Two Layer Neural Network									
	Neuron 2-2 (4)	**Neuron 3-1 (5)**	**Neuron 3-2 (6)**	**Neuron 2-2** (4)	**Neuron 3-1** (5)	**Neuron 3-2** (6)	**Neuron 2-2** (4)	**Neuron 3-1** (5)	**Neuron 3-2** (6)
MSE	0.4661	0.4715	0.2607	0.3325	0.2706	0.3119	0.1369	0.1771	**0.1790**
RMSE	0.6827	0.6867	0.5106	0.5766	0.5202	0.5585	0.3700	0.4208	0.4231
SSE	17.7119	17.9191	8.6034	9.9743	8.1188	9.3563	5.0651	6.5529	**6.6236**
Deep Neural Network with Three Layers									
	Neurons 3-2-1 (7)	**Neurons 4-2-1 (8)**	**Neurons 6-3-1 (9)**	**Neurons 3-2-1 (7)**	**Neurons 4-2-1 (8)**	**Neurons 6-3-1 (9)**	**Neurons 3-2-1 (7)**	**Neurons 4-2-1 (8)**	**Neurons 6-3-1 (9)**
MSE	0.4807	0.3030	0.1027	0.2543	0.2677	0.3020	0.1840	0.1879	0.1776
RMSE	0.6933	0.5505	0.3205	0.5043	0.5174	0.5495	0.4290	0.4335	0.4214
SSE	18.2679	10.0001	3.3901	7.6292	8.0296	9.0591	6.8092	6.9532	6.5693

Similarly, in the second phase, we use the news index, NYSE index, and WTI oil price as input variables and gold price as output variables. Finally, we use the News index, NYSE index, and gold price as the WTI oil price index predictors. The objective of these indexes is to determine how they are interconnected and dependent on one another.

These results are presented in Table 2, which displays MSE, RMSE, and SSE, showing the networks' predictive accuracy. Thus, the lower the values of these statistics, the greater the prediction accuracy. Considering the single-layer neural network for these three indices, it is evident that the smallest and highest MSE values in the NYSE index are 0.5472 and 0.7085, respectively. The lowest MSE value suggests that the model accuracy is relatively high.

In the gold price index, the highest and lowest MSE values are 0.8724 and 0.3445, which depicts that network 1, with only one neuron in the first layer, has more model accuracy than network 3, with 4 neurons in the first layer.

In the case of WTI oil price, the MSE value of network 1 with only one neuron has more model accuracy than networks 2 and 3. The highest and lowest MSE values in the WTI oil index are 0.1585 and 0.1835, respectively.

We gradually increased the hidden layers to observe the prediction accuracy of models. However, increasing hidden layers may increase the network's complexity and the models' overfitting. By considering network 6 of the NYSE index, which contains 3 neurons in the first layer and 2 neurons in the second layer, it is evident that the mean square error (0.2607) and the sum of square error (8.6034) is relatively less than other networks. So, network 6 has the highest prediction compared to any different network combination.

Furthermore, the gold price index and its combinations as single layer network, two-layer network, and deep neural network are also taken into account. In its deep neural network with three layers, network 7 shows us 3 possible combinations of layers: the first layer contains 3 neurons, the second layer comprises 2 neurons, and the third layer has 1 neuron, and its MSE value is very small compared to other combinations. Similarly, WTI Oil price is also showing different combinations of hidden layers. When network 6 is considered, it shows that the first layer contains 3 neurons and the second layer comprises 2 neurons. It is showing very high prediction as compared to other combinations of networks. Among these three outcome variables, the networks with relatively high prediction will be used further to check the relative importance of covariates.

By observing the table in further detail, we see that when NYSE was taken as an output variable, network 9 with three hidden layers (6 neurons in the first hidden layer, 3 neurons in the second, and 1 neuron in the third hidden layer) achieved the highest prediction accuracy. The MSE was 0.1027, and SSE was 3.3901. Results have suggested that the News index significantly impacts the outcome variables. It can be causal as the News index can directly affect the oil prices, further impacting the NYSE index.

The relative importance of predictors in Neural Network Models

Neural networks are considered black boxes because the relationship between input and output is either unknown or provides little insight. We implemented the Olden algorithm that provided each input's relative importance and directional relationship between them. For relative importance, we chose only those networks that provide plausible results regarding the directional relationship between inputs and output. Therefore, we select network 6 for the NYSE index, Network 7 for the gold price, and network 6 for the WTI oil price for the relative importance of the News index. The results are presented in Table 2.

Table 4: Different Combinations of Neurons for Predictions

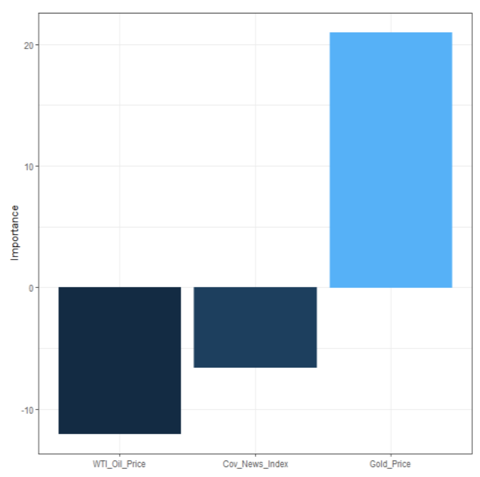
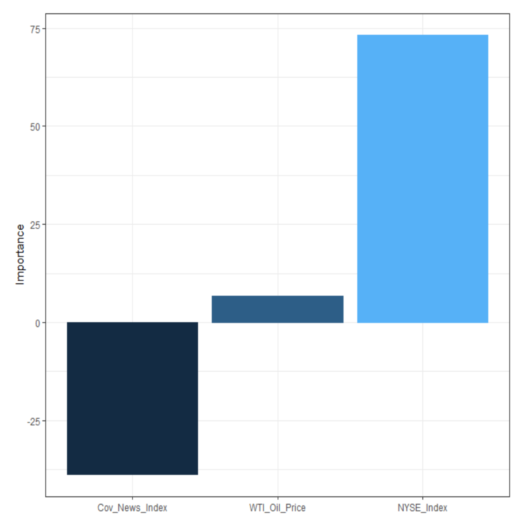
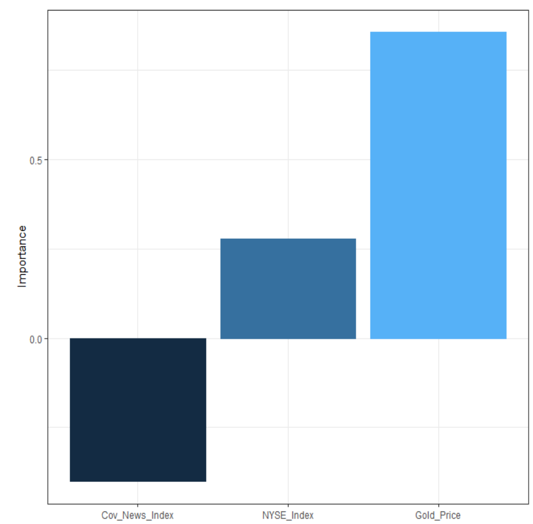
Dependent Variable NYSE Index		**Dependent Variable Gold Price**		**Dependent Variable WTI Oil**	
Neural Network Model 6		**Neural Network 7**		**Neural Network 6**	
Inputs	Relative Importance	Inputs	Relative Importance	Inputs	Relative Importance
Gold Price	20.9393	NYSE Index	73.1697	Gold Price	0.8561
WTI Oil Price	-12.0328	COVID News Index	-38.8222	COVID News Index	-0.4012
COVID News Index	-6.5548	WTI Oil Price	6.6246	NYSE Index	0.2787
					

Table 3 indicates that the News index and WTI Oil price have a negative relationship with the NYSE index. The most important predictor of the NYSE is the gold price index. It gets a magnitude of 20.94. The directional relationship suggests that as the gold prices increase, the NYSE index also improves. However, WTI oil price has a negative association with the NYSE. This indicates that as the oil prices rise, the NYSE index decreases. Finally, the News index has a negative relation with the NYSE index for prediction; its magnitude for prediction is -6.5548. Though this index has a relatively lower magnitude, it still impacts the NYSE index. During the coronavirus crisis, gold acted as a safe-haven (Ji et al., 2020), while stock markets responded negatively (Mazur et al., 2021). Hence, similar to other stock exchange indexes, the NYSE has also been negatively affected by COVID-19 (Tlemsani et al., 2020).

This fact aligns with our analysis that the diminution in the stock prices of the NYSE stock index is mainly due to COVID-19, and with the increase in the News prediction, stock prices encountered extreme deterioration in their market values. Similarly, the oil market faces unprecedented losses due to a significant downturn in oil demand, and investments in the oil market also lead to substantial losses.

Currently, the drop in oil prices is mainly due to COVID-19. Moreover, the slowdown of the economy due to the pandemic also resulted in a significant reduction in oil prices in the history of the oil market. The result demonstrates that an increase in negative News about the coronavirus coincides with the falling prices of WTI oil and NYSE stock.

Our second output variable, the gold price index, indicates that the highest predictor is the NYSE index. NYSE index showed a high prediction for gold prices, and its magnitude is relatively high, i.e., 73.1697. There is a positive relationship between the NYSE index and gold prices. It is important to mention that the News index became the second-highest predictor of the gold price index. The directional relationship between Gold price and the News index is negative, suggesting that the gold prices decrease as the COVID News increases. The magnitude is also relatively high, with -38.82. However, the WTI oil price shows a lesser magnitude than the NYSE index and COVID-19 news index.

Finally, the results of our third output variable, the WTI oil price index, suggest that the gold prices index is a higher predictor of WTI oil prices. Furthermore, the News article remains the second predictor. The NYSE index is the lowest predictor of the WTI oil index.

It is important to comment on the magnitude of all three networks; regarding their magnitude, network 7 has the highest values. The reason is that adding a hidden layer increases the weights of neurons. This ultimately increases the magnitude of all the inputs. We can conclude that all three indexes are interconnected, which means that changes in any index lead to changes in other indexes. Furthermore, the News index also remained a significant predictor, impacting all the indexes.

CONCLUSION:

There is a vast body of literature that employs neural networks for prediction. We constructed a novel index that explains the News stories published in the mainstream media of the US. Our objective is to determine the interconnection of the NYSE index, Gold price index, and WTI oil price index, along with the impact of the News.

We trained 27 networks, 9 for each model, from simple to two hidden layer networks. We simultaneously take the NYSE index, Gold price index, and WTI oil price index as output variables in each model to observe the interconnectedness and accuracy of prediction. The News index is taken as an input variable in all the models and its impact on these indexes. The MSE, RMSE, and SSE values are taken as the main criteria to check the accuracy of the models. In the first phase, we take the NYSE index as the output variable and the News index, gold price, and WTI oil price as input variables.

Similarly, in the second phase, we use the gold price index as the output variable and the News index, NYSE index, and WTI oil price as input variables. Finally, we use the News index, NYSE index, and gold price as the WTI oil price index predictors. We take those networks that provide high accuracy and plausible directional relationships between input and output variables. We use the connection weight approach to observe the relative importance of input variables that help predict output variables. The results suggest that all the indexes are interconnected, where the increase/decrease of any index impacts the other commodity index.

Further, the News index remains the second highest predictor for gold prices and WTI oil indexes. It is also evident that during COVID-19, WTI oil prices were the lowest in history. By employing a neural network, it is evident that these indexes are interconnected and depend upon one another. In addition, the News index also seems to be an important predictor of these commodities.

The results of this study provide valuable insights for investors, policymakers, or market analysts, allowing them to recognize that fluctuations in the index of one commodity can impact another commodity. This understanding is vital for making informed investment decisions in the dynamic and interconnected field of commodity trading.

A constraint inherent in this study lies in its utilization of a limited time dimension, which may potentially impart implications on the obtained results.

Future research endeavors could extend the scope to encompass indexes from various countries, thereby facilitating an investigation of the interconnections between stock exchanges and commodity markets.

REFERENCES

Ali, S., & Yang, X. (2010). *Dynamic and advanced data mining for progressing technological development: Innovations and systemic approaches* (1st ed.). Information Science Reference.

Bell, T. B. (1997). Neural nets or the logit model? A comparison of each model’s ability to predict commercial bank failures. *Intelligent Systems in Accounting, Finance and Management*, *6*, 249–264.

Bishop, C. M. (1995). Training with Noise is Equivalent to Tikhonov Regularization. *Neural Computation*, *7*(1), 108–116.

Ecer, F. (2013). Comparing the bank failure prediction performance of neural networks and support vector machines: The Turkish case. *Economic Research-Ekonomska Istraživanja*, *26*(3), 81–98.

Enke, D., & Thawornwong, S. (2005). The use of data mining and neural networks for forecasting stock market returns. *Expert Systems with Applications*, *29*(4), 927–940. https://doi.org/10.1016/j.eswa.2005.06.024

Gangopadhyay, K., Jangir, A., & Sensarma, R. (2016). Forecasting the price of gold: An error correction approach. *IIMB Management Review*, *28*(1), 6–12. https://doi.org/10.1016/j.iimb.2015.11.001

Gogas, P., Papadimitriou, T., & Agrapetidou, A. (2018). Forecasting bank failures and stress testing: A machine learning approach. *International Journal of Forecasting*, *34*, 440–455. https://doi.org/10.1016/j.ijforecast.2018.01.009

Gong, X. L., Liu, X. H., Xiong, X., & Zhuang, X. T. (2019). Forecasting stock volatility process using improved least square support vector machine approach. *Soft Computing*, *23*(22), 11867–11881. https://doi.org/10.1007/s00500-018-03743-0

Hamid, S. A., & Iqbal, Z. (2004). Using neural networks for forecasting volatility of S&P 500 Index futures prices. *Journal of Business Research*, *57*(10), 1116–1125. https://doi.org/10.1016/S0148-2963(03)00043-2

Iqbal, J., Saeed, A., & Khan, R. A. (2023). The relative importance of textual indexes in predicting the future performance of banks: A connection weight approach. *Borsa Istanbul Review*, *23*(1), 240–253. https://doi.org/10.1016/j.bir.2022.10.004

Jardin, P. du. (2017). Dynamics of firm financial evolution and bankruptcy prediction. *Expert Systems with Applications*, *75*, 25–43. https://doi.org/10.1016/j.eswa.2017.01.016

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, *71*. https://doi.org/10.1016/j.irfa.2020.101526

Khashei, M., & Bijari, M. (2010). An artificial neural network (p, d, q) model for timeseries forecasting. *Expert Systems with Applications*, *37*(1), 479–489. https://doi.org/10.1016/J.ESWA.2009.05.044

Kristjanpoller, W., & Minutolo, M. C. (2015). Gold price volatility: A forecasting approach using the Artificial Neural Network–GARCH model. *Expert Systems with Applications*, *42*(20), 7245–7251. https://doi.org/10.1016/J.ESWA.2015.04.058

Lardic, S., & Mignon, V. (2008). Oil prices and economic activity: An asymmetric cointegration approach. *Energy Economics*, *30*(3), 847–855. https://doi.org/10.1016/J.ENECO.2006.10.010

Lek, S., Delacoste, M., Baran, P., & Dimopoulos, I. (1996). Application of neural networks to modelling nonlinear relationships in ecology. *Ecological Modelling*, *90*, 39–52.

Li, F. (2010). The information content of forward-looking statements in corporate filings - A naïve Bayesian machine learning approach. *Journal of Accounting Research*, *48*(5), 1049–1102. https://doi.org/10.1111/j.1475-679X.2010.00382.x

Lineesh, M. C., John, J., Minu, K. K., & John, C. J. (2010). Analysis of Nonstationary Nonlinear Economic Time Series of Gold Price-A Comparative Study. *International Mathematical Forum*, *5*(34), 1673–1683. https://www.researchgate.net/publication/228967304

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, *38*. https://doi.org/10.1016/j.frl.2020.101690

Olden D, J., & Jackson A, D. (2002). Illuminating the “black box”: a randomization approach for understanding variable contributions in artificial neural networks. *Ecological Modelling*, *154*(1–2), 135–150. https://doi.org/10.1016/S0304-3800(02)00064-9

Olden, J. D., & Jackson, D. A. (2002). Illuminating the “black box”: a randomization approach for understanding variable contributions in artificial neural networks. *Ecological Modelling*, *154*, 135–150. https://doi.org/10.1016/S0304-3800(02)00064-9

Olden, J. D., Joy, M. K., & Death, R. G. (2004). An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling*, *178*(3–4), 389–397. https://doi.org/10.1016/j.ecolmodel.2004.03.013

Panchal, G., Ganatra, A., Kosta, Y. P., & Panchal, D. (2011). Behaviour analysis of multilayer perceptrons with multiple hidden neurons and hidden layers. *International Journal of Computer Theory and Engineering*, *3*(2), 332–337.

Patuelli, R., Reggiani, A., Nijkamp, P., & Blien, U. (2006). New Neural Network Methods for Forecasting Regional Employment: an Analysis of German Labour Markets. *Spatial Economic Analysis*, *1*(1), 7–30. https://doi.org/10.1080/17421770600661568

Ramyar, S., & Kianfar, F. (2019). Forecasting Crude Oil Prices: A Comparison Between Artificial Neural Networks and Vector Autoregressive Models. *Computational Economics*, *53*(2), 743–761. https://doi.org/10.1007/s10614-017-9764-7

Ristolainen, K. (2018). Predicting banking crises with artificial neural networks: The role of nonlinearity and heterogeneity. *The Scandinavian Journal of Economics*, *120*(1), 31–62. https://doi.org/10.1111/sjoe.12216

Salton, G., & McGill, M. J. (1986). *Introduction to Modem Information*. 375–384. http://portal.acm.org/citation.cfm?id=1893971.1894017

Tam, K. (1991). Neural network models and the prediction of bank bankruptcy. *Omega International Journal of Management Sciences*, *19*(5), 429–445. https://doi.org/10.1016/0305-0483(91)90060-7

Tlemsani, I., Alghamdi, M., Balhareth, S., Alsaleh, F., Alomair, M., & Alqutaim, M. (2020). The Impact of Coronavirus (COVID-19) on New York Stock Exchange. *Asian Journal of Finance & Accounting*, *12*(2), 28–38. https://doi.org/10.5296/AJFA.V12I2.17685

Wen, F., Yang, X., Gong, X., & Lai, K. K. (2017). Multi-Scale Volatility Feature Analysis and Prediction of Gold Price. *International Journal of Information Technology and Decision Making*, *16*(1), 205–223. https://doi.org/10.1142/S0219622016500504

Wilson, R. L., & Sharda, R. (1994). Bankruptcy prediction using neural networks. *Decision Support Systems*, *11*(5), 545–557. https://doi.org/10.1016/0167-9236(94)90024-8

Yi, J., & Prybutok, V. R. (1996). A neural network model forecasting for prediction of daily maximum ozone concentration in an industrialized urban area. *Environmental Pollution*, *92*(3), 349–357. https://doi.org/10.1016/0269-7491(95)00078-X