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METHODS

Predicting option prices and volatility with high-frequency data using neural network

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A neural network utilizes a huge amount of data for analysis and prediction. This paper predicts option prices and volatility using a neutral network based on high-frequency intraday data. We focus on short-term predictions because option prices and volatility, in fact, are very volatile and almost impossible to predict. We find that neural network can predict option prices and volatility by using predictors constructed from the prices of option and its underlining index, especially in the short term, which is what practitioners care about more in practice.

Keywords: option, neural network, volatility, high-frequency data, price prediction

1. Introduction and literature review

An neural network mimics the brain neural network. The artificial neural network contains an input layer, an output layer, and the inside layers. The network collects the information from the input layer and outputs the processed information to provide useful outcomes.

The artificial neural network model provides a new tool to study the price movement of financial products and economic indices, and numerous studies using the artificial neural network models have been done on it (1, 2). Some studies use an artificial neural network model to focus on GDP growth rate predictions, CPI rate predictions, and other major economic indices (3–7). For economic activities, artificial neural network models have been used to predict the default and bankruptcy for consumer borrowings (8, 9).

For financial instrument price prediction, many studies utilize a huge amount of financial data and try to forecast hidden relationships. For example, the price prediction of the financial derivative using an artificial neural network model can provide suitable results compared with a closed-formed option model (10). Various researchers are using artificial neural network models for option pricing (11, 12). Considering the degree of using the integration of the artificial neural network model, two major types of models are available: weak hybrid models and strong hybrid models (13, 14). The prediction based on the artificial neural network model for price movement is refined using traditional statistical models (14).

There are various research works on the prediction of major stock indices. For instance, Yao et al. (15) predicted the price performance movements of the Nikkei 225 index using an artificial neural network model. Gradojevic et al. (16) used an artificial neural network model based on the data of expire time and the moneyless of the underlying instruments to predict the S&P-500 European options, and empirical tests provided the proper results for the option pricing. An artificial neural network model with multiple levels of functions is used by Morelli et al. (17) to predict option price and forecast the hidden pricing movement relationship between financial derivatives and the option-related variables. Shakya et al. (18) used artificial neural network models based on evolving algorithms to model demand scenarios, and the results of the approach provided the proper price accuracy of the price predictions compared with the traditional closed-formed models.

There are numerous studies on option pricing based on literature reviews, and our approach in this study applied an artificial neural network model for the option pricing movements and compared it with the short-term and

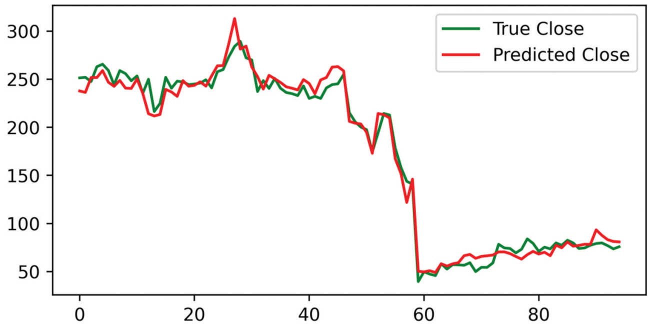

FIGURE 1 | True and predicted close prices (in sample).

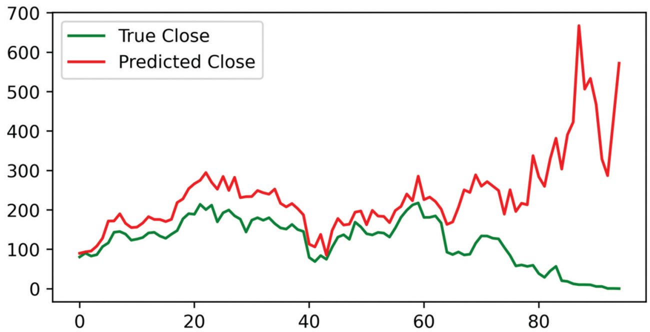

FIGURE 2 | True and predicted close prices (out of sample).

long-term periods. This paper focuses on the short-term prediction because option prices and volatility, in fact, are very volatile and almost impossible to predict. The results show that neural network can predict option prices and volatility by using predictors constructed from the prices of option and its underlining index, especially in the short term, which is what financial practitioners care about more in financial market trading.

2. Data and results

This paper studies the predictability of option close prices by using the "IO2003C4000" call option prices. That being said, the 2003 series of call option's underlined index is the CSI 300 Index and the strike price is 4000. The expiration date of the option is March 20, 2020, the third Friday of the call option contract's expiration month. We also use the CSI 300 Index prices and other variables to construct several predictors that are used to predict the call option volatility by a neural network. Our dataset's frequency is half an hour (30 min), ranging from December 23, 2019, to March 20, 2020. In particular, we compute the following predictors: returns on the index, rolling volatility of index returns, implied volatility, and implied prices of the option. Note that we set the risk-free rate to be 2% per year, and assume no dividend when computing these predictors. The strike price is 4000. We compute the rolling volatility of the index returns using the prior 24 observations.

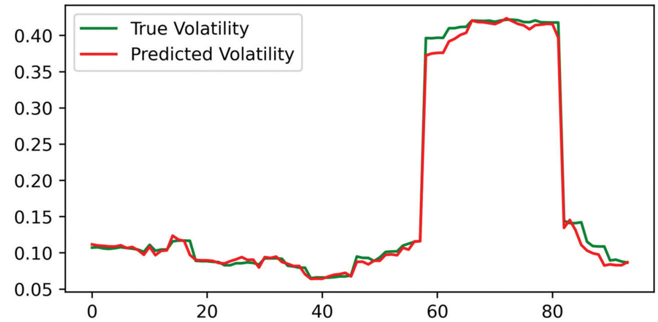

FIGURE 3 | True and predicted volatility (in sample).

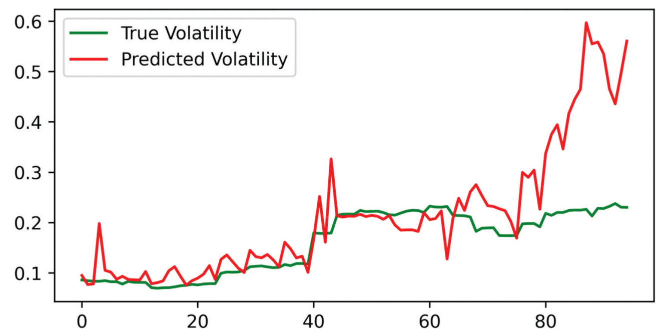

FIGURE 4 | True and predicted volatility (out of sample).

This paper uses the index price, index returns, rolling volatility of index returns, implied volatility, and implied prices of the option to predict option prices by the neural network. We use the first half of the dataset to train the model and the second half to test the model. We find that the neural network is expected to fit the data quite well in the training set, as shown in **Figure 1**. **Figure 2** shows that the model based on our predictors can predict the option prices in the short term but cannot predict the prices well in the long term. **Figures 3**, **4** show the in-sample and out-of-sample predictions of neural networks on option volatility. We can see that the predicted volatility fits the true volatility quite well, and the predicted one is able to predict the trend of the option volatility out of sample.

We also conduct research on predicting option returns. We find that a neural network with predictors constructed as above is not able to predict the option returns. We conjecture that is because the option return is very volatile and computing return by interdifferentiation makes the process lose a lot of memory, which is very important for the prediction. We are able to predict prices because the price process keeps the memory. One might suspect that the price process is unstable in the long run. We note that we focus on short-run prediction in the option cases. Therefore, the unstable price process is not a big issue in this case. In addition, the results on volatility prediction show that neural network is able to predict the uncertainty in option markets.

3. Conclusion

The artificial neural network model provides a new tool to study the price movement of financial products. Our approach in this study applied an artificial neural network model for the option pricing movements and compared it with the short-term and long-term time periods. This paper focuses on the short-term prediction because option prices and volatility, in fact, are very volatile and almost impossible to predict. The results show that a neural network can predict option prices and volatility by using predictors constructed from the prices of option and its underlining index, especially in the short term.

Since the Shanghai Shenzhen 300 stock index option started only in December 2019 and not much study has been done on the artificial neural network model for forecasting the stock index call option prices, our research approach develops an approach to examine the Chinese market, which is an imperfect market. The test result of our approach indicates that the neural network with predictors constructed above is not able to predict the option returns in the stock index option, and we conjecture that is because the option return is very volatile and computing return by interdifferentiation makes the process lose a lot of memory, which is very important for the prediction. In contrast, we are able to predict prices because the price process keeps the memory. One might suspect that the price process is unstable in the long run. We note that we focus on the short-run prediction in the option cases. Therefore, the unstable price process is not a big issue in this case. In addition, our results show that a neural network can predict option volatility.

For future improvement of our artificial neural network model, we will combine the artificial neural network with traditional statistical models, such as GARCH for the optimization of the stock index options, and we will examine the data various financial markets and further study the long-term trend in terms of the price movements in the derivatives markets.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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