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Review Paper

A Review of Deep Learning Models for Price Prediction in Agricultural Commodities

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ABSTRACT

Price fluctuations in agricultural commodities have a negative impact on the country's GDP. Price prediction assists the agricultural supply chain in making necessary decisions to minimize and manage the risk of price fluctuations. Although traditional models for forecasting, such as ARIMA and exponential smoothing, are widely used, it is difficult to predict price fluctuations accurately, especially when dealing with large amounts of data. To overcome this lacuna, various machine learning and deep learning models have recently been used to forecast price series. To be precise, the most significant finding is that deep learning models are suitable for predicting commodity prices.

HIGHLIGHTS

- RNNs have been applied for forecasting time series data in most scientific and industrial fields, but mainly in commodity price forecasting.
- RNNs, such as the gated recurrent unit, LSTM neural network, and improvement models, can be powerful prediction alternatives to traditional neural networks and can obtain better prediction results.

Keywords: Commodity Price, deep learning, recurrent neural network, time series

Volatility in agricultural commodity prices is an ongoing concern where policymakers, as well as all participants in the food supply chain, are interested. There need to be a better understanding of what is expected in future evolution. Farmers in some countries, now face several risks that were previously absorbed by market and price support policies (Matthews, 2010). Nonlinearity, uncertainty, and dynamics are complex volatility characteristics of agricultural commodity prices that make prediction difficult with high chances of uncertain results (Cheng, 2015). Currently, there are two types of agricultural commodity price forecasting methods that are traditional forecasting and intelligent forecasting. Traditional forecasting techniques include three methods such as autoregressive moving average (ARIMA), Exponential smoothing, and Autoregressive Conditional Heteroskedasticity (ARCH) (Gowthaman, 2022; Jadhav, 2018). These traditional forecasting models require a long time to process the data, and they have difficulty projecting accurate price changes (Chen, 2019). Additionally, the majority of these techniques operate under the presumption that time series data is stationary and linear. Besides, real-time series data that is dynamic, non-linear, and non-stationary is not sufficiently captured (Karia, 2011). With the advancements in machine learning methods, many researchers use intelligent forecasting methods to predict the price of products, such as Neural Networks (NN), Support Vector Regression (SVR), and Genetic algorithms (GA) (Duan, 2017). These intelligent

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forecasting methods can outshine traditional methods. However, they can't process temporal data (Chen, 2019). To overcome this, a new class of emerging forecasting methods like recurrent neural networks (RNN), is helpful in the temporal correlation of time series analysis. As a special RNN model, long short-term memory (LSTM) avoids vanishing gradient (problem for highly dependent data) and exploding gradient during training effectively (Pascanu, 2013; Hochreiter, 1997). Ahmed, (2010) opines that machine learning techniques can outperform conventional econometrics techniques. With the use of feature attention and temporal attention, they successfully forecasted prices, which explains the relationships between input factors and outcomes. Ran *et al.* (2019) utilized an LSTM model with an attention mechanism for the travel-time prediction where this mechanism was able to focus well on the variations in input features, and the attention-based LSTM model outperformed alternative baseline models. An evolutionary attention-based LSTM model was proposed by Li *et al.* (2019), and it was used to analyze data from Beijing's particulate matter 2.5 (ug/m^3) levels. By autonomously choosing crucial input variables through financial time-series prediction using an attention-based LSTM model, Zhang *et al.* (2019) successfully addressed a long-term dependence issue. LSTM models are non-parametric, they can handle non-linear patterns appropriately and do not require the error term to follow a distribution, which is one of the goals of using them. Ly *et al.* (2021) opines that unit roots do not affect LSTM models since they do not need the underlying data to follow a stationary process.

1. Deep learning models

This section provides an overview of the theoretical background of the selected deep learning models. We describe deep learning neural networks and their activation function.

1.1 Recurrent Neural Networks

In the 1980s, Williams and Zipser created the first recurrent neural networks (RNN). It takes into account the dimension of time to improve outcomes when analyzing time series data. It was used in sequence analysis techniques for processing text, sound, and video (Zhang, 2017). Fig. 1 illustrates a basic RNN structure that includes input vectors (x), hidden unit vectors (H), and hidden state vectors (O). Here, at each time step, the hidden units generate a concealed state vector. A network structure at time t, along with its previous and following time steps, is shown in the Fig. 2 graphs as t, t-1, and t + 1. The weight values between various levels are represented by W, U, and V. The dynamic information from the sequences can endure and flow from one-time step to the next in the network due to the interconnected hidden units forming a self-looped structure, which aids the RNN's ability to remember previous information.

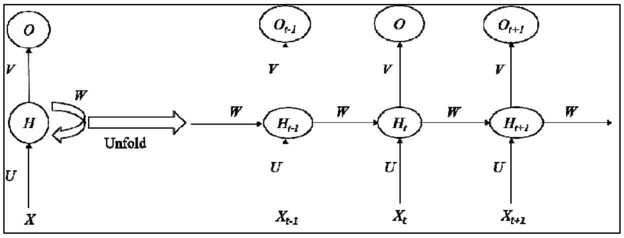

Fig. 1: Self-loop structure of recurrent neural networks

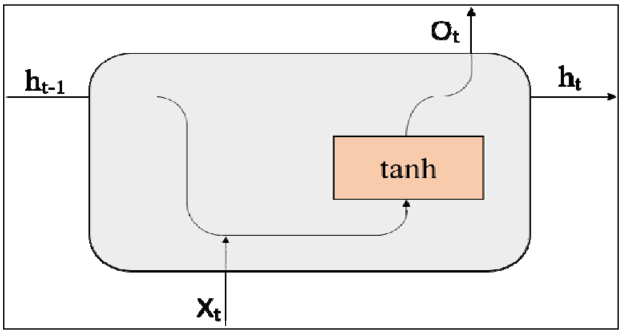

Fig. 2: Recurrent Neural Network

Previous hidden state (h_t) can be formulated as;

$$h_t = \tanh\left(U.x_t + W.h_{t-1}\right) \qquad \ldots(1)$$

RNN deals with finding and modeling relations and extracting information from time series data. In recent times, RNN has tackled a wide range of problems in which it replaces its standard activation functions with discrete wavelet transformation. In particular, it is compared to traditional activation function like the sigmoid and tangents hyperbolics. It is evident that better information flow regulation could lead to a rise in modelling accuracy. However, vanishing gradients are a drawback of RNN. Therefore, long-term non-stationary dependencies are harder to get detected by RNN (Motazedian, 2019). To address this issue and create a defined memory capacity, RNNs are enlarged using elongated recurrent skip connections. This allows the capture of dependencies in time series data. Without the need for network-wide propagation, the skip connections allow the direct processing of data from previous time steps. Therefore, the average duration of the skip links has a significant impact on whether long-term or short-term dependencies are absorbed more so than the other. According to Qin *et al.* (2017), RNNs are especially useful for predicting highly dynamic, time-variant systems that are subject to stationary or non-stationary short-term dependencies.

1.2 Gated recurrent unit (GRU)

In 2014, Cho *et al.* proposed and established the gated recurrent unit (GRU) to address the vanishing gradient issue that affected conventional recurrent neural networks (RNN). GRU has several long short-term memory characteristics in which a gating mechanism is used by both LSTM and GRU algorithms to regulate the memorization process. The advantage of GRU is that it has fewer parameters than LSTM, which results in more efficient computing with less complexity (Wang, 2018). Reset and update gates are the only gates present in GRU, because it chooses which data should be saved or erased, the update gate in an LSTM is identical to the forget and input gates. The reset gate determines how much information needs to be forgotten. As a result, GRU takes less time to train than LSTM.

The structure of GRU is shown in Fig. 3; a relationship between the input and output for GRU can be written as:

$$r_t = \sigma\left(w_r.x_t + u_r.h_{t-1} + b_r\right) \qquad \ldots(2)$$

$$z_t = \sigma\left(w_z.x_t + u_z.h_{t-1} + b_z\right) \qquad \ldots(3)$$

$$a_t = \tanh\left(w_n.x_t + u_n\left(r_t * h_{t-1}\right) + b_n\right) \qquad \ldots(4)$$

$$h_t = \left(1 - z_t\right).h_{t-1} + z_t * a_t \qquad \ldots(5)$$

Where r_t is the reset gate, z_t is the update gate, α_t is the memory content, σ and *tanh* are the activation functions, and h_t is the final memory at the current time step. The reset and update gates have values from 0 to 1 through the sigmoid function in equations (1) and (2). On the other hand, the memory content, using the reset gate to store the relevant information from the past, has a value between -1 and 1 through *tanh*.

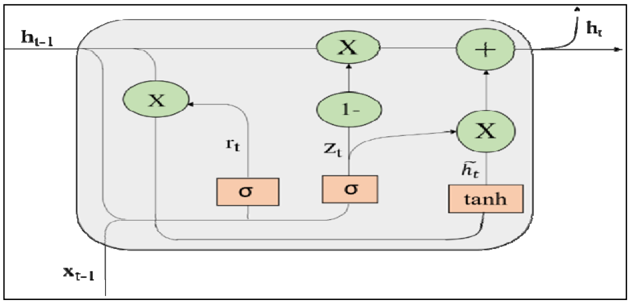

Fig. 3: Gated recurrent unit neural network

1.3 Long Short-Term Memory networks

Long short-term memory (LSTM) is a special type of RNN. Hochreiter and Schmidhuber (1997) introduced the LSTM network, which was continually refined in subsequent works such as Gers *et al.* 1999 and 2000; Cho *et al.* 2014. RNNs have been successfully applied in various fields, such as speech recognition, language modelling, machine translation, image captioning, text recognition, and action detection in video streams (Mikolov *et al.* 2014; Ullah *et al.* 2017). Since the LSTM network is capable of handling sequence dependence among observed inputs, it is well-suited to sequence prediction problems, especially for non-linear and complex time-series data (Guo *et al.* 2016; Hsu, 2017).

Due to the vanishing gradient phenomenon, the RNN is unable to capture multiple time dependencies and long-term dependencies. Gating mechanisms are created as a result to take the place of activation functions. Three gates, an input, a forget gate, and an output gate found in each LSTM cell enable changes to be made to a cell's state that are iteratively propagated to capture long-term dependencies. The network can memorize numerous time dependencies because of this controlled information flow within the cell. The primary application of LSTM is the modelling of long-term dependencies. The Gated Recurrent Unit (GRU) is an alternative to LSTM that predicts long-term dependencies with superior short-term information integration (Cho, 2014). GRU has an update and reset gate, whereas LSTM has a gating system and a more condensed cell structure. The cell state in GRU can be changed at each iteration and updated with recent data via the reset gate. The change gradient that can be realized at each iteration is constrained by a mechanism provided by LSTM. Unlike GRU, LSTM does not permit the complete discarding of historical data. According to research by Chung *et al.* (2014) on cell architecture, cells with a gating mechanism perform noticeably better than cells without a gating mechanism, i.e., the traditional RNN. In the context of a comprehensive investigation of variants of several network architectures, Britz *et al.* (2017) established the superiority of LSTM over GRU. It might be discovered that the LSTM gating mechanism aids in the filtering of unimportant input data and enhances modelling precision for time-variant behaviour. Besides inheriting the structure of a chain-like repeating hidden layer in a neural network from the RNN, the LSTM has a redesigned sophisticated memory block in the hidden layer, which mainly consists of four parts: forget gate, input gate, output gate, and memory cell as shown in Fig. 4. At a given time '*t*', the mechanism of the LSTM can simply be concluded in the following steps.

1. Decide the extent of information throw away from the output at last time step $h_{t-1}$and new input x_t at forget gate f_t:

$$f_t = \sigma\left(w_f\left[h_{t-1}, X_t\right] + b_f\right) \qquad \ldots(6)$$

2. Determine how much information should be added to memory cell state C_t at the input gate i_t, and a candidate memory cell state C_t is updated:

$$i_t = \sigma\left(w_i\left[h_{t-1}, X_t\right] + b_i\right) \qquad \ldots(7)$$

$$\tilde{C}_t = \tanh\left(w_c\left[h_{t-1}, X_t\right] + b_c\right) \qquad \ldots(8)$$

3. Update current memory cell state C_t using C_{t-1} and C_t:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \qquad \ldots(9)$$

4. Calculate the output h_t to next memory cell at output gate O_t:

$$O_t = \sigma\left(w_o\left[h_{t-1}, X_t\right] + b_o\right) \qquad \ldots(10)$$

$$h_t = o_t * \tanh\left(c_t\right) \qquad \ldots(11)$$

Where *f*, *i*, *o*, and C represent forget gate, input gate, output gate, and memory cell state, respectively. *W*, *U*, and b denote the input weight, recurrent weight, and bias of a certain hidden layer component, respectively. σ and *tanh* are the logistic sigmoid function and hyperbolic tangent function as activation function, respectively.

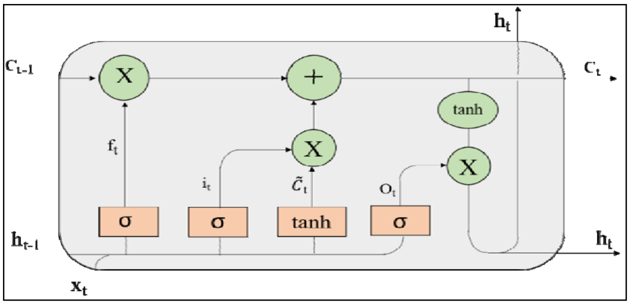

Fig. 4: Long short term memory neural network

The output value varies with the activation function. The activation function sometimes referred to as the transfer function, is a mathematical formula that predicts the output of neurons and is subdivided into linear and nonlinear functions. The outcomes of a linear activation function are also linear between the input and output layers. For practical application, however, such a linear relationship is insufficient because the issues entail complicated information and a variety of characteristics, including image, video, text, and sound. A neural network with a nonlinear activation function can overcome the limitations of the linear activation function. The rectified linear unit (ReLU) and leaky ReLU are examples of nonlinear activation functions because the slope is not constant for all values. Especially for ReLU, the slope is either 0 for negative values or 1 for positive values.

1.4 Measurement criteria

Measurement criteria are critical for explaining the forecast performance of deep learning models. The typical evaluation metrics for commodity price forecasting are RMSE (Root mean square error) and MAPE (Mean absolute percentage error).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t}\times 100$$

2. Related past studies on agricultural commodity prices time series

Deep learning (DL), an essential component of artificial intelligence (AI), has made significant strides in recent years. DL automatically identifies key properties from the data. Other Machine learning (ML) methods gain from deep learning-driven methods because they don't rely on feature engineering (Dairi *et al.* (2021)). Nassar *et al.* (2020) showed that deep learning models, LSTM, and CNN-LSTM are effective in the precise prediction of fresh produce prices for up to three weeks in advance using time series datasets of vegetables, fruits, and flowers. They did this by comparing the performance of deep learning price prediction models with eight statistical as well as benchmark machine learning models. The LSTM neural network was shown effective by Sabu and Kumar (2020) when they employed time-series and machine learning models to estimate the monthly prices of arecanuts in Kerala. When comparing the appropriateness of ARIMA and deep learning models on various datasets, including daily, weekly, and monthly data, Weng *et al.* (2019) determined that the deep learning approach was the best one for predicting agricultural product prices.

In a different study by Chen *et al.* (2019), wavelet analysis was used to lessen the noise in the cabbage data. The refined normalised data was then applied to the LSTM model, which produced superior accurate results. Zhu *et al.* (2018) summarised the main deep learning approaches and demonstrated how DL techniques including Convolutional Neural Network (CNN), RNN, and Generative Adversarial Network (GAN) are gaining popularity among researchers working on farm price forecasts. The wheat prices dataset was analysed using the LSTM method by Rasheed *et al.* in 2021. Their investigation showed that LSTM was outperforming other traditional machine learning and statistical time series models substantially

All the studies cited above and details of related studies found in Table 1 lead to the following few important inferences.

1. There are many studies with various models (statistical, ML, and DL-based) used for prediction tasks of many agricultural commodity prices.
2. Literature studies indicate that deep learning models perform better as compared to machine learning in the tasks of agricultural commodity price forecasting.

Table 1: Related Studies

Name of the Author	**Name of the commodities**	**Deep learning model used**	**Results**
Chen, *et al*.	Chili, Tomato	LSTM Baseline models: ARIMA, SVR, Prophet, XGboost	The LSTM was forecasted to produce the best results.
Manogna, *et al.*	Cotton seed, caster seed, rape mustard seed, soybean seed, and guar seed	ARIMA, TDNN, LSTM	LSTM was forecasted with high accuracy.
Gu, *et al.*	Cabbage, Radish	LSTM, GCN-LSTM, DA-RNN, DIA-LSTM	DIA-LSTM performed the best result.
Kurumatani, K.	Cabbage, Tomato, Lettuce	LSTM (Recurrent neural network)	LSTM model provided a better forecast.
Ly, *et al.*	Cotton seed, Castor seed, Rape mustard seed, Guar seed, soybean seed	LSTM Baseline models: ARIMA, TDNN	The optimum performance was obtained by the LSTM.
Jin, *et al.*	Chinese cabbage, Radish	LSTM	LSTM provided a better forecast.
Murugesan, *et al.*	Rice, Wheat, Gram, Banana, Groundnut.	LSTM, Bi LSTM, Stacked LSTM, CNN LSTM, Conv LSTM	Among five models LSTM model obtain promising results.
Prakash and Farzana	Tomato	LSTM	The LSTM is one of the most effective models for dealing with nonlinear parameters.

2.1 Training Time

Deep learning with many parameters requires distributed training where training time is critical. Training time is the product of the deep learning models that must be performed to reach the desired level of accuracy. To achieve optimum performance, each deep learning model requires a varied amount of training time. Hence, we compared the training time for each model to know which model is more efficient. To experience information training time in the best, worst, and average circumstances, Wang *et al.* (2018) conducted forecasting tests for LSTM and GRU. LSTM and GRU's training timeframes in the three scenarios shown in table 2 indicate that GRU is superior to LSTM since its longest training period is shorter than its best period.

2.2 Forecast Horizon

The forecast horizon, which is the amount of time in the future that a model can anticipate, has a significant impact on the forecast's performance and characteristics. Ouyang *et al*. (2019) studied a long-short-term time series network model for predicting agricultural commodity prices. The data set covers the period from 2006-2019 in which they set the horizon = 3, 6, 9, 12, 15, 18, 21, and 24, respectively. The RMSE values of a different model for different horizons are shown in table 3. The larger the horizons, the worse the predicted results. LSTM performs better than other neural network methods (RNN, CNN) and traditional models (ARIMA, VAR). Specifically, LSTM outperforms the neural baseline RNN, CNN, ARIMA, and VAR by 6.52, 21.68, 91.70, and 91.69 % in the RMSE metric, respectively, when the horizon is 24, suggesting the much better performance of the LSTM method.

2.3 Comparison with other models

In this section, deep learning models are compared with other machine learning models and traditional models in table 4. In 2020, Sabu *et al*. proposed a predictive analysis in agriculture to predict commodity price forecasting in Kerala, India. It consists of the monthly data of arecanuts from 14 districts of Kerala for the period 2007-2017. Consequently, LSTM outperformed SARIMA and holt-winter models with the lowest RMSE values.

Chen *et al*. (2021) compared LSTM, support vector regression, ARIMA, XGBoost, and Prophet. They considered the weekly price of tomatoes and chilli for 10 years (2009-2019). For tomato, LSTM obtained the lowest MSE among the models, followed by XGBoost, PROPHET, ARIMA, and lastly SVR. However, in the case of chilli price data, XGBoost had the lowest MSE, followed by LSTM.

Table 2: The training time of LSTM vs. GRU

Model	The best case/s	The worst case/s	The average case/s
LSTM	393.01	400.57	396.27
GRU	354.92	379.57	365.40

Table 3: Evaluation of predictive model (RMSE) over multiple forecast horizons

Model	3 (RMSE)	6 (RMSE)	9 (RMSE)	12 (RMSE)	15 (RMSE)	18 (RMSE)	21 (RMSE)	24 (RMSE)
LSTM	0.0347	0.0444	0.0551	0.0636	0.0678	0.0721	0.0821	0.0831
RNN	0.0395	0.0522	0.0578	0.0703	0.0704	0.0784	0.0855	0.0889
CNN	0.0415	0.0514	0.0701	0.0738	0.1077	0.0895	0.1037	0.1061
ARIMA	1.0018	1.0006	1.0021	1.0029	1.0029	1.0022	1.0022	1.0013
VAR	1.0002	1.0002	1.0002	1.0002	1.0002	1.0002	1.0002	1.0002

Table 4: Comparison of models for vegetable Price data

Models	SVR (MSE)	LSTM (MSE)	ARIMA (MSE)	XGBoost (MSE)	Prophet (MSE)
Tomato	0.674	0.378	0.538	0.583	0.691
chilli	0.641	0.438	0.752	0.432	0.456

CONCLUSION

In this review, we have presented several preliminary publications on the applications of RNNs in time series analysis and forecasting. As we have summarized, RNNs have been applied for forecasting time series data in most scientific and industrial fields, but mainly in commodity price forecasting. In addition, we present the structure, processing flow, and advantages of RNNs in this review. Furthermore, RNNs, such as the gated recurrent unit, LSTM neural network, and improvement models, can be powerful prediction alternatives to traditional neural networks and can obtain better prediction results. In the case of a single model, most studies explain that LSTM shows better performance than other machine learning models because it has internal memory to overcome the vanishing gradient problem. Comparisons between the deep learning models and other machine learning models conclude that LSTM was better used in predicting agricultural commodity price forecasts. This review provides useful guidance for RNN modelling and novel research fields in subsequent studies.

REFERENCES

Ahmed, N.K., Atiya, A.F., Gayar, N.E. and El-Shishiny, H. 2010. An empirical comparison of machine learning models for time series forecasting. *Econometric Rev.*, **29**(5-6): 594-621.

Britz, D., Goldie, A., Luong, M.T. and Le, Q. 2017. Massive exploration of neural machine translation architectures. *arXiv preprint arXiv: 1703.03906*.

Chen, Q., Wen, D., Li, X., Chen, D., Lv, H., Zhang, J. and Gao, P. 2019. Empirical mode decomposition based long short-term memory neural network forecasting model for the short-term metro passenger flow. *PloS One*, **14**(9): e0222365.

Chen, Q., Lin, X., Zhong, Y. and Xie, Z. 2019. Price prediction of agricultural products based on wavelet analysis-lstm. In *2019 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)* (pp. 984-990). IEEE.

Chen, Z., Goh, H.S., Sin, K.L., Lim, K., Chung, N.K.H. and Liew, X.Y. 2021. Automated agriculture commodity price prediction system with machine learning techniques. *arXiv preprint arXiv:2106.12747*.

Cheng, C., Sa-Ngasoongsong, A., Beyca, O., Le, T., Yang, H., Kong, Z. and Bukkapatnam, S.T. 2015. Time series forecasting for nonlinear and non-stationary processes: a review and comparative study. *Iie Transactions*, **47**(10): 1053-1071.

Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H. and Bengio, Y. 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*.

Chung, J., Gulcehre, C., Cho, K. and Bengio, Y. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*.

Dairi, A., Harrou, F., Zeroual, A., Hittawe, M. M. and Sun, Y. 2021. Comparative study of machine learning methods for COVID-19 transmission forecasting. *J. Biomed. Informatics*, **118**: 103791.

Duan, Q., Zhang, L., Wei, F., Xiao, X. and Wang, L. 2017. Forecasting model and validation for aquatic product price based on time series GA-SVR. *Transactions of the Chinese Soc. of Agril. Engineer.*, **33**(1): 308-314.

Gers, F.A., Schmidhuber, J. and Cummins, F. 2000. Learning to forget: Continual prediction with LSTM. *Neural Computation*, **12**(10): 2451-2471.

Gu, Y.H., Jin, D., Yin, H., Zheng, R., Piao, X. and Yoo, S.J. 2022. Forecasting agricultural commodity prices using dual input attention LSTM. *Agric.*, **12**(2): 256.

Guo, T., Xu, Z., Yao, X., Chen, H., Aberer, K. and Funaya, K. 2016. Robust online time series prediction with recurrent neural networks. In *2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA)* (pp. 816-825). Ieee.

Gowthaman, T., Kumar, K. S., Adarsh, V. S. and Bhattacharyya, B. 2022. Trend Analysis and ARIMA Models for Water Quality Parameters of Brahmani River, Odisha, India. *Int. J. Environ. Clim. Change*, **12**(12): 219-228.

Hochreiter, S. and Schmidhuber, J. 1997. Long short-term memory. *Neural Computation*, **9**(8): 1735-1780.

Hsu, D. 2017. Time series forecasting based on augmented long short-term memory. *arXiv preprint arXiv: 1707.00666*.

Jadhav, V., Chinnappa, R.B. and Gaddi, G.M. 2017. Application of ARIMA model for forecasting agricultural prices.

Jin, D., Yin, H., Gu, Y. and Yoo, S.J. 2019. Forecasting of vegetable prices using STL-LSTM method. In *2019 6th International Conference on Systems and Informatics (ICSAI)* (pp. 866-871). IEEE.

Karia, A.A. and Bujang, I. 2011. Progress accuracy of CPO price prediction: Evidence from ARMA family and artificial neural network approach. *Int. Res. J. Finance and Econo.*, **64**(64): 66-79.

Kurumatani, K. 2020. Time series forecasting of agricultural product prices based on recurrent neural networks and its evaluation method. *SN Appl. Sci.*, **2**(8): 1-17.

Li, Y., Zhu, Z., Kong, D., Han, H. and Zhao, Y. 2019. EA-LSTM: Evolutionary attention-based LSTM for time series prediction. *Knowledge-Based Syst.*, **181**: 104785.

Ly, R, Traore, F. and Dia, K. 2021. Forecasting commodity prices using long-short-term memory neural networks. *Int. Food Policy Res. Inst.*, Vol. 2000.

Manogna, R.L. 2021. Innovation and firm growth in agricultural inputs industry: empirical evidence from India. *J. Agribusi. in Dev. and Emerg. Econ.*, **11**(5): 506-519.

Matthews, A. 2010. Perspectives on addressing market instability and income risk for farmers. In *Joint AES and SFER conference on The Common Agricultural policy post 2013*. Edinburgh.

Mikolov, T., Joulin, A., Chopra, S., Mathieu, M. and Ranzato, M. A. 2014. Learning longer memory in recurrent neural networks. *arXiv preprint arXiv:1412.7753*.

Motazedian, Z. and Safavi, A.A. 2019. Nonlinear and Time Varying System Identification Using a Novel Adaptive Fully Connected Recurrent Wavelet Network. In *2019 27th Iranian Conference on Electrical Engineering (ICEE)*, pp. 1181-1187. IEEE.

Murugesan, R., Mishra, E. and Krishnan, A.H. 2021. Deep Learning Based Models: Basic LSTM, Bi LSTM, Stacked LSTM, CNN LSTM and Conv LSTM to Forecast Agricultural Commodities Prices.

Nassar, L., Okwuchi, I.E., Saad, M., Karray, F. and Ponnambalam, K. 2020. Deep learning based approach for fresh produce market price prediction. In *2020 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-7). IEEE.

Ouyang, H., Wei, X. and Wu, Q. 2019. Agricultural commodity futures prices prediction via long-and short-term time series network. *J. Appl. Econ.*, **22**(1): 468-483.

Pascanu, R., Mikolov, T. and Bengio, Y. 2013. On the difficulty of training recurrent neural networks. In *International conference on machine learning* (pp. 1310-1318). PMLR.

Prakash, N. and Farzana, G.S. 2019. Short Term Price Forecasting of Horticultural Crops Using Long Short Term Memory Neural Network. In *International Conference on Computational and Bio Engineering*, pp. 111-118. Springer, Cham. 10.1007/978-3-030-46943-6_12.

Ran, X., Shan, Z., Fang, Y. and Lin, C. 2019. An LSTM-based method with attention mechanism for travel time prediction. *Sensors*, **19**(4): 861.

Rasheed, A., Younis, M. S., Ahmad, F., Qadir, J. and Kashif, M. 2021. District Wise Price Forecasting of Wheat in Pakistan using Deep Learning. *arXiv preprint arXiv:2103.04781*.

Sabu, K.M. and Kumar, T.M. 2020. Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala. *Procedia Computer Sci.*, **171**: 699-708.

Tang, Q., Shi, R., Fan, T., Ma, Y. and Huang, J. 2021. Prediction of Financial Time Series Based on LSTM Using Wavelet Transform and Singular Spectrum Analysis. *Mathematical Problems in Engineering, 2021*.

Ullah, A., Ahmad, J., Muhammad, K., Sajjad, M. and Baik, S. W. 2017. Action recognition in video sequences using deep bi-directional LSTM with CNN features. *IEEE Access*, **6**: 1155-1166.

Wang, F., Yu, Y., Zhang, Z., Li, J., Zhen, Z. and Li, K. 2018. Wavelet decomposition and convolutional LSTM networks based improved deep learning model for solar irradiance forecasting. *Appl. Sci.*, **8**(8): 1286.

Wang, Y., Liao, W. and Chang, Y. 2018. Gated recurrent unit network-based short-term photovoltaic forecasting. *Energies*, **11**(8): 2163.

Weng, Y., Wang, X., Hua, J., Wang, H., Kang, M. and Wang, F.Y. 2019. Forecasting horticultural products price using ARIMA model and neural network based on a large-scale data set collected by web crawler. *IEEE Transactions on Computational Social Systems*, **6**(3): 547-553.

Williums, R.J. and Zipser, R.A. 1989. A learning algorithm for continually training neural networks. *Neural Computation*, **1**: 270-280.

Zhang, Q., Wang, H., Dong, J., Zhong, G. and Sun, X. 2017. Prediction of sea surface temperature using long short-term memory. *IEEE Geoscience and Remote Sensing Letters*, **14**(10): 1745-1749.

Zhang, X., Liang, X., Zhiyuli, A., Zhang, S., Xu, R. and Wu, B. 2019. AT-LSTM: An attention-based LSTM model for financial time series prediction. In *IOP Conference Series: Materials Science and Engineering*. IOP Publishing, **569**(5): 052037.

Zhu, N., Liu, X., Liu, Z., Hu, K., Wang, Y., Tan, J. and Guo, Y. 2018. Deep learning for smart agriculture: Concepts, tools, applications, and opportunities. *Int. J. Agril. and Biolog. Engineer.*, **11**(4): 32-44.