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Improving the Accuracy of Food Commodity Price Prediction Model Using Deep Learning Algorithm

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Abstract:- The world market for agricultural commodities is essential to maintaining both economic stability and food security. However, due to its intrinsic volatility, this market is subject to price fluctuations caused by a variety of variables, including supply chain interruptions, geopolitical events, and economic conditions. Predicting food commodity prices accurately and on time is essential for all parties involved, including farmers, traders, policymakers, and consumers. The existing method proposed a hybrid LSTM-CNN model to forecast weekly prices of oats, corn, soybeans, and wheat in the U.S., finding that hyperparameter tweaking over 15 weeks affected its accuracy. Despite its strengths, the LSTM-CNN model faced challenges such as complexity, computational cost, and overfitting, highlighting the need for better optimization and hybrid approaches to improve prediction accuracy. The Whale Optimization Algorithm (WOA) was used in this study to optimize hyperparameters and train deep neural network architecture for food commodity price prediction in Nigeria. The study utilized four performance metrics: RMSE, MSE, MAE, and R^2. The proposed model achieved the lowest RMSE (0.0071-0.0073), MSE (0.0061), and MAE (0.0082-0.0083) values, indicating higher accuracy in predictions compared to CNN-LSTM and CNN models. Additionally, it achieved the highest R^2 values (0.972-0.975), further demonstrating its superior performance in forecasting food commodity prices.

Keywords:- *Deep Learning, Whale Optimisation, Multilayer Perceptron, Commodity, Prediction And Long Short-Term Memory.*

I. INTRODUCTION

The world market for agricultural commodities is essential to maintaining both economic stability and food security. However, due to its intrinsic volatility, this market is subject to price fluctuations caused by a variety of variables, including supply chain interruptions, geopolitical events, and economic conditions. Predicting food commodity prices accurately and on time is essential for all parties involved, including farmers, traders, policymakers, and consumers [1]. This problem statement tackles the urgent requirement to use deep learning algorithms to improve the accuracy of food commodity price predictions. To make price prediction easier, various models are still being developed.

When it comes to sequence-related tasks, such as time series prediction, LSTM-CNN (Long Short-Term Memory - Convolutional Neural Network) models are strong and efficient [2]. However, when it comes to commodity price prediction, they have some limitations. Such as complexity and computational cost when working with a big dataset requiring a lot of time and resources; overfitting which can produce inaccurate predictions performed on unknown data; and hyper parameter tuning i.e, taking several iterations before getting the ideal hyperparameter setting [3].

The study of [4] proposes a hybrid LSTM-(CNN) model to forecast weekly oat, corn, soybean, and wheat prices in the United States market. The CNN-LSTM networks have shown promise in modeling temporal data, but their performance relies heavily on optimal hyperparameter settings. Additionally, the effectiveness of LSTM-CNN models for commodity price prediction depends on efficient feature engineering, data preparation, and model evaluation [5].

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It's important to properly build and optimize LSTM models, include domain knowledge in the model creation process, and take into account hybrid approaches that mix deep learning with other methods to lessen these disadvantages. WOA is a metaheuristic algorithm inspired by the hunting behavior of whales, which has been successfully applied to various optimization problems. This paper proposes a novel approach for food commodity price prediction using a Long Short-Term Memory (LSTM) network optimized by the Whale Optimization Algorithm (WOA) for hyper parameter tuning.

The goal is to advance the traditional forecasting method by utilizing an appropriate DL algorithm to estimate the prices of four commodities that are often consumed in Nigerian households. The four basic commodities are Maize, Sugar, Rice and Beans. The paper is structured as follows: related work, methodology, findings, and conclusion sections.

II. RELATED WORK

Numerous studies have explored AI-based algorithms for commodity price prediction, showing high reliability and detection rates. According to Malhotra and Maloo, (2017), the main factors influencing food inflation in India and a statistical evaluation of their relative importance using BRT have been reviewed, but also the Indian government is to bring in major agricultural policy reforms and build synergetic investment partnerships with private players for lasting effect on agricultural growth and ultimately, rural poverty rate.

The study of [6] explains the use of the ARCH and GARCH models to predict the cost of staple foods based on a wide range of factors, such as crude prices and weather, the study uses multivariate models since GARCH is very consistent and does not alter the available data, it is inferred that ARCH is stronger than GARCH.

Similarly, [7], developed a novel ML strategy for agricultural commodity prices, a differential evolution algorithm with biological inspirations for the best lag time selection, but to properly manage possible risk, it is beneficial for all parties involved to pay attention to external factors as well as the projected outcome of the commodity price and to move quickly by adopting marketing techniques.

Furthermore, [8]Applied ANN, ARIMA and ELM models to determine how the COVID-19 lockdown affected rice prices, as well as evaluating the effect of the COVID-19 related shutdown on rice prices, as large portion of the population in Asia, particularly in India, consumes rice, therefore data on its prices need to be used to build models using suitable time series and ML models.

According to [9], uses ML to determine the factors that are predictive of having access to a healthy diet. It is necessary to identify the non-demographic variables of access to wholesome foods.

[10] conducted an experimental evaluation to estimate the price of six different daily commodities using the state-of-the-art ML algorithms, AdaBoost, GradientBoost, XGBoost, Bagging, SVM, and LightGBM. However, seek to work with time series and regional data of daily commodities.

[11], performed a study lately that separated the El Niño and La Niña phases to shed light on the ENSO's capacity to predict the realized variance of the returns of agricultural commodity prices. The study used a ML approach. However, by assessing ENSO for forecasting of daily or weekly realized variances, it is fascinating to explore in detail the varied implications of El Niño and La Niña events on the prediction ability of economic activity and inflation of key agricultural commodities exporters.

[12] researched to predict the relationship between the price of crude palm oil (CPO) and the prices of other vegetable oils, crude oil, and exchange rates, also used ML techniques to forecast the price of CPO based on the prices of other commodities. To enhance CPO price predictions, relevant attributes must be incorporated, feature selection techniques must also be included to increase forecasting accuracy.

[13], Using metrics for accuracy, precision, sensitivity, specificity, and misclassification rate, evaluate the SVM, RF, NB, CT, and NN ML techniques. The NN model achieved the maximum accuracy and the experimental findings according to the comparative analysis, also demonstrate that the NN model has the lowest rate of misclassification. Research need to be conducted to lessen excessive volatility by integrating some new data set attributes into the model that predicts how quickly onion prices will climb and fall.

[14]design an automated agriculture commodity price prediction system with novel machine learning techniques such as the ARIMA, LSTM, SVR, Prophet and XGBoost. There is need to investigate the requirements of farmers when carrying out agricultural activities, and these studies should be integrated into the system to provide a more straightforward, thorough manner to meet the farmers' knowledge demands. The choice for the prediction engine is LSTM.

III. METHODOLOGY

The Whale Optimization Algorithm (WOA) by[15], a meta-heuristic algorithm, was used in this study to optimize hyperparameters and train deep neural network architectures for food commodity price prediction. The problem is defined by the cost function, parameter search space, and constraint method. Given the high rate of product inflation, this system aims to enhance price prediction accuracy. The dataset, sourced from secondary sources, will undergo pre-processing to remove noise before application of the chosen techniques. The proposed system's steps and architecture are detailed in Fig. 1.

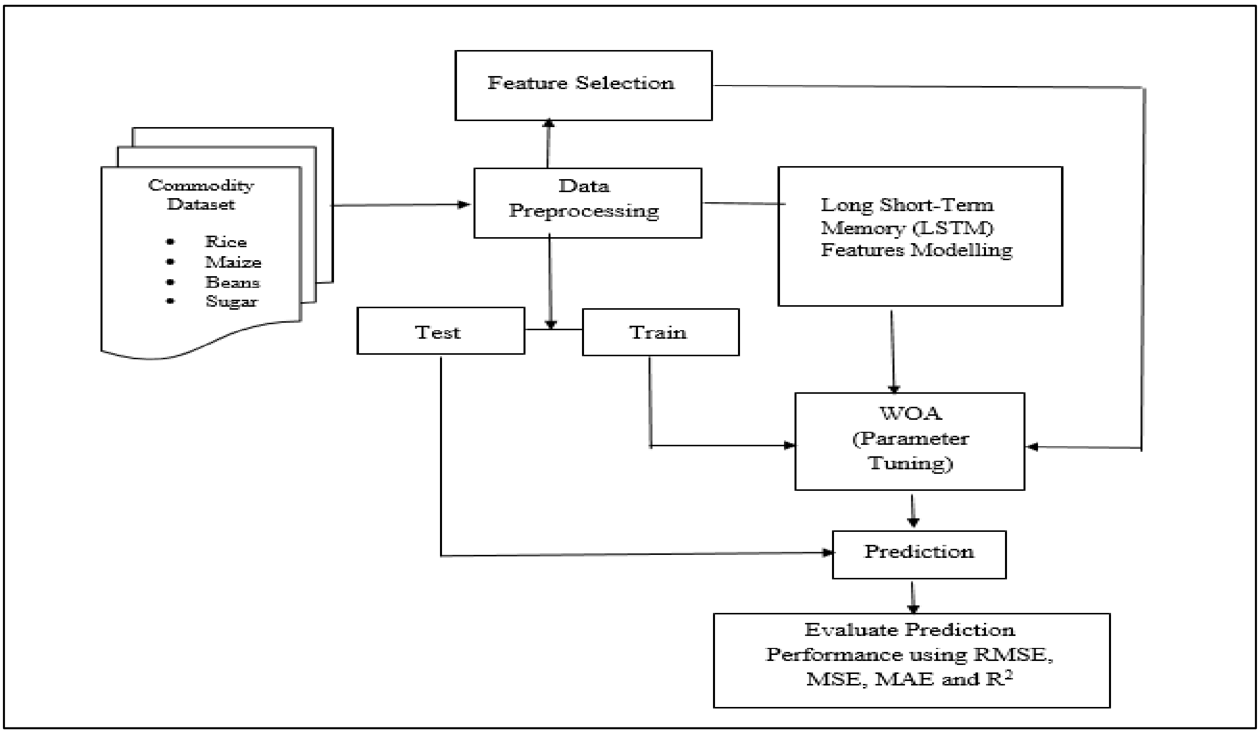

Fig. 1: Proposed Model for Food Commodity price prediction using DL

A. Dataset Preprocessing and Normalization

- Initial dataset loading and connection to the database.
- Data normalization using min-max strategy to ensure a mean of zero and variance of one.

B. Long Short-Term Memory (LSTM):

- LSTM networks, a type of RNN with feedback connections, will process and predict time-series data. LSTM networks are suitable for tasks such as speech recognition and anomaly detection.

C. Whale Optimization Algorithm (WOA)

- WOA, inspired by the bubble-net feeding behavior of humpback whales, optimizes mathematical functions.
- WOA generates random solutions, adjusting search agents' positions to avoid local optima.
- K-fold cross-validation will assess the models' performance.

D. LSTM Network Training

- WOA-LSTM vectors include biases and weights for input-to-hidden and hidden-to-output layers.
- MATLAB R2021a will be used for model creation and construction.

E. Dataset Description

- The study will focus on rice, maize, beans, and sugar, using historical records from the World Food Programmed Price Database.

F. Choice of Metrics

- The model's performance will be evaluated using RMSE, MAE, MSE, and R^2 in the MATLAB Neural Network (NN-tools) package.

IV. RESULT AND DISCUSSION

In this section, the proposed WOA approach for training deep network is evaluated on commodity datasets obtained from the World Food Programmed Price Database. The chapter presents the result obtained after simulating the network on MATLAB 2021a. The results are presented in tabular and graphical forms which are analyzed using standard performance evaluation metrics as specified during the design. All the experiment was conducted on MATLAB 2021 using the system specification defined in the previous section. To achieve our objective, first, we set the Number of search agents to 30 and the Maximum number of iterations to 500 to enable us to load details of the selected benchmark.

TABLE I. PARAMETER SETTINGS

.SN	Parameter	Setting
1	Input Layer	Input size
2	Hidden Layer	5
3	Fully Connected Layer	1
4	SoftMax Layer	1
5	Classification Layer	1
6	Max Epochs	7
7	Mini Batch Size	27
8	Gradient Threshold	1
9	Verbose	False
10	Execution Environment	CPU
11	Number of Hidden Neurons	500

A. Results Presentation

The findings of this study are presented in two parts. Initially, the prediction accuracy (MSE, RMSE, MAE, and R2) for various time horizons is used to assess the suggested model. Next, an additional assessment of the performance was conducted using cutting-edge methodologies. Following the models' simulations on the same dataset, Table II displays the outcomes that were attained.

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TABLE II. EXPERIMENTAL FINDINGS

Algorithms	No. of Weeks	RMSE	MSE	MAE	R^2
Proposed WOA-LSTM	12	0.0073	0.0061	0.0083	0.975
	24	0.0072	0.0061	0.0082	0.972
	48	0.0071	0.0061	0.0082	0.972
CNN-LSTM	12	0.0086	0.00876	0.0092	0.869
	24	0.0088	0.0078	0.0092	0.891
	48	0.0091	0.0074	0.0092	0.921
CNN	12	0.0094	0.0094	0.0089	0.0070
	24	0.0095	0.0095	0.0094	0.0072
	48	0.0096	0.0096	0.0099	0.0074

B. Short Term Forecast

Predicting the price changes of commodities over a brief period, usually a few days to several months but less than a year, is known as short-term commodity price forecasting. Three short forecast horizons 12, 24, and 48 weeks were chosen for this study in order to predict and assess the model's performance. For traders, investors, companies, and policymakers to make educated judgments regarding purchasing, selling, production scheduling, risk management, and economic policy, this kind of forecasting is crucial. In order to navigate volatile markets, react to market trends, and make timely and informed decisions in a variety of economic sectors, short-term commodity price forecasting is essential. Four performance metrics RMSE, MSE, MAE, and R2 that were employed in the study were used to elaborate on the findings.

C. Root Mean Square Error (RMSE)

Root Mean Square Error, or RMSE for short, is a metric used to assess how accurate a predictive model, like a model for predicting commodities prices. The average of the squared discrepancies between expected and actual values is determined by RMSE. It's a means of measuring the degree to which the model's predictions deviate from the observed values. Better accuracy is shown by a lower RMSE value, which shows that the model's predictions are closer to the real values. On the other hand, a bigger RMSE number denotes more differences between the actual and projected values, which suggests a lesser level of accuracy. Regression analysis and time series forecasting frequently employ RMSE to evaluate the effectiveness of predictive models. It offers a single metrics to assess the efficacy of model upgrades or to compare several models. A lower RMSE in a commodity price prediction model means that the model is more accurate in predicting commodity prices, which is important information for supply chain planning, trading, investing, and risk management decisions. Therefore, based on Table 5, the suggested model achieves the lowest RMSE values at 12, 24, and 48 weeks, respectively, of 0.0073, 0.0072, and 0.0071. After that, the CNN-LSTM model was used, and at 12, 24, and 48 weeks, it achieved RMSE values of 0.0086, 0.0088, and 0.0091, respectively. With higher RMSE values of 0.0094, 0.0095, and 0.0096 at 12, 24, and 48 weeks, respectively, the CNN model performed the worst out of all the models.

D. Mean Square Error (MSE)

A popular statistic used in the context of predicting food prices and other predictive modeling activities is Mean Squared Error (MSE). MSE can be used to assess how well predictive models work when it comes to predicting food prices. Since price estimation is essential for making decisions in trading, supply chain management, risk assessment, and market analysis, a food price prediction model with a reduced mean square error (MSE) is seen to be more accurate. The average squared difference (MSE) between a dataset's actual and anticipated values is calculated. The overall inaccuracy or difference between the expected and actual values is quantified. Better accuracy is suggested by a lower MSE value, which shows that the model's predictions are closer to the actual values. On the other hand, a higher MSE value denotes greater errors between the actual and projected values, which suggests a lower level of accuracy.

As a result, in 12, 24, and 48 weeks, respectively, the suggested model achieves the lowest MSE values of 0.0061, 0.0061, and 0.0061 from Table 5. After that, the CNN-LSTM model was used, and at 12, 24, and 48 weeks, it achieved MSE values of 0.00876, 0.0078, and 0.0074, respectively. With higher MSE values of 0.0094, 0.0095, and 0.0096 at 12, 24, and 48 weeks, respectively, the CNN model performed the worst out of all the models.

E. Mean Absolution Error (MAE)

Both MAE and MSE can be used to assess model performance in the context of predicting food prices, with MAE offering information on the average magnitude of prediction errors. Another statistic that is frequently used in predictive modeling, particularly the prediction of food prices, is MAE, or Mean Absolute Error. The average absolute difference between a dataset's actual and anticipated values is measured using MAE. It gives an indication of the typical size of the forecast mistakes. Like MSE, a lower MAE number suggests improved accuracy because it shows that the model's predictions are closer to the actual values. On the other hand, lower accuracy is shown by larger absolute discrepancies between anticipated and actual values, which is indicated by a higher MAE value. Whereas MAE concentrates on absolute differences (considering all errors equally), MSE takes into account the squared differences between predicted and actual values (which penalizes larger errors more). When extreme values or outliers in the data have a substantial impact on the accuracy assessment, MAE is frequently chosen.

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As a result, in 12, 24, and 48 weeks, respectively, the suggested model achieves the lowest MAE values of 0.0083, 0.0082, and 0.0082 from Table 3. Next in line was the CNN-LSTM model, which achieves MAE values at 12, 24, and 48 weeks, respectively, of 0.0092, 0.0092, and 0.0092. With greater MAE values of 0.0089, 0.0094, and 0.0099 at 12, 24, and 48 weeks, respectively, the CNN model performed the worst out of all the models.

F. R^2

R2 is a metric used to evaluate the model's goodness of fit in predictive modeling tasks, such as predicting food prices. A high R^2 implies that the model is accurate or dependable. R^2 is frequently used to evaluate the overall performance of predictive models in conjunction with other metrics such as MSE, MAE, and RMSE. It offers information on how well the model matches the observed data. A higher R^2 value suggests a better model fit to the data in food price prediction or any regression-based prediction task, but it's crucial to take into account additional metrics and thoroughly assess the model to guarantee its accuracy and dependability.

As a result, in 12, 24, and 48 weeks, respectively, the suggested model achieves the greatest R^2 values of 0.975, 0.972, and 0.972 from Table 5. The CNN-LSTM model came next, achieving R2 values of 0.869, 0.891, and 0.921 at 12, 24, and 48 weeks, in that order. With lower R2 values of 0.007, 0.0072, and 0.0074 at 12, 24, and 48 weeks, respectively, the CNN model performed the worst out of all the models.

V. CONCLUSION

The Whale Optimization Algorithm (WOA) was used in this study to optimize hyperparameters and train deep neural network architecture for food commodity price prediction. Short-term commodity price forecasting, essential for traders, investors, companies, and policymakers, was conducted over 12, 24, and 48-week horizons. The study utilized four performance metrics: RMSE, MSE, MAE, and R^2. The proposed model achieved the lowest RMSE (0.0071-0.0073), MSE (0.0061), and MAE (0.0082-0.0083) values, indicating higher accuracy in predictions compared to CNN-LSTM and CNN models. Additionally, it achieved the highest R^2 values (0.972-0.975), further demonstrating its superior performance in forecasting food commodity prices.

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