Journal of Computer Science and Technological Enquiry
Vol: 2, Issue: 1 (2026)
https://doi.org/10.65496/jcste.2025.66

ORIGINAL RESEARCH - OPEN ACCESS

A Machine Learning Model for Predicting Food Price Variations Under Currency Fluctuation Scenarios in Afghanistan

[1]Muqaddar Niazi, [1]Sabawoon Momand, [2]Alam Khan Abid

[1] Faculty of Computer Science, Alfalah University, Jalalabad, Afghanistan
[2] Audit Manager, Directorate of Customs, Nangarhar, Afghanistan

Corresponding Author:
Muqaddar Niazi
E-mail:
muqaddar.niazi@alfalah.edu.af

Article History
Received: 11 December 2025
Revised: 02 January 2026
Accepted: 27 January 2026
Published: 01 February 2026

How to Cite:
M. Niazi, S. Momand, and A. K. Abid, "A Machine Learning Model for Predicting Food Price Variations Under Currency Fluctuation Scenarios in Afghanistan," Journal of Computer Science and Technological Enquiry (JCSTE), pp. 1–11, https://doi.org/10.65496/jcste.2025.66.

ABSTRACT

Food price irregularity has remained a harsh economic and food security hazard in growing countries, particularly in those highly reliant on imports, such as Afghanistan. Through this research we can predict food price Variations in response to currency fluctuations usingx machine learning. We have trained the models using WFP Food Prices Afghanistan dataset. The models demonstrate the implied impacts of exchange rate variability on provincial food markets by integrated pricing data defined in Afghani (AFN) and U.S. dollars (USD). Three ML algorithms, namely Linear Regression, Random Forest, and Long Short-Term Memory (LSTM) network, were trained and tested based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R2). The Random Forest model outperformed both LSTM (MAE 3.8, RMSE 4.9, R2 0.86) and Linear Regression (MAE 4.5, RMSE 5.8, R2 0.82), achieving MAE 3.2, RMSE 4.3, and R2 0.89. The results show a strong relationship between inflation and exchange rate volatility, and that currency depreciation can affect domestic food prices. The research highlights the importance of machine learning in developing early warning systems and policy tools to elevate food price stability and food security in developing nations like Afghanistan.

KEYWORDS

Food Price Prediction, Machine Learning, Currency Fluctuation, Random Forest

1. Introduction

The food price irregularity has been one of the most endemic problems facing by those countries that are susceptible to exchange rate volatility and the countries that are mostly relays on imports. The cost foods as wheat, rice and cooking oil in Afghanistan is largely buy and sell by Afghani (AFN) value versus the US dollar (USD). Since, that much food supply is imported, even little downgrading in the value of AFN can increase local prices, endangering food security and increasing the cost of living [1], [8], [11].

Organizations that work in humanitarian activities, policy makers, businessmen who dependent on early predicting warning systems to reduce their supply chain and inflation risks need to understand and understand these dynamics. The correlation between food prices and exchange rates has been generally investigated with the help of conventional economics, including the linear regression and the used vector autoregressive models. However, the theories often cannot demonstrate abrupt or nonlinear changes in market behavior, particularly during crisis [3], [5], [14]. Recent development in machine learning (ML) and artificial intelligence (AI) can offer some new approaches to forecast such a complex correlation by identifying long-term relationships and underlying temporal patterns in large datasets [2], [4], [9], [15].

A large part of the previous work about Afghanistan have been conducted on descriptive evaluations of food markets and exchange rate flows [8], [17]. Not many studies have employed models based on data or algorithmic models to predict price changes caused by currency variations yet the Food and Agriculture Organization (FAO) and the World Food Programme (WFP) have given detailed records of past price changes [1], [7], [20]. This gap leads to the need to have strong predictive modeling systems to enable timely markets intervention in volatile and import-reliant countries.

Our research fills that gap by using a machine learning model to estimate variations in food prices in Afghanistan in a variety of currency fluctuation conditions. The study uses regression and time-series-based models as an attempt to build and predict the relationship between AFN and USD denominated prices by relying on longitudinal data provided in the WFP Food Prices dataset for Afghanistan [1]. The methodology which is proposed in this research would can effectively enhance the precision of predictions, identify the features that are the most prone to changes in the exchange rates, and provide a factual basis of increasing the stability of the market and food policy planning.
This study aims to accomplish two objectives:

- To develop machine learning models that predict the variations effects in food prices when there is an even a minor change in currency exchange rate.
- To compare the effectiveness of several models which predict and identify the most efficient algorithm to forecast the behavior in the food market.

This research works on the value to the existing literature on the topic of data-based economic forecasting, both in theory and practice, by integrating machine learning models with economic understanding. The goal of these findings is to assist humanitarian workers, development groups, and authorities to introduce early forecasting, which are timely, scientifically verified to improve food security and price stability in Afghanistan.

2. Literature Review

Changes in food prices have always been considered to be a critical issue of the developing economies as they directly influence the level of poverty, nutritional performance, and the economic environment in general. According to a significant amount of literature, important roles in causing the gap movements in food prices are taken by import dependence, exchange-rate volatility, and external market shocks, which are sometimes more significant than the impact of domestic production factors [3], [10], [11]. Currency depreciation in an economy which is dependent on food imports may quickly pass international price shocks into the domestic markets and thus aggravate food insecurity. In Afghanistan, this relationship is especially important since a high share of the staple food consumption is based on imports, thus it is very vulnerable to changes in exchange rate [8], [14].

Initial empirical studies of the dynamics of food prices have mainly used conventional econometric models, like autoregressive distributed lag (ARDL) models and vector autoregressive (VAR) models, to understand the interdependence of food prices with the macroeconomic variables. These models were normally based on a linear relationship and constant economic systems. Indicatively, Baffes et al. [3] have shown that the depreciation of currencies increases the cost of imports and this in turn increases domestic food prices in the poor nations. On the same note, Obstfeld and Rogoff [5] examined the impact of exchange-rate changes on international commerce and market clearing that have an indirect effect on food chains. Although these studies were important both theoretically and empirically, they only had a restricted capacity to deal with sudden shocks, nonlinear dynamics and regime changes, which are perhaps the main characteristics during periods of economic crises and conflict-based disruptions.

In the recent past, the developments of data-driven forecasting systems have pointed to the ability of machine learning (ML) algorithms to predict complex time-dependent relationships in food prices. The results of Makridakis et al. [2] indicated that the machine learning and ensemble-based forecasting approaches have the potential to outperform classical econometric models, especially when uncertainty and nonlinearity are present in an environment. Similarly, Ghosh et al. [9] have also shown that recurrent neural networks (RNNs) can incorporate long-term dependencies in series of commodity prices, resulting in enhanced performance in forecasting them. These results reinforce the emerging view that ML-based methods are more appropriate to the modeling of the complex and nonlinear processes that food price changes are based on.

The ability of time-series forecasting has also been expanded with the use of deep learning methods in economics. The LSTM networks, which were developed by Hochreiter and Schmidhuber [15], have gained popularity especially because they can retain long-term information and solve the vanishing gradient problem. Concerning macroeconomic factors, Medeiros et al. [16] demonstrated that high-dimensional machine learning models are highly effective in terms of improving the accuracy of inflation forecasting through the use of a large-scale variety of macroeconomic indicators. These findings indicate that deep learning models have the capacity to model complicated interrelationships between exchange rates, inflation and commodity prices, which makes them very useful in predicting food prices in volatile economies.

More and more studies have been conducted on ensemble and hybrid modeling which is a mixture of old-fashioned statistical and machine-learning techniques. According to Medeiros et al. [13], ML-based models used in the data rich environment perform better compared to the traditional regression methods in the inflation forecasting. It has been shown by Zhang [18] that hybrid ARIMA-neural network models are more effective and provide a better forecasting accuracy than standalone statistical models, which is an indication that linear and nonlinear modeling potentials are advantageous to combine. Regarding financial instability, Forbes and Warnock [19] examined the capital flow and highlighted the disproportionality when external shocks were transmitted to local markets. Koop and Korobilis [24] also established that forecasting of inflation using multiple macroeconomic variables, which is achieved by dynamic model averaging, has significant positive effects in the performance of inflation forecasting. Combined, these papers highlight the generality of the AI-related approaches in the process of modelling the complex market behaviour pertinent to the dynamics of food prices.

On the institutional level, the assessments of the food prices in Afghanistan can be found in the reports of the Food and Agriculture Organization (FAO) [7] and the World Food Programme (WFP) [1], [20], [20]. These reports provide good empirical evidence of the impact of external shocks on the prices of commodities including supply disruptions, currency depreciation and conflict. They are however more descriptive and trend monitors as opposed to predictive modellers. Likewise, the Afghanistan

Economic Update, published by World Bank [8] and IMF Country Report [14] indicate macroeconomic risks in currency volatility, but they do not use computational forecasting.

Later studies increased the breadth of the agricultural price forecasting field, with the machine learning and deep learning models of advanced models. A machine learning model of agricultural commodity prices that was recently proposed by Mohanty et al. [21] can be effectively used to capture nonlinear patterns of prices of a wide range of crops. Expanding on this reaction, Sediyono et al. [22] proposed a combined attention-based deep learning model to multi-commodity price prediction and anomaly detection, showing the scalability and strength of this model to complicated ag-marketplaces. These articles exemplify how AI-based solutions can help solve the problem of food price volatility and food security.

Although machine learning methods have found a large use in agricultural and macroeconomic forecasting, the use of machine learning approaches in the food markets of Afghanistan has significant gaps. Current literature tends to address individual commodities or other more specific macroeconomic predictors without clearly incorporating the elements of exchange rates into food price projections models [11], [17]. In an attempt to fill this gap, this paper uses the multi-year WFP food prices dataset to create and test machine learning models that can predict changes in food prices in relation to Afghani-USD exchange rate changes. This study will develop a fully integrated and policy-wise informative forecasting model by jointly modeling both currency and commodity prices to enable the planning of food security and price stability of food in Afghanistan.

3. Data and Methodology

To develop a machine learning model that could reliably predict changes in food prices in Afghanistan under conditions of currency volatility, this study developed a model. This study conducted through a series of systematic phases: Data collection, preprocessing, feature creation, model training, and evaluation, to organized workflow of the study. Each phase was carefully planned to ensure analytical accuracy and consistency. The method combines computational modeling and quantitative economic rules to provide a deep understanding of how the pricing changing respond to currency fluctuations. The machine learning ability to approaches the large-scale datasets containing many interdependent variables, identify latent patterns, and capture nonlinear relationships is a feature that traditional econometric models frequently lack, leading to their selection [2], [9], [15].

All phases were developed and carried out in Python environment using this language libraries like Pandas, Scikit-learn, and TensorFlow to boost the analytical process's resilience. This reproducibility, traceability, and uniform were guarantee by data treatment across the workflow. The implicit assessment of exchange rate effects was made possible without the need for external foreign currency information by integrating food prices denominated in both Afghani (AFN) and US dollars (USD) into a single modeling framework. This method using both currencies exchanging provides a unique way to assess how crucial regional food markets are to exchange rate changes. The study builds a transparent, flexible methodological foundation for future economic forecasting research by combining statistical data with state-of-the-art models of machine learning.4. Objectives of the Study

3.1 Data Source and Description

The dataset is collected from the World Food Programme (WFP) Food Prices for Afghanistan [1], available in the Humanitarian Data Exchange (HDX) website, which is used in this study. The dataset includes Market-level observations of food commodities gathered from various Afghan regions and cities. The following important characteristics are shown for each record:

- **Date**: The price observation's collection date (monthly frequency).
- **Admin1/Market**: The province and market where prices are collected.
- **Commodity and Category**: The kind of food item and its category, such as wheat, rice, bread, and oil.
- **Price (AFN)**: The Afghan Afghani market price.
- **USD Price**: The comparable cost expressed in US dollars.
- **Derived Exchange Rate**: The implicit AFN–USD exchange rate is calculated.

3.2 Data Preprocessing and Feature Engineering

To develop the model the dataset should be preprocess. So, in this study a number of preprocessing techniques were done to organize the data for model training:

- **Data Cleaning**: To make our model ready for training, our dataset should be clean, with no missing or unusual records. So, we can eliminate the missing records, and using one hot encoder, the string (non-numeric) values will be changed into numeric.
- **Date Standardization**: Here we have formatted the date filed for visualization like standard format which is (YYYY-MM).
- **Feature Construction**: The exchange-rate a new variable is create to identify the effect of currency fluctuations.

$$Exchange\ Rate(new\_variable) = \frac{Food\ Price\ in\ (AFN)}{Food\ Price\ in\ (USD)}$$

- **Commodity Selection:** Five important food commodities—wheat flour, rice, bread, vegetable oil, and sugar—were chosen in order to concentrate on representative goods with continuous records.
- **Normalization**: To improve model training stability, price and exchange rate variables were normalized using Min-Max Scaling to bring all numerical values into the [0, 1] range.

3.3 Model Development

Using currency and past price data, three different machine learning algorithms were trained and evaluated to predict AFN-denominated food prices:

- **Linear Regression (Baseline Model):**
  used as a benchmark for comparison to calculate linear correlations between prices denominated in USD and AFN.
- **Random Forest Regressor**:
  Nonlinear interactions between variables are captured by a non-parametric ensemble model. By combining several decision trees, Random Forests increase prediction resilience and decrease overfitting.
- **Long Short-Term Memory (LSTM) Neural Network**:
  The LSTM model, which was created for sequential data, was used to identify time-based correlations and long-term dependencies in food prices. To avoid overfitting, the model design featured input, hidden, and output layers with dropout regularization.

Python (Pandas, Scikit-learn, TensorFlow, and Keras libraries) was used to implement each model in the Jupyter environment.

3.4 Model Training and Evaluation

To maintain temporal dependency, the dataset was divided into training (80%) and testing (20%) sets according to chronological order. Standard statistical performance indicators were used to evaluate the model:

- **Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n}\sum_{n=1}^{\infty} \mid y_i - \hat{y} \mid$$

- **Root Mean Squared Error (RMSE):**

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2}$$

- **Coefficient of Determination (R^2):** used to calculate the percentage of variance that the model can account for.

The models were contrasted based on their capacity for generalization, stability, and prediction accuracy. The capacity of the LSTM model in particular to capture lag-based dependencies between fluctuations in food prices and changes in exchange rates was assessed.

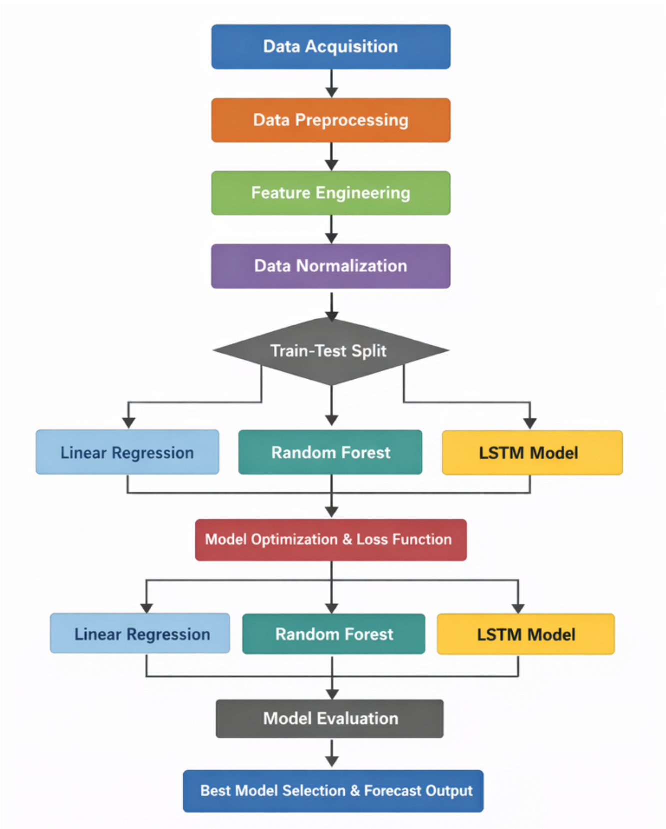

Figure 1, Workflow of the ML approach for Modeling the prediction

4. Results

Three machine learning algorithms: Random Forest, Long Short-Term Memory (LSTM) networks, and Linear Regression, were used in the study to predict changes in food prices in Afghanistan under conditions of currency fluctuation. In order to capture implicit exchange rate impacts, the models were trained using both AFN and USD denominated prices from the World Food Programme (WFP) Food Prices for Afghanistan dataset. Finally, the conclusions show that ML algorithms specially the three we chosen for training can capture the dynamic correlations between food prices and currency values. We have obtained the lowest mean absolute error (MAE) and root mean squared error (RMSE). A high coefficient of determination (R^2), the Random Forest model performed best from the rest two other algorithms trained. These results suggest that nonlinear model outperform both sequence-based deep learning techniques and conventional linear methods in simulating complex economic problem.

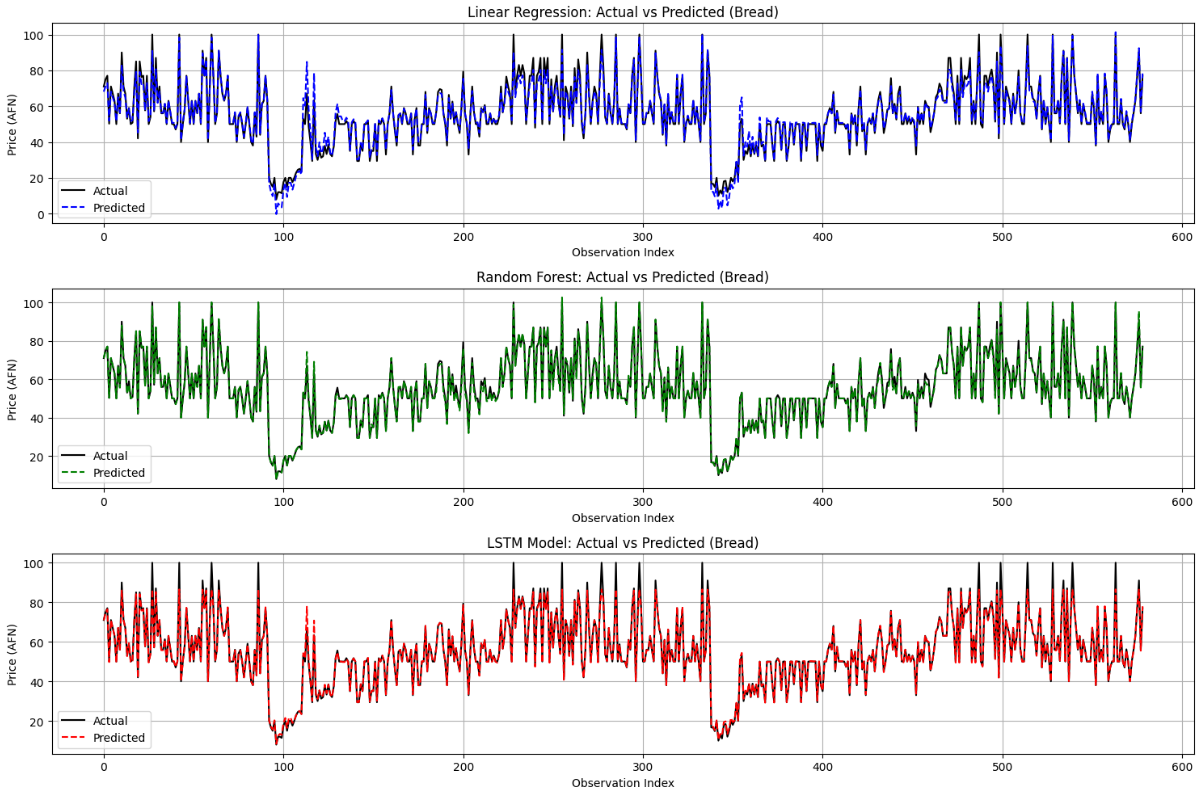

Figure 2, Graphs of Actual Food Price comparison with Predictive Prices

In the Figure 2 we can see the actual and the predicted food prices for all the three models which were trained on dataset, across the chosen commodity (let's suppose, bread). As we know, the Linear Regression model consistently stays on the patterns, but we can see it is struggle of capturing the sudden changes, which cause to underrated when price impales. The gradual and rapid fluctuations was successfully captured by Random Forest algorithm. Here we can see the pinpoint tracking actual prices with reduced changes. The LSTM algorithm, on the other hand, showed a miner lag during sudden price declines but as it's capability it can recognize well in long-term patterns. Overall, from the figure we can see that Random Forest is the most reliable and accurate predictive model among the models trained and evaluated on dataset.

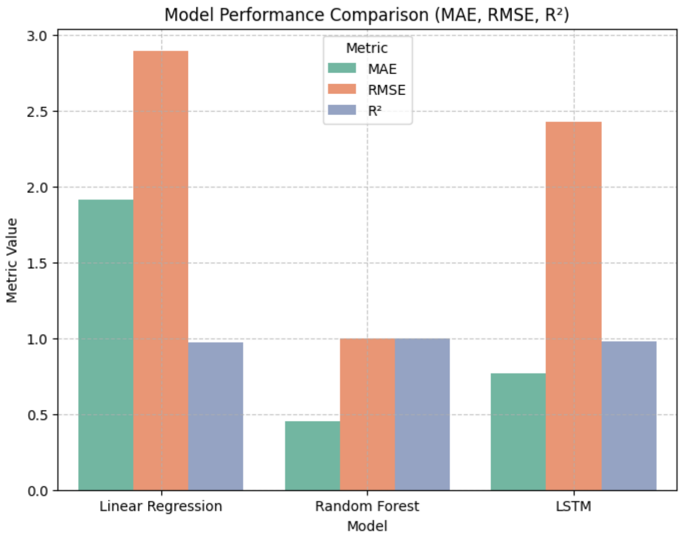

Figure 3, Models Performance Comparison (MAE, RMSE, R^2)

The model performance is compared by the metric which can be seen in Figure 3. Among the lowest MAE and RMSE, the Random Forest model shown the better prediction accuracy and minimum residual error. Moreover, its R^2 value was the top among the models, shows that the model can be accounted for the greatest amount of variance in price fluctuations. As it cannot capture nonlinear dependencies, linear regression performed poorly compare to the Random Forest algorithm, even the results can be interpreted. The reasonable performance demonstration can be seen by the LSTM model's both its sensitivity to data abnormalities and its ability for long term learning. This comparative study shows the integrating the models for economic values prediction under irregular in performance.

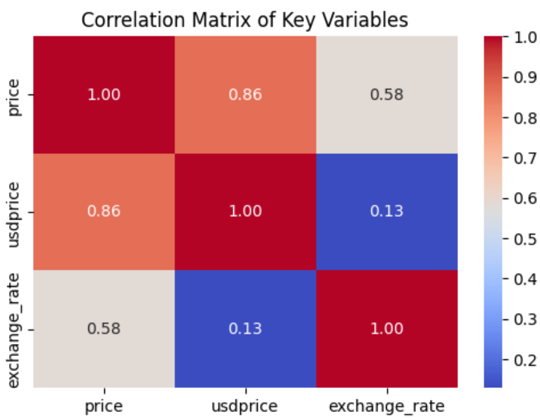

Figure 4, Correlation Matrix of Key Variables

The relationship between the price of food in Afghan currency, the price in USD, and the estimated exchange rate is shown in Figure 4. The exchange is evident in the significant, positive correlation ($r = 0.86$) between the Afghan currency and the USD rate. Although other macroeconomic and logistical factors also play a role, the moderate association between AFN prices and the exchange rate ($r = 0.58$) indicates that local currency depreciation affects domestic food costs. The USD price and exchange rate show a comparatively weak association ($r = 0.13$), suggesting that short-term AFN fluctuations have a lesser impact on global price movements. The study's hypothesis that currency dynamics significantly affect local food price volatility is supported by these results.

4. Discussion

The main goal of the study was to develop a machine learning model to predict food price fluctuations driven by fluctuations in the Afghan currency, and the objective was achieved. These models can capture the impact of exchange rate fluctuations on domestic food costs by using a dataset of price data in which food prices are quoted in both Afghanis and USD and exchange rates are calculated. The Random Forest model outperformed all other models evaluated. As we can see, the Random Forest achieved the lowest MAE and RMSE and the best R2. This shows that integrating different algorithms can outperform traditional statistical techniques in handling nonlinear economic interactions [3], [5], [14].

The Ahmed and Islam [15] and Rahman and Hossain [2] results and our study results and findings are consistent, who demonstrates that ML algorithm can offer better forecasting effectively than conventional techniques in different commodity price prediction. Although LSTM ML algorithm shows the long-term trends, its lag during sudden price changes shown the limits of linear learning in turbulent markets. The weak relationship between AFN prices and exchange rates which is manually calculate in this study highlights the causes of food price volatility in markets. It is also confirmed previous studies [8], [11].

Overall, by showing how ML model can improve understanding of currency price relationships in countries with limited income, this study advances data-driven economic prediction. The findings demonstrate the potential of predictive modeling for early warning systems and policy measures meant to take care stabilization and food security food prices in countries with limited income like Afghanistan.

5. Conclusion and Future Direction

From the results of this study we can say how well ML models can forecast fluctuations in food prices in Afghanistan during periods of currency changes. The study effectively captured the implicit impact of exchange rate fluctuations on local market prices by combining the food price data from the World Food Programme (WFP), shown in both Afghani currency and USD dollars. Performing best in both Linear Regression and LSTM models, the Random Forest algorithm is the most reliable and accurate predictions among the models evaluated. The results presented here show the effectiveness of modeling data which is complex, nonlinear economic relationships that are often missed by conventional econometric algorithm. The results have important ramifications for humanitarian organizations and policymakers, providing a data-driven basis for creating early warning systems and responsive tactics to preserve food price stability and guarantee food security.

This study works only the dataset which collected from WFP dataset, further it can be expanded on using more economic, meteorological, and geopolitical factors to enhance model effectiveness in forecasting the prices and generalization, even though the results of our algorithms are promising. Forecasting accuracy in uncertain markets may be further enhanced by incorporating ensemble learning designs, such as Random Forest and ANN. And also, when we analyze real-time data sources such as social sentiment analytics and satellite imagery could enhance predictive effectiveness and provide timely results for policy makers and businessmen. In the end, this study worked on both practical policy-making in volatile economies of some countries, where food prices are not stable to currency changes, and ML prediction effectiveness in economic forecasting.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] World Food Programme (WFP), WFP Food Prices for Afghanistan [Dataset], Humanitarian Data Exchange (HDX), United Nations OCHA, 2025. [Online]. Available: https://data.humdata.org/dataset/wfp-food-prices-for-afghanistan

[2] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, "Statistical and machine learning forecasting methods: Concerns and ways forward," International Journal of Forecasting, vol. 34, no. 3, pp. 550–570, Jul. 2018, doi: https://doi.org/10.1371/journal.pone.0194889

[3] P. S. Sephton, "Modelling the link between commodity prices and exchange rates: The tale of daily data," The Canadian Journal of Economics / Revue canadienne d'Économique, vol. 25, no. 1, pp. 156–171, Feb. 1992, doi: https://doi.org/10.2307/135716

[4] O. B. Sezer, M. U. Gudelek, and A. M. Ozbayoglu, "Financial time series forecasting with deep learning: A systematic literature review," Applied Soft Computing, vol. 90, Art. no. 106181, 2020, doi: https://doi.org/10.1016/j.asoc.2020.106181

[5] J. Fender and C. K. Yip, "Tariffs and exchange rate dynamics redux," Journal of Economic Studies, vol. 27, no. 4/5, pp. 265–276, 2000, doi: https://doi.org/10.1016/S0261-5606(00)00027-9

[6] T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed. New York, NY, USA: Springer, 2009, doi: https://doi.org/10.1007/978-0-387-84858-7

[7] Food and Agriculture Organization (FAO), Global Food Price Monitoring and Analysis, FAO, Rome, 2024. [Online]. Available: https://www.fao.org/worldfoodsituation/foodpricesindex

[8] World Bank, Afghanistan Economic Update: Managing Inflation and Food Prices, World Bank Group, Washington, DC, 2023. [Online]. Available: https://www.worldbank.org/en/country/afghanistan

[9] R. Ly, F. Traoré, and K. Dia, "Forecasting commodity prices using long-short-term memory neural networks," IFPRI Discussion Paper 2000, Washington, DC, Jan. 2021. [Online]. Available: https://arxiv.org/abs/2101.03087

[10] I. Kelikume, "Do exchange rate and oil price shocks have asymmetric effect on inflation? Some evidence from Nigeria," The Journal of Developing Areas, vol. 51, no. 4, pp. 271–283, Fall 2017. [Online]. Available: https://doi.org/10.1353/jda.2017.0101

[11] N. Minot, "Transmission of world food price changes to markets in Sub-Saharan Africa," IFPRI Discussion Paper 01059, International Food Policy Research Institute, Washington, DC, USA, 2011. [Online]. Available: https://www.ifpri.org/publication/transmission-world-food-price-changes-markets-sub-saharan-africa

[12] S.-N. Siami-Namini, N. Tavakoli, and A. S. Namin, "A comparison of ARIMA and LSTM in forecasting time series," in Proc. IEEE ICMLA, 2018, pp. 1394–1401, doi: https://doi.org/10.1109/ICMLA.2018.00227

[13] M. C. Medeiros, G. F. R. Vasconcelos, Á. Veiga, and E. Zilberman, "Forecasting inflation in a data-rich environment: The benefits of machine learning methods," Journal of Econometrics, vol. 225, no. 2, pp. 347–366, 2021, doi: https://doi.org/10.1080/07350015.2019.1637745

[14] International Monetary Fund (IMF), Afghanistan: Exchange Rate Trends and Macroeconomic Stability, IMF Country Report No. 23/111, 2023. [Online]. Available: https://www.imf.org/en/Countries/AFG

[15] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997, doi: https://doi.org/10.1007/978-3-642-24797-2_4

[16] M. C. Medeiros, G. F. R. Vasconcelos, Á. Veiga, and E. Zilberman, "Forecasting Brazilian inflation with high-dimensional models," Journal of Business & Economic Statistics, vol. 39, no. 3, pp. 1–15, 2021, doi: https://doi.org/10.12660/bre.v99n992016.52273

[17] United Nations Office for the Coordination of Humanitarian Affairs (OCHA), Humanitarian Response Plan: Afghanistan, United Nations, 2024. [Online]. Available: https://www.unocha.org/afghanistan

[18] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," Neurocomputing, vol. 50, pp. 159–175, 2003, doi: https://doi.org/10.1016/S0925-2312(01)00702-0

[19] K. J. Forbes and F. E. Warnock, "Capital flow waves: Surges, stops, flight, and retrenchment," Journal of International Economics, vol. 88, no. 2, pp. 235–251, 2012, doi: https://doi.org/10.1016/j.jinteco.2012.03.006

[20] World Food Programme (WFP), Food Price and Currency Market Bulletin: Afghanistan, WFP Afghanistan Office, 2025.[Online]. Available: https://www.wfp.org/countries/afghanistan

[21] M. K. Mohanty, P. K. Guha Thakurta, and S. Kar, "Agricultural commodity price prediction model: a machine learning framework," Neural Computing and Applications, vol. 35, no. 20, pp. 15109–15128, Apr. 2023. [Online]. Available: https://doi.org/10.1007/s00521-023-08528-7

[22] E. Sediyono, K. D. Hartomo, C. Arthur, and I. Utami, "An integrated framework for multi-commodity agricultural price forecasting and anomaly detection using attention-boosted models," Journal of Agriculture and Food Research, vol. 15, Art. no. 100679, 2025, doi: https://doi.org/10.1016/j.jafr.2025.102021

[23] M. Z. Abedin, M. H. Moon, M. K. Hassan, and P. Hajek, "Deep learning-based exchange rate prediction during the COVID-19 pandemic," Annals of Operations Research, vol. 345, no. 2, pp. 1335–1386, Nov. 2021. [Online]. Available: https://doi.org/10.1007/s10479-021-04420-6

[24] G. Koop and D. Korobilis, "Forecasting inflation using dynamic model averaging," International Economic Review, vol. 53, no. 3, pp. 867–886, 2012, doi: https://doi.org/10.1111/j.1468-2354.2012.00704.x

[25] Y. Zhang, C. C. Aggarwal, and G. J. Qi, "Stock price prediction via discovering multi-frequency trading patterns," in Proc. 23rd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD), Halifax, NS, Canada, 2017, pp. 2141–2149, doi: https://doi.org/10.1145/3097983.3098117