Explainable Artificial Intelligence for Inflation Forecasting with SHAP, Random Forest, and LSTM: An Application to Algeria

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Abstract. Accurate inflation forecasting is crucial for effective policymaking, yet inflation dynamics often lack transparency. This study applies Explainable Artificial Intel-ligence (XAI) to analyze inflation in Algeria by combining SHapley Additive exPlanations (SHAP) with Random Forest (RF) and Long Short-Term Memory (LSTM) models. While LSTM better captures extreme inflation episodes and RF provides smoother forecasts, the main contribution lies in explaining model pre-dictions. SHAP results identify food inflation as the dominant driver, followed by lagged producer inflation and the GDP deflator, revealing strong nonlinear and temporal effects, whereas energy inflation plays a limited role. In addition, the analysis highlights how machine-learning models can complement traditional econometric approaches by capturing complex interactions and regime-dependent behaviors that are difficult to observe with linear frameworks. Overall, integrating ML models with XAI enhances transparency, supports informed policy decisions,and provides robust, interpretable evidence to better understand and manage inflationary pressures in Algeria’s evolving macroeconomic environment context effectively.

Keywords Inflation forecasting, Random Forest, Explainable AI, Economic indicators, LSTM Time-series analysis

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1 Introduction

Inflation—a sustained rise in the general price level—erodes purchasing power. In Algeria, it is driven by domestic demand, cost-push factors such as food and energy prices, and structural constraints. Recent shocks, including post-pandemic disruptions and global supply-chain issues, have intensified inflation, while institutional and cen-tral bank limitations have reduced policy effectiveness [1]. Empirical evidence shows that Algerian inflation is persistent and time-varying, reflecting the vulnerabilities of developing economies [2].

Accurate inflation forecasting is essential for monetary policy, fiscal planning, and economic stability [3]. Traditional time series methods, such as ARIMA [4] and Prophet [5], are widely used but often fail to capture nonlinear dynamics and complex interactions among macroeconomic indicators.

Machine learning offers effective alternatives. RF [6] captures high-dimensional, nonlinear relationships with robust performance [7], while LSTM [8] models temporal dependencies and long-term effects in inflation data [9]. However, both can be hard to interpret, limiting their use in policy analysis.

We apply SHAP [10] to interpret predictions from RF and LSTM models, identifying key contemporaneous and lagged drivers of inflation to enhance transparency and policy relevance. The analysis uses data from the World Bank Inflation Database [11], covering multiple price indices and reporting frequencies.

The paper is organized as follows: Section 2 reviews machine learning and XAI approaches for inflation modeling. Section 3 presents the dataset, RF and LSTM models, and SHAP-based interpretation. Section 4 reports experimental results and key inflation drivers, and Section 5 concludes with findings, policy implications, and future research directions.

2 Literature Review and Related Work

Explainable AI (XAI) enhances the transparency of machine and deep learning models by making their predictions interpretable [12], which is crucial for inflation forecast-ing and policy decisions. XAI methods include model-agnostic and model-specific approaches, as well as global and local explanations such as feature importance, par-tial dependence plots (PDP) [13], LIME [14], and SHAP [10], helping to identify key drivers and capture nonlinear effects.

Machine learning models, including Random Forest (RF) [6], Gradient Boosting and XGBoost [15], Support Vector Regression (SVR) [16], are widely used for infla-tion forecasting, capturing nonlinear relationships and often outperforming traditional time-series models.

Deep learning approaches such as LSTM [8], Gated Recurrent Unit (GRU) [17], and Temporal Convolutional Networks (TCN) [18] further improve forecasts by modeling sequential patterns, long-term dependencies, and complex nonlinear dynamics.

Aras et al. [19] use machine learning to forecast inflation while ensuring inter-pretability, applying XAI methods like SHAP to reveal how economic variables drive predictions.

Bathula et al. [20] use deep learning models (Transformer, N-Beats, and LSTM) with XAI to forecast inflation and assess feature importance using key macroeconomic indicators.

While informative, these studies rarely provide a systematic comparison of interpretability across machine learning and deep learning models, a gap this study addresses using SHAP for both RF and LSTM.

3 Proposed Methodology

This study aims to identify the key drivers of inflation in Algeria using XAI techniques. Random Forest and LSTM models capture nonlinear and temporal dynamics, while SHAP explains variable contributions

3.1 Data Description and Structure

We forecast inflation using two complementary models cross-country comparable mea-sures across multiple price indices (PIs), including headline CPI, core CPI, food CPI, energy CPI, producer prices, and the GDP deflator. Spanning January 2003 to December 2020, the data are reported monthly and quarterly, providing 216 monthly observations per country and indicator. Organized in a multi-sheet Excel file, each sheet corresponds to a specific indicator and frequency, with rows representing coun-tries, columns representing time periods, and cells containing inflation values. The inclusion of multiple indices per country increases the effective sample size, enabling robust modeling of inflation dynamics over time.

Example: Constructing Annual Inflation from Monthly CPI Data
Table 1 provides an example, reporting December CPI values for selecte countries over the period 2016–2020. Using December observations ensures temporal consistency and minimizes seasonal effects, making them suitable for the computation of annual inflation rates.

Annual inflation is calculated as the year-on-year percentage change in December CPI, as defined in Equation 1:

$$\text{Inflation Rte (\%)} = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100, \quad (1)$$

where CPIt and CPIt−1 denote the December CPI values for the current and previous year, respectively

Table 1: Example of December CPI Values for Selected Countries (2016–2020)

Country	2016	2017	2018	2019	2020
Algeria	188.50	192.30	198.50	207.90	215.21
Brazil	112.45	115.67	118.97	123.44	129.01
China	93.14	94.66	96.48	99.69	99.96

Table 2 shows annual inflation rates, highlighting magnitude and temporal changes across Algeria, Brazil, and China, providing a clear view of their inflation dynamics.

Table 2: Annual Inflation Rates (%) for Selected Countries (2016–2020)

Country	2016	2017	2018	2019	2020
Algeria	–	2.03	3.20	4.94	3.52
Brazil	–	2.87	2.85	3.73	4.52
China	–	1.63	1.87	3.34	0.27

3.2 Inflation Modeling with Random Forest and LSTM

We forecast inflation using RF and LSTM models, which capture nonlinear and tem-poral dynamics. The input features include six macroeconomic indicators: Headline CPI, Food CPI, Energy CPI, Core CPI, GDP Deflator, and Producer Inflation. A 5-year sliding window ($WINDOW = 5$) incorporates each year's value along with its lags from $t - 1$ to $t - 5$. Features are normalized to $[0, 1]$, and for LSTM, data are reshaped into a 3D tensor (Samples, 1, Features) to model temporal dependencies.

- **Random Forest:** An ensemble of decision trees built on random subsets of data and features to capture nonlinear relationships with inflation. We used 300 trees (n estimators=300) for stable predictions and set random state=42 for reproducibility. This setup balances robustness, interpretability, and computatiōnal efficiency.

- **LSTM Neural Networks:** LSTM, a recurrent neural network, models sequentialdata and long-term dependencies, making it suitable for inflation forecasting. The network uses memory cells and gates to retain relevant information. Our model has an input layer with historical inflation and macroeconomic indicators (timesteps = 1, features), a single LSTM layer with 64 units and ReLU activation, a dense layer with 32 ReLU neurons, and an output neuron predicting next-period inflation. It was trained with the **Adam optimizer** for 150 epochs, batch size 4, minimizing MSE. **SHAP's DeepExplainer** was applied for local and global interpretability of feature contributions.

RF and LSTM models are applied separately to capture different aspects of inflation: RF models nonlinear relationships among current indicators, while LSTM captures temporal dependencies. This framework also allows SHAP analysis to identify each model's key inflation drivers.

- Feature Importance and Interpretability: SHAP To interpret the predictions of both RF and LSTM models, we use SHAP. It is a game-theoretic approach that assigns each feature an importance value for a par-ticular prediction. It provides consistent and theoretically grounded explanations, making complex machine learning models interpretable for policy analysis .

The SHAP framework decomposes a model's output into contributions from each feature, allowing identification of the most influential predictors of inflation. By applying SHAP to both static (RF) and sequential (LSTM) models, we can com-pare the relative importance of contemporaneous versus lagged economic indicators, offering transparent insights into the drivers of inflation.

4 Experimental Results and Discussion

This study analyzes Algerian inflation with RF and LSTM, using SHAP for inter-pretability and performance assessment.

4.1 Comparative Performance of RF and LSTM Models in Inflation Forecasting

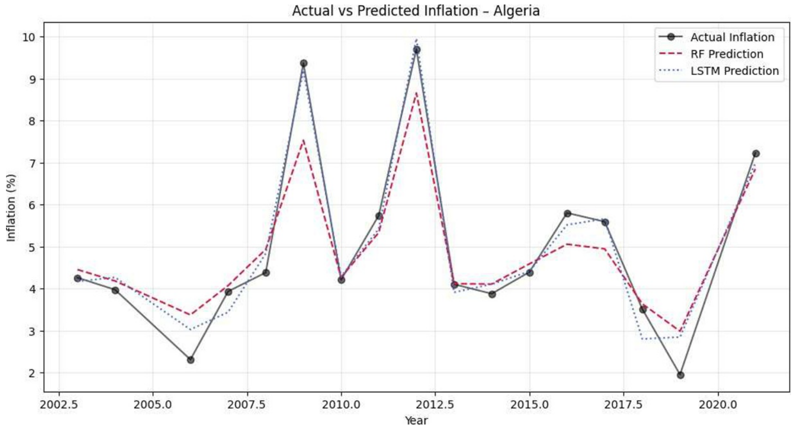

Fig. 1: Actual vs. predicted inflation from RF and LSTM models.

Table 3 shows that LSTM outperforms RF across all metrics, reflecting its superior ability to capture temporal dependencies, while RF models nonlinear effects from current indicators, highlighting their complementary strengths.

Table 3: Regression Metrics for RF and LSTM Models

Model	MSE	RMSE	MAE
Random Forest	19.25	4.39	2.84
LSTM	7.87	2.80	2.45

Figure 1 compares the actual inflation in Algeria with the forecasts generated by the RF and LSTM models over the period 2003–2020. The LSTM model, depicted by the blue dotted line, demonstrates superior performance in capturing both volatil-ity and extreme movements in inflation, particularly during the pronounced spikes observed around 2009 and 2012, where its predictions closely align with the observed values. In contrast, the RF model, shown by the red dashed line, exhibits a tendency to underpredict during high-volatility episodes and to overpredict during pronounced downturns, such as the sharp decline in 2019, reflecting a comparatively smoother and more conservative estimation behavior. While both models successfully track the overall inflation trend, the closer alignment of the LSTM forecasts with actual obser-vations indicates a stronger capability to model the non-linear dynamics and temporal dependencies characterizing inflation fluctuations in Algeria.

To interpret the predictions from both the RF and LSTM models, we employed two complementary visualizations: a bar chart and a dot plot. The bar chart ranks features by their overall influence on each model, establishing a clear hierarchy of importance. The dot plot provides additional insight by showing the direction of each feature's effect, with color-coded points indicating whether high or low values increase or decrease the predicted inflation.

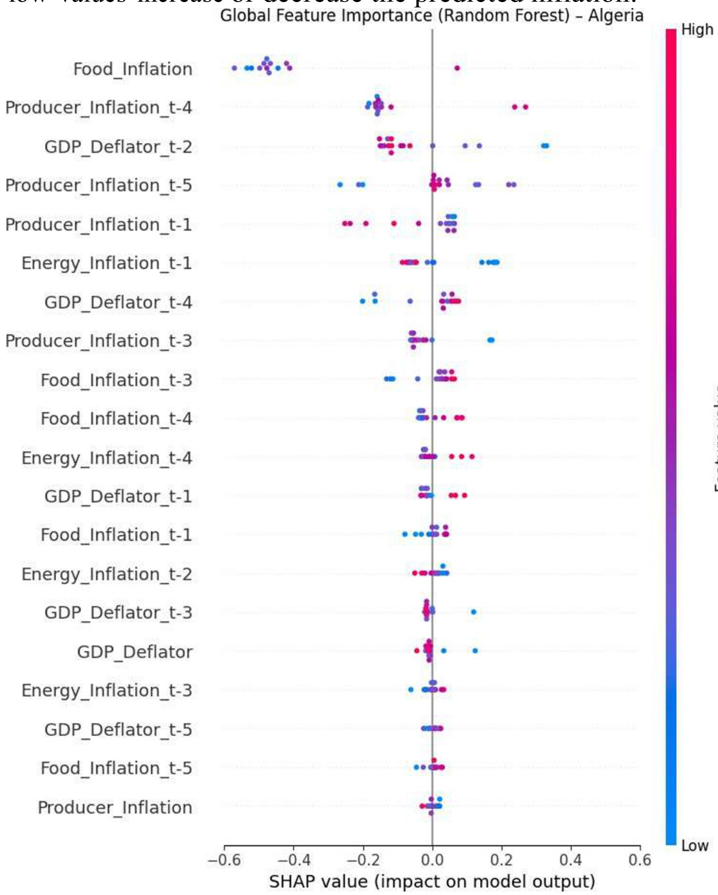

Fig. 2: SHAP summary for Random Forest, showing feature impacts and direction.

4.1.1 SHAP-Based Feature Explanations for the RF Model

Figure 2 shows the SHAP summary for the Random Forest model forecasting Algerian inflation, highlighting feature importance and direction. Food inflation is the dominant driver, followed by lagged producer inflation ($t-1$, $t-3$, $t-4$, $t-5$) and GDP deflators, while energy inflation has a smaller, more dispersed impact. The results confirm the temporal persistence of inflation and the ability of Random Forest, interpreted via SHAP, to capture nonlinear and delayed effects.

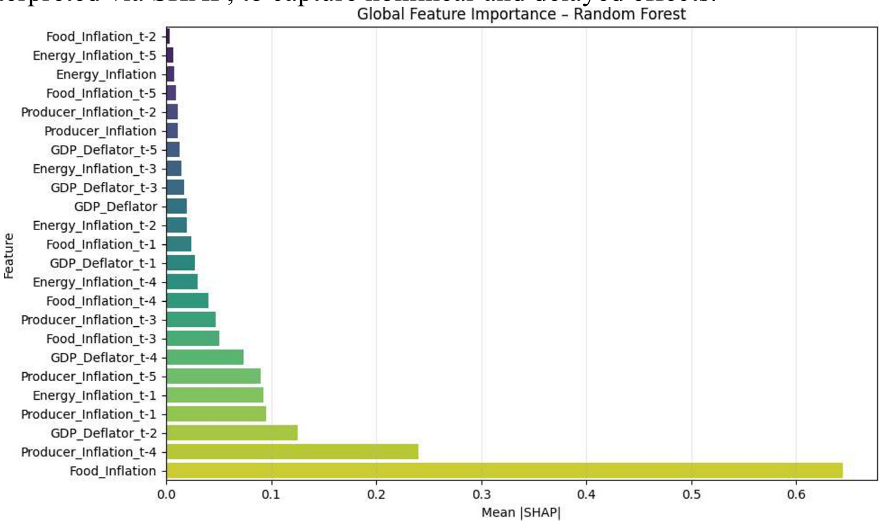

Fig. 3: Global feature importance for the Random Forest model.

Figure 3 presents the feature importance derived from a RF model using mean absolute SHAP values ($|SHAP|$). The plot highlights that current *Food Inflation* is the dominant predictor, with an importance score of approximately 0.65, more than twice that of the second most influential feature, *Producer Inflation*$_{t-4}$. This emphasizes a notable time-lagged pass-through effect from production costs to overall inflation. Lagged variables such as *GDP Deflator*$_{t-2}$ and *Producer Inflation*$_{t-1}$ are also highly weighted, indicating that the historical price momentum plays a greater role than contemporaneous energy metrics. In contrast, *Energy Inflation* ranks low (< 0.05), suggesting that either energy price shocks are relatively stable in this dataset or their effects are indirectly captured through food and production costs.

4.1.2 SHAP-Based Feature Explanations for the LSTM Model

Figure 4 shows the global feature importance from the LSTM model (mean absolute SHAP values). Food Inflation is the most influential predictor (~ 0.65), more than twice that of Producer Inflation$_{t-4}$, highlighting time-lagged pass-through. Lagged variables like GDP Deflator$_{t-2}$ and Producer Inflation$_{t-1}$ emphasize historical infla-tion dynamics, while Energy Inflation (< 0.05) has a minor impact, suggesting indirect or limited effects during the period.

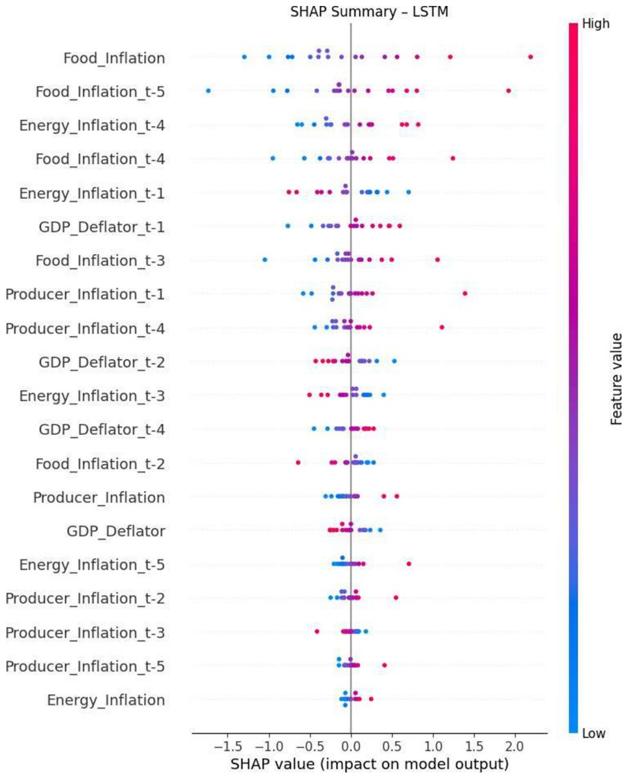

Fig. 4: LSTM SHAP summary showing feature impacts on predictions.

Figure 5 shows a horizontal bar chart of global feature importance for the LSTM model (mean absolute SHAP values). Food Inflation is the dominant predictor, followed by its five-period lag ($Food\ Inflation_{t-5}$), highlighting the role of both current and historical food prices. Other influential features include lagged energy indices ($Energy\ Inflation_{t-4}$), while GDP Deflator and Producer Inflation have lower impact. Features are ordered by importance, with a color gradient emphasizing the model's focus on inflation-related variables over time.

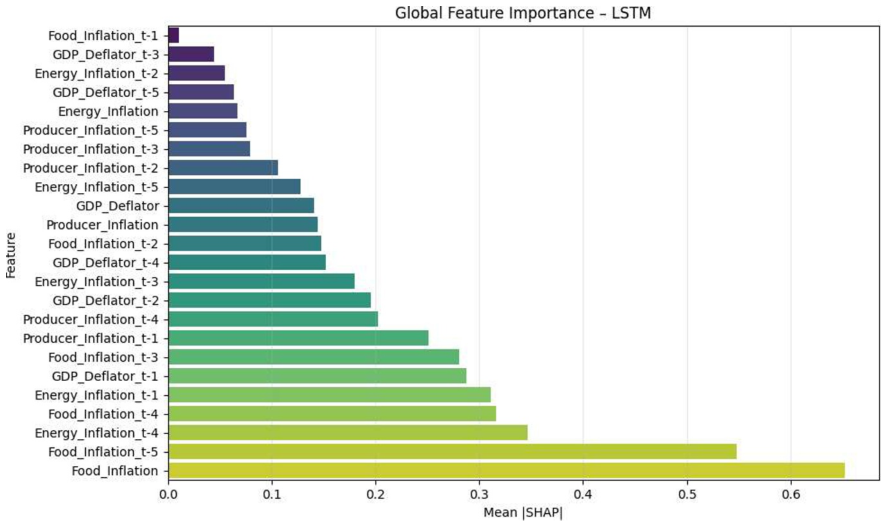

Fig. 5: Global feature importance for the LSTM model based on mean absolute SHAP values.

5 Conclusion

This study demonstrates that combining RF and LSTM models effectively forecasts inflation in Algeria and identifies key drivers. RF captures nonlinear effects of cur-rent indicators, while LSTM accounts for temporal and lagged dependencies. SHAP analysis shows food inflation as the dominant driver, with GDP deflator and producer prices contributing through lagged effects. Integrating machine learning with XAI offers transparent, policy-relevant insights. Limitations include a single-country focus and data limitations; future work could extend the approach to multiple countries, more indicators, and scenario-based policy analysis

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