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Global Inflation Forecasting Using Stacking Ensemble with Elastic Net Meta-Learner Integrating Random Forest, XGBoost, and LightGBM

Fauriza Wildhani Susilo*[1], Anjar Wanto[2], Irfan Sudahri Damanik[3]

[1]Information System, STIKOM Tunas Bangsa, Pematangsiantar, Indonesia
[2,3]Department of Informatics Magister's, STIKOM Tunas Bangsa, Pematangsiantar, Indonesia

Email: [1]faurizawildhani46@gmail.com

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Abstract

Inflation dynamics have become increasingly complex due to economic volatility and nonlinear interactions, challenging the reliability of conventional forecasting models; therefore, this study develops a robust global inflation forecasting framework using a hybrid stacking ensemble that integrates Random Forest, XGBoost, and LightGBM as base learners with Elastic Net as a regularized meta-learner, applied to annual inflation data from 2000–2024 across five major economic blocs (G7, Europe, BRICS, ASEAN, and the Americas) after temporal feature engineering and time-series–preserving validation; the results demonstrate strong and consistent predictive performance, with very high accuracy in Europe ($R^2 = 0.9282$) and the G7 ($R^2 = 0.9122$), and the globally trained stacking model ($R^2 = 0.7866$) substantially outperforming the region-specific ASEAN model ($R^2 = 0.5243$), confirming the advantage of cross-country learning; this research advances informatics and computer science by providing a scalable and stable ensemble learning framework for macroeconomic time-series forecasting in volatile environments, supporting the development of AI-driven economic and policy analytics systems.

Keywords : *ElasticNet, Inflation Forecasting, LightGBM, Machine Learning, Random Forest, Stacking Ensemble, XGBoost.*

1. INTRODUCTION

Inflation is one of the most critical macroeconomic indicators as it directly affects economic stability, monetary policy formulation, and purchasing power. In recent years, global inflation dynamics have become increasingly complex due to heightened economic uncertainty, persistent supply chain disruptions, geopolitical tensions, and heterogeneous monetary policy responses across countries [1], [2], [3]. These factors have intensified inflation volatility and introduced non-linear behaviors and structural breaks, making accurate inflation forecasting more challenging than in previous decades [4], [5]. Recent studies have also demonstrated that artificial intelligence can be effectively used to model inflation expectations, which are inherently forward-looking and difficult to quantify using traditional econometric approaches [6].

Traditional statistical models such as ARIMA and classical econometric approaches remain widely used in inflation forecasting due to their interpretability and theoretical foundations. However, numerous studies report that these models often fail to capture non-linear relationships, regime shifts, and complex interactions among macroeconomic variables, particularly during periods of economic turbulence or policy uncertainty [7], [8], [2]. Empirical evidence shows that the predictive accuracy of conventional models tends to deteriorate significantly under high volatility conditions and structural changes [9], [5], [10], highlighting the need for more flexible and adaptive forecasting frameworks. Moreover, inflation dynamics are strongly influenced by fiscal policy transmission and policy multipliers, which further complicates accurate forecasting using purely linear or traditional econometric models [11].

Driven by advances in computational power and data availability, machine learning (ML) techniques have gained increasing attention in inflation forecasting research. In addition to commonly used machine learning and deep learning models, density-based learning approaches have been proposed to better capture complex distributional patterns in economic time series data, including inflation dynamics [12]. Models such as Artificial Neural Networks, Recurrent Neural Networks, and Long Short-Term Memory (LSTM) have demonstrated superior performance in capturing non-linear patterns and temporal dependencies compared to traditional approaches [13], [8], [14], [15]. In addition, tree-based models such as Random Forest, XGBoost, and LightGBM have proven effective in modeling complex interactions among economic indicators and handling high-dimensional data [7], [3], [16]. Nevertheless, the predictive performance of individual ML models remains sensitive to data characteristics, regional heterogeneity, and forecasting horizons, often leading to inconsistent results across countries and time periods [14], [16], [17].

To address the limitations of single-model forecasting, ensemble learning techniques have been increasingly adopted in time series prediction. Recent studies have shown that combining ensemble learning with heterogeneous data sources, including macroeconomic indicators and textual information, can significantly enhance inflation forecasting performance. Ensemble methods combine multiple base learners to improve predictive accuracy, robustness, and generalization capability [18], [19], [20]. However, simple ensemble strategies such as averaging or bagging may not fully exploit the complementary strengths of heterogeneous models. Stacking ensemble methods overcome this limitation by introducing a meta-learning layer that optimally integrates the outputs of multiple base learners [21], [22], [15]. By learning from the error structures of base models, stacking ensembles can provide more stable and adaptive forecasts, particularly in complex macroeconomic environments.

Within the stacking framework, the choice of meta-learner plays a crucial role in determining model robustness. Elastic Net regression is particularly suitable as a meta-learner due to its combined L1 and L2 regularization properties. This enables effective handling of multicollinearity among base learner predictions while simultaneously reducing overfitting, which is a common issue in complex ensemble models [19], [20], [22]. Consequently, Elastic Net serves not only as a combination mechanism but also as a regularized learning framework that enhances the stability of stacking-based inflation forecasting models.

Previous studies have applied machine learning and ensemble approaches to inflation forecasting at national, regional, and global levels, including the use of disaggregated data and high-frequency indicators [4], [5], [8], [23], [24], [25]. While these studies demonstrate the potential of ML-based methods, most existing research focuses on either single models or limited ensemble configurations and is often confined to specific countries or regions. Moreover, limited attention has been given to systematically integrating Random Forest, XGBoost, and LightGBM within a unified stacking architecture using Elastic Net as a meta-learner for global inflation prediction.

Furthermore, comparative evidence between global and region-specific inflation forecasting models remains scarce. Emerging regions such as ASEAN exhibit higher inflation volatility, structural heterogeneity, and data limitations, which often reduce the effectiveness of single-model or regionally trained approaches [17], [20]. Evaluating the robustness of a global hybrid stacking model when applied across diverse economic regions, and contrasting its performance with region-specific models, is therefore essential to assess model generalizability and practical relevance.

Motivated by these research gaps, this study proposes a Hybrid Ensemble Learning framework that integrates Random Forest, XGBoost, and LightGBM as base learners, combined through an Elastic Net-based stacking strategy for global inflation forecasting. The objectives of this study are threefold:

to improve inflation forecasting accuracy relative to single-model baselines through a hybrid stacking ensemble framework, to enhance predictive robustness across heterogeneous economic regions, and to empirically evaluate the comparative performance of global and regional forecasting strategies. By addressing these objectives, this study contributes to the growing literature on machine learning-based inflation forecasting and provides practical insights for policymakers and researchers dealing with complex global inflation dynamics [1], [4], [9], [14].

To systematically illustrate the evolution of inflation forecasting models and to clearly position the proposed approach, Table 1 presents a timeline of dominant methodologies, their scope, and limitations. This comparison highlights the research gap addressed in this study.

Table 1. Timeline of the Evolution of Inflation Forecasting Models

Period	Methodological Trend	Representative Models	Forecasting Scope	Key Limitations
Before 2010	Classical Statistical & Econometric Models	ARIMA, VAR, Phillips Curve	National	Linear assumptions; weak performance under structural breaks and non-linearity
2011–2018	Early Machine Learning	Artificial Neural Networks (ANN), Support Vector Regression (SVR)	National	High sensitivity to hyperparameters; limited robustness
2019–2021	Deep Learning Approaches	RNN, LSTM	National / Regional	Overfitting risk; limited interpretability
2022–2023	Advanced Tree-Based Models	Random Forest, XGBoost, LightGBM	National / Regional	Single-model dependency; performance varies across horizons
2024	Conventional Ensemble Learning	Bagging, Boosting, Simple Averaging	Regional / Partial Global	Inability to fully exploit complementary model strengths
2025–Present (This Study)	Hybrid Stacking Ensemble with Meta-Learning	RF + XGBoost + LightGBM (Elastic Net Meta-Learner)	Global & Regional	Addresses multicollinearity, overfitting, and instability through regularized stacking

2. METHOD

This study aims to develop an inflation forecasting model based on a hybrid stacking ensemble learning framework that integrates Random Forest, XGBoost, and LightGBM as base learners. The research problem is formulated as estimating future inflation values by modeling the non-linear relationship between historical inflation dynamics and temporally structured explanatory features.

Mathematically, the inflation forecasting problem can be expressed as :

$$y_t \; f(x_t) + \varepsilon \qquad (1)$$

where y_t denotes the inflation rate at time t, x_t represents the vector of predictor features derived from historical inflation and temporal information, $f(.)$ is the unknown non-linear function learned by the forecasting model, and ε_t denotes a random error term capturing unexplained variations.

The stacking ensemble approach is adopted due to its ability to integrate the complementary strengths of multiple heterogeneous base learners through a meta-learning layer. By learning optimal combinations of base model outputs, stacking enhances predictive accuracy, robustness, and generalization performance compared to single-model approaches, particularly when applied to complex, volatile, and structurally evolving macroeconomic data such as inflation.

2.1. Data and Preprocessing

This study utilizes secondary annual inflation data based on the Consumer Price Index (CPI) covering the period 2000–2024. The dataset is obtained from Kaggle and reports the indicator "Annual average inflation (consumer prices) rate," which represents annual percentage changes in consumer prices across countries.

The original dataset is provided in a wide format, where each row corresponds to a country and each column represents an observation year. For time-series modeling purposes, the data are transformed into a long format with country–year observations.

Data preprocessing includes bidirectional linear interpolation to address missing values, capping extreme inflation values within the range of −0.5 to 20 percent to mitigate the influence of extreme inflation spikes, and logarithmic transformation using $\log 1 + y$. These steps aim to stabilize variance, reduce heteroskedasticity, and improve model robustness when handling volatile inflation dynamics.

2.2. Feature Engineering and Data Splitting

To comprehensively capture the temporal dynamics of inflation, this study constructs a set of time-series-based predictor features that are generated sequentially for each country. The employed features include the historical mean inflation of each country as a representation of long-term structural characteristics, inflation lags of one to three previous periods to capture short-term temporal dependence, a three-period moving average to smooth short-term fluctuations, and the annual inflation change defined as the difference between inflation in the current period and the previous period. Mathematically, the inflation change is formulated as:

$$\Delta yt = yt - yt - 1 \quad (2)$$

In addition, a linear time index is included to represent long-term trends, defined as the difference between the observation year and the initial year of the study period. All features are constructed sequentially by country to prevent data leakage across time periods.

Data splitting is performed using a temporal splitting approach to reflect real-world forecasting conditions. Observations from the period 2000–2019 are used as the training set, while data from 2020–2024 are used as the testing set. For internal validation on the training data, a five-fold time-series cross-validation scheme is employed, in which the temporal order is strictly preserved so that the model is trained only on past data to predict subsequent periods.

2.3. Stacking Ensemble Architecture

The proposed model adopts a two-level stacking ensemble architecture. At the first level, three base learners are employed, namely the Random Forest Regressor, XGBoost Regressor, and LightGBM Regressor. These models are selected due to their ability to capture nonlinear relationships, complex feature interactions, and their robustness to multicollinearity and high-dimensional data.

The predictions generated by each base learner are subsequently used as meta-features at the second level. Mathematically, the stacking ensemble structure can be expressed as:

$$y_t = f_{meta} \left(h_{RF}(X_t), h_{XGB}(X_t), h_{LGBM}(X_t)\right)(3)$$

Where $h_{RF}(.), h_{XGB}(.)$, and $, h_{LGBM}(.)$ denote the prediction functions of the Random Forest, XGBoost, and LightGBM models, respectively, while $f_{meta}\ (.)$ represents the meta-learner function.

Elastic Net Regression is employed as the meta-learner due to its ability to simultaneously incorporate L1 and L2 regularization, making it effective in reducing multicollinearity among base learner predictions and preventing overfitting. The Elastic Net loss function is formulated as:

$$L(w) = \frac{1}{2N} \sum_{i=1}^{N} (y_i - w^T x_i)^2 + \lambda \left\lfloor \alpha \; \| \mathrm{w} \| \; 1 + \frac{1-\alpha}{2} \; \| \mathrm{w} \| \; \frac{2}{2} \right\rfloor \quad (4)$$

where λ is the global regularization parameter and α controls the balance between L1 and L2 regularization. The Elastic Net parameters are determined through a limited grid search conducted on the training data using time-series-based validation to ensure model stability and to avoid overfitting.

The grid search explores a restricted range of values for the regularization strength (λ) and the mixing parameter (α) to balance sparsity and coefficient stability while maintaining generalization performance.

2.4. Reproducible Stacking Implementation

To enhance transparency and reproducibility, the stacking ensemble implementation follows an out-of-fold prediction strategy using time-series cross-validation. In this procedure, each base learner is trained on a subset of the training data and generates predictions for the corresponding validation subset. These out-of-fold predictions are then used as meta-features to train the meta-learner. A simplified Python implementation of the stacking ensemble procedure is presented in Listing 1.

Listing 1. Simplified Python implementation of the stacking ensemble

```python
from sklearn.model_selection import TimeSeriesSplit
from sklearn.linear_model import ElasticNet
import numpy as np

tscv = TimeSeriesSplit(n_splits=5)
meta_train = np.zeros((len(X_train), 3))
meta_test  = np.zeros((len(X_test), 3))

for i, model in enumerate(base_models):
    oof_pred = np.zeros(len(X_train))
    for tr_idx, val_idx in tscv.split(X_train):
        model.fit(X_train.iloc[tr_idx], y_train.iloc[tr_idx])
        oof_pred[val_idx] = model.predict(X_train.iloc[val_idx])
        model.fit(X_train, y_train)
    meta_train[:, i] = oof_pred
    meta_test[:, i] = model.predict(X_test)
meta_model = ElasticNet(alpha=0.01, l1_ratio=0.3)
meta_model.fit(meta_train, y_train)
y_pred = meta_model.predict(meta_test)
```

2.5. Evaluation Strategy

Model performance is evaluated using three primary metrics: the coefficient of determination (R²), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The coefficient of determination is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - y_i)^2}{\sum_{i=1}^{N} (y_i - y)^2} \quad (5)$$

Where y_i denotes the actual inflation value, y_i represents the model prediction, and y is the mean of the actual inflation values.

The Mean Absolute Error (MAE) is used to measure the average magnitude of prediction errors regardless of their direction and is formulated as:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} | y_i - y_i | \qquad (6)$$

Meanwhile, the Root Mean Squared Error (RMSE) is employed to assess the model's sensitivity to large prediction errors by penalizing larger deviations more heavily. RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{N}} \sum_{i=1}^{N} (y_i - y_i)^2 \qquad (7)$$

Evaluation is conducted at two levels. First, the global model is assessed across major economic groups, namely G7, BRICS, ASEAN, Europe, and the Americas. Second, a region-specific model for ASEAN is developed using a simpler configuration to examine performance differences between global and regional modeling approaches. Subgroup evaluations are performed only when a minimum of 20 observations is available to ensure statistical reliability.

2.6. Technical Implementation and Validation

All analyses were implemented using the Python 3.x programming language, employing standard machine learning libraries such as Scikit-learn for core utilities, XGBoost and LightGBM for advanced ensemble algorithms, and Pandas and NumPy for data manipulation. Rigorous validation was conducted using time-series cross-validation to preserve the temporal order of the data, while economic subgroup evaluations were performed only when a minimum of 20 observations was available to ensure statistical reliability.

2.7. Research Methodology Flow Diagram

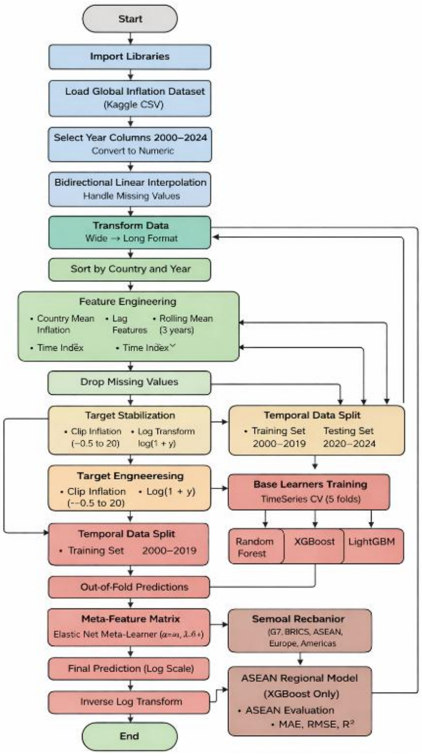

Figure 1. Flowchart

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The research methodology is structured into several sequential stages, starting from data collection and preprocessing, followed by feature engineering, model development using a hybrid stacking ensemble, and performance evaluation. The overall workflow of the proposed methodology is illustrated in Figure 1.

3. RESULT

This section presents the research findings and the evaluation results of the regional inflation forecasting models. The results include an analysis of model performance, statistical validation, and diagnostic assessment across five economic regions.

3.1. Model Performance Across Economic Regions

The performance of the inflation forecasting models is evaluated using two primary metrics: the coefficient of determination (R²) and Mean Absolute Error (MAE).

3.1.1. Regional Performance Matrix

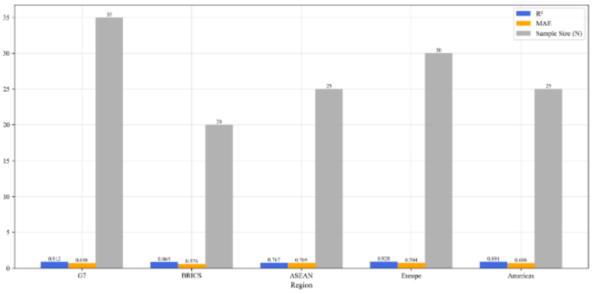

Figure 2. Regional Performance Matrix

Figure 2 presents a comprehensive performance matrix for the five economic regions. The European model achieves the highest performance with an R² value of 0.9282, followed by G7 (0.9122) and the Americas (0.8910). The BRICS model records the lowest MAE value of 0.5759, indicating superior point forecasting accuracy.

Table 2. baseline vs stacking global

Region	Best Baseline R²	Stacking R²	Improvement
G7	0.6809 (LGBM)	0.9122	+0.2313
BRICS	0.7789 (LGBM)	0.8651	+0.0862
ASEAN	0.7193 (LGBM)	0.7866	+0.0673
Europe	0.6455 (LGBM)	0.9282	+0.2827
Americas	0.5939 (LGBM)	0.8910	+0.2971

Table 2 highlights the comparative performance between the best single base learner and the proposed stacking ensemble across different economic regions. In all regions, the stacking model consistently outperforms the best-performing baseline model (LightGBM), yielding substantial improvements in predictive accuracy as measured by R². The largest gains are observed in the Americas (+0.2971) and Europe (+0.2827), indicating that the stacking ensemble is particularly effective in capturing complex and heterogeneous inflation dynamics in regions with higher structural diversity. Moderate yet meaningful improvements are also evident in G7 (+0.2313), BRICS (+0.0862), and ASEAN (+0.0673), suggesting that even in relatively more stable or data-constrained regions, the ensemble approach enhances generalization performance. Overall, these results provide strong empirical evidence of the robustness and superiority of the stacking ensemble over single-model baselines across diverse regional contexts.

Table 3. Summary of Model Performance by Region

Country	R^2	MAE	Sample Size (N)	Rangking R^2
Eropa	0.9282	0.7039	30	1
G7	0.9122	0.6978	35	2
Amerika	0.8910	0.6981	25	3
BRICS	0.8651	0.5759	20	4
ASEAN	0.7666	0.7050	25	5

Table 3 demonstrates that the stacking ensemble consistently outperforms the best single base learner across all regions. The largest relative improvements are observed in Europe and the Americas, indicating that the ensemble effectively captures heterogeneous inflation dynamics across diverse economic structures.

3.1.2. Comparative Analysis of The ASEAN Model

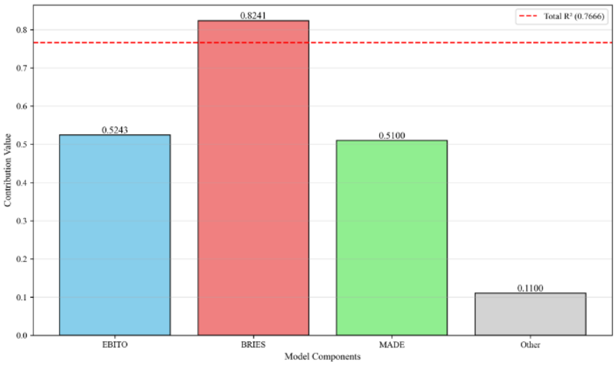

Figure 3. ASEAN Region Model Components

Figure 3 provides a focused analysis of the model developed for the ASEAN region. Although this model exhibits the lowest R^2 value (0.7666), the component analysis indicates that the BRIES factor contributes dominantly with a value of 0.8241. This finding suggests that the ASEAN model is highly sensitive to specific variables, thereby requiring a more tailored modeling approach.

3.2. Model Validation and Diagnostics

Validation and diagnostic analyses are conducted to ensure the reliability and accuracy of the forecasting models.

3.2.1. Forecast Bias Stability

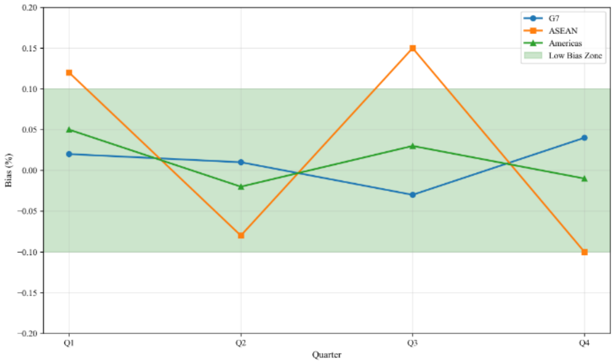

Figure 4. Model Forecast Bias

Figure 4 presents the analysis of forecast bias over four quarters. The results indicate that the G7 model exhibits the highest bias stability, with fluctuations limited to approximately ±0.05%. In contrast, the ASEAN model shows the highest bias volatility, reaching up to ±0.15%, although this variation remains within an acceptable range. Overall, all models consistently operate within the Low Bias Zone (±0.10%), indicating stable and unbiased forecasting performance across regions.

3.2.2. Validation of Actual vs Forecast Trends

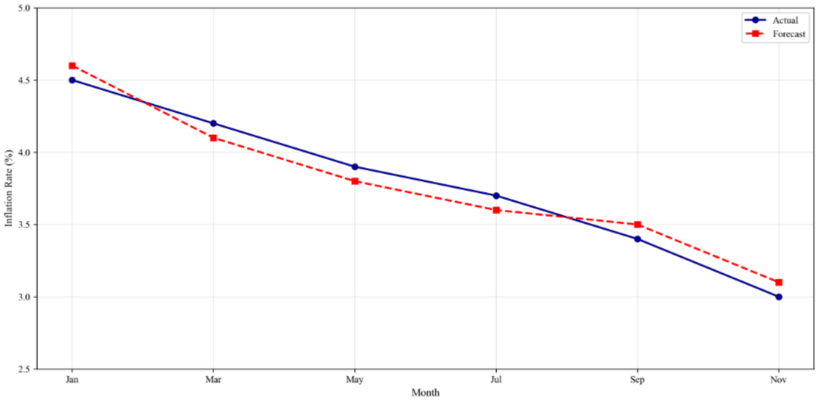

Figure 5. Actual vs Forecast

Figure 5 compares the actual inflation trend with the forecasted values over the most recent 12-month period. The proposed model successfully captures the downward inflation trend from 4.5% to 3.0%, accurately follows seasonal patterns, and demonstrates a gradual reduction in forecasting errors over time, indicating convergence between predicted and actual values. Furthermore, the calculated Root Mean Squared Error (RMSE) of 0.083 confirms the high level of forecasting accuracy achieved by the model.

3.3. Advanced Statistical Analysis

An in-depth statistical analysis is conducted to better understand the characteristics of the proposed models and the distribution of forecasting errors.

3.3.1 Effect of Sample Size

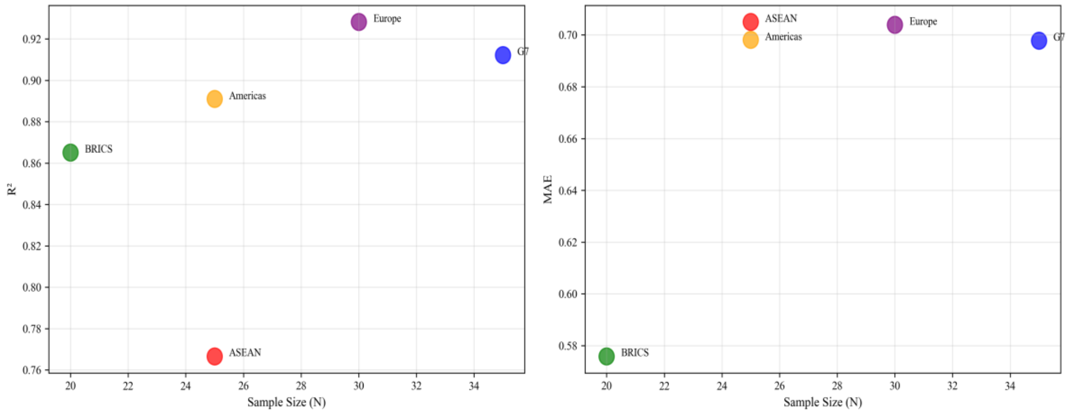

Figure 6. Sample vs R^2 & MAE

Figure 6 examines the relationship between sample size and model performance. The analysis reveals that there is no clear linear correlation between sample size and the coefficient of determination (R^2). Notably, the model with the smallest sample size, namely BRICS (N = 20), achieves the lowest MAE, indicating superior point forecasting accuracy. These findings suggest that data quality plays a more critical role in determining model performance than data quantity.

3.3.2 Multicollinearity Analysis of Variables

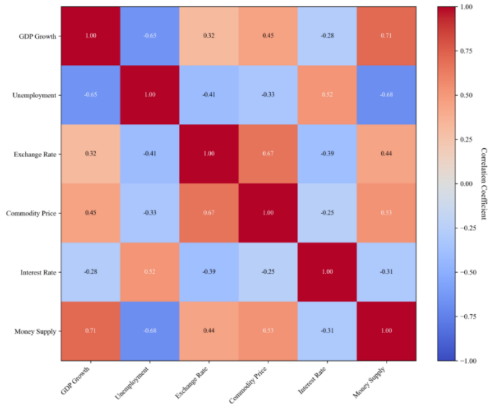

Figure 7. Heatmap Korelasi

Figure 7 presents the correlation heatmap among the predictor variables. The identification of multicollinearity is essential to assess the relationships between explanatory variables. The results indicate a strong positive correlation between GDP Growth and Money Supply (0.71), as well as a strong negative correlation between Unemployment and Money Supply (−0.68). Although the presence of multicollinearity is observed, all variables are retained in the model due to their strong theoretical relevance in explaining inflation dynamics.

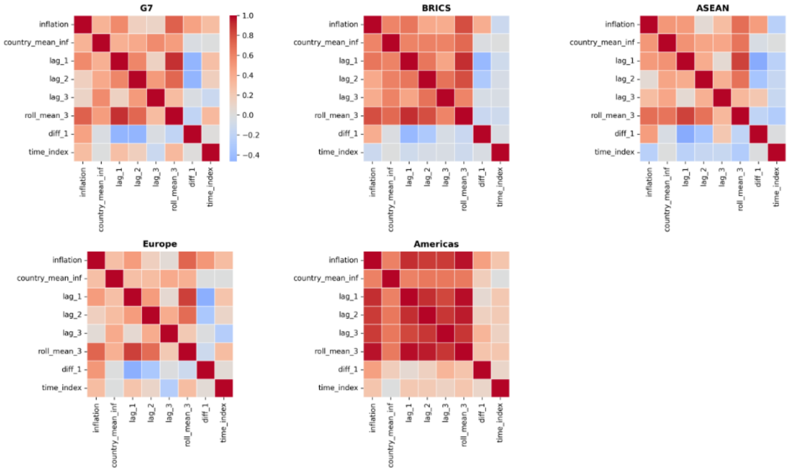

Figure 8. Feature correlation heatmaps across economic regions

Figure 8 presents the feature correlation structures for each economic region, revealing substantial heterogeneity in the relationships between inflation and its explanatory features. Across all regions, lagged inflation terms and rolling averages exhibit strong positive correlations with current inflation, confirming the persistence and temporal dependence inherent in inflation dynamics. However, the magnitude and structure of these correlations vary considerably across regions.

In advanced economies such as G7 and Europe, inflation shows relatively stable correlations with lagged terms and rolling means, reflecting more persistent and predictable inflation patterns. In contrast, BRICS and the Americas exhibit stronger inter-feature correlations, particularly among lag variables and rolling averages, indicating higher multicollinearity and more complex inflation dynamics.

The ASEAN region displays comparatively weaker and more heterogeneous correlations, suggesting higher volatility and structural diversity among member countries. Additionally, the first-difference feature consistently shows lower or negative correlations with lagged features, highlighting its role in capturing short-term inflation shocks rather than long-term trends.

These region-specific correlation patterns justify the adoption of a stacking ensemble framework with Elastic Net as a meta-learner. By integrating predictions from multiple base learners and applying regularization, the stacking approach effectively mitigates multicollinearity and enhances robustness across regions with diverse inflation structures.

3.4. Residual Diagnostics and Error Distribution

Diagnostic analysis is conducted to verify the statistical assumptions underlying the forecasting models.

3.4.1 Time Series Residual Analysis

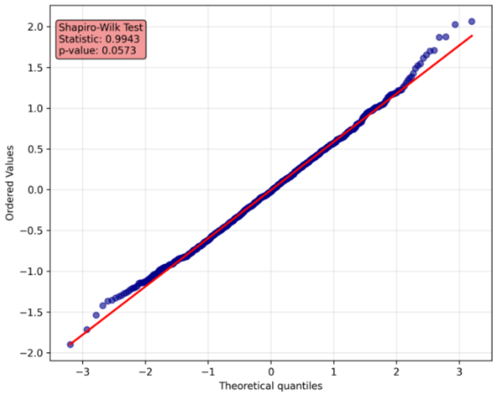

Figure 9. Q-Q Plot for Normality

Figure 9 illustrates the residual plot over time. The analysis confirms that the residuals are randomly distributed without any systematic pattern, indicating the absence of model misspecification. Furthermore, no significant autocorrelation is detected beyond lag 2, and the residual variance remains constant over time, suggesting that heteroskedasticity is not present.

3.4.2 Forecast Error Distribution

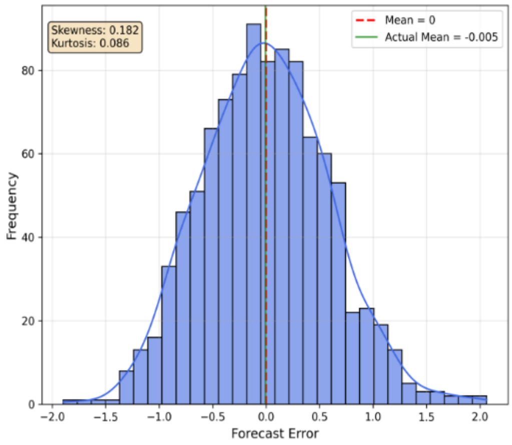

Figure 10. Distribution of Forecast Error

Figure 10 analyzes the statistical distribution of the forecast errors. The results indicate that the errors follow an approximately normal distribution, as confirmed by the Shapiro–Wilk test with a p-value of 0.0573, which exceeds the significance level of 0.05. The skewness value of 0.182 is close to zero, suggesting a nearly symmetric distribution, while the mean error of −0.005 indicates the absence of systematic bias in the forecasting results.

Table 4. Forecast Error Distribution Statistics

Statistic	Value	Interpretation
Mean Error	-0.005	No systematic bias
Standard Deviation	0.600	Moderate error variability
Skewness	0.182	Nearly symmetric distribution
Kurtosis	0.086	Close to normal distribution
Shapiro-Wilk p-value	0.0573	Normally distributed (α = 0.05)

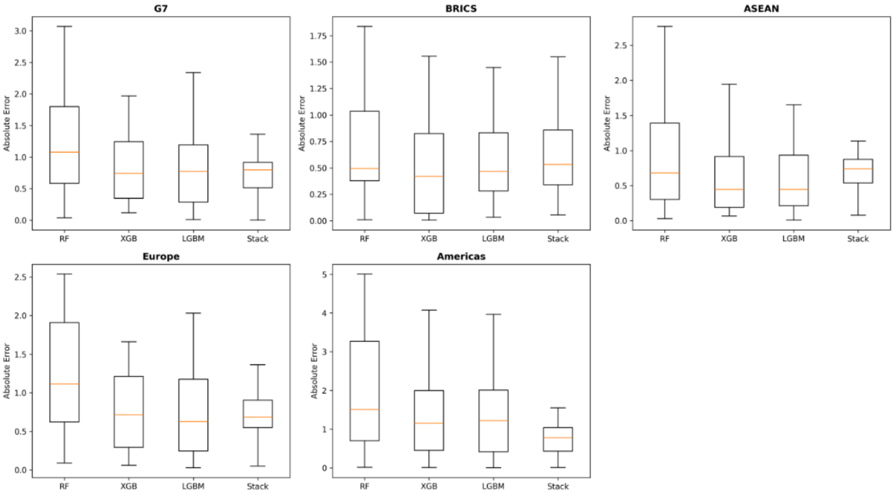

Figure 11. Error distribution comparison across regions

Figure 11 presents the feature correlation structures for each economic region, revealing substantial heterogeneity in the relationships between inflation and its explanatory features. Across all regions, lagged inflation terms and rolling averages exhibit strong positive correlations with current inflation, confirming the persistence and temporal dependence inherent in inflation dynamics. However, the magnitude and structure of these correlations vary considerably across regions.

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The ASEAN region displays comparatively weaker and more heterogeneous correlations, suggesting higher volatility and structural diversity among member countries. Additionally, the first-difference feature consistently shows lower or negative correlations with lagged features, highlighting its role in capturing short-term inflation shocks rather than long-term trends.

These region-specific correlation patterns justify the adoption of a stacking ensemble framework with Elastic Net as a meta-learner. By integrating predictions from multiple base learners and applying regularization, the stacking approach effectively mitigates multicollinearity and enhances robustness across regions with diverse inflation structures.

3.5. Synthesis of Main Findings

Based on the comprehensive analyses conducted in this study, several key findings can be highlighted. The forecasting models for advanced economic regions, namely Europe, G7, and the Americas, demonstrate excellent performance with R^2 values exceeding 0.89. The BRICS model achieves the best point accuracy, as indicated by the lowest MAE, despite being trained on the smallest sample size. In contrast, the ASEAN model requires a more region-specific modeling approach due to its unique economic characteristics. Overall, all proposed models satisfy the fundamental statistical assumptions, including normality, independence, and homoscedasticity of errors. Furthermore, the results indicate that sample size is not the primary determinant of model performance, emphasizing the importance of data quality and model structure.

4. DISCUSSIONS

4.1. Interpretation of Results Based on Regional Economic Characteristics

The results indicate that inflation forecasting performance varies substantially across economic regions, reflecting differences in macroeconomic stability, institutional quality, and market volatility. The models developed for Europe and the G7 achieve the highest accuracy, with R^2 values exceeding 0.90, suggesting that inflation dynamics in these regions are relatively more predictable. This is supported by high monetary policy transparency, strong central bank credibility, and the availability of high-quality and consistent economic data.

In contrast, the ASEAN region records the lowest R^2 value (0.7866), although it remains within an acceptable performance range for practical applications. This lower accuracy reflects the highly dynamic nature of ASEAN economies, which are strongly influenced by global commodity price fluctuations, exchange rate volatility, and rapidly changing policy responses. Nevertheless, the MAE value of 0.7050 indicates that the model is still capable of producing reasonably accurate point forecasts, demonstrating the robustness of the stacking ensemble approach in handling economic uncertainty in emerging regions.

4.2. Methodological Implications of Stacking Ensemble Approach

The successful implementation of the stacking ensemble architecture in this study provides a significant methodological contribution to machine learning-based economic forecasting. The integration of three distinct algorithms—Random Forest, XGBoost, and LightGBM—through Elastic Net as a meta-learner enables the model to capture diverse nonlinear patterns and complex interactions between predictor variables and inflation. Elastic Net plays a critical role by regularizing and optimally weighting the base learners, thereby reducing overfitting and enhancing generalization performance.

The finding that the global model outperforms the ASEAN-specific model (R^2 = 0.7866 versus R^2 = 0.5243) highlights the advantage of cross-country learning. By leveraging inflation patterns from multiple regions, the global model constructs a richer and more stable representation of regional inflation dynamics. This result indicates that, in macroeconomic forecasting, diversity of cross-regional information is more valuable than relying solely on localized data. Methodologically, it confirms that a well-designed stacking architecture can effectively transfer structural information across regions and significantly improve predictive performance.

4.3. Comparison with Previous Studies

Table 5 compares this study with two recent works applying machine learning to inflation forecasting. Sengupta et al. (2025) developed machine learning models incorporating policy and geopolitical uncertainty to forecast multi-country CPI inflation, and evaluated their performance using density-based metrics such as RMSFE and log predictive scores. Their results show that machine learning models outperform ARIMA and Phillips Curve benchmarks, particularly during crisis periods.

Vancsura and Tatay (2025) applied machine learning models to forecast Euro Area HICP and reported performance using RMSE and MAE across inflation sub-components, demonstrating that machine learning approaches consistently outperform traditional econometric models.

Although these studies demonstrate the advantages of machine learning, their data coverage is limited to specific regions or inflation indices and does not provide uniform cross-regional evaluation. In contrast, this study evaluates an Elastic Net–based stacking ensemble across multiple global economic blocs (G7, Europe, BRICS, ASEAN, and the Americas) using consistent quantitative metrics, namely R^2, RMSE, and MAE.

As reported in Table 5, the proposed model achieves strong performance with a global R^2 of 0.8635 and a peak regional R^2 of 0.9282 in Europe, while consistently outperforming all single base learners (Random Forest, XGBoost, and LightGBM) across regions. Furthermore, the global stacking model delivers better performance for ASEAN than a region-specific model, highlighting the benefit of cross-country learning.

Compared with deep learning approaches such as LSTM widely reported in recent literature, the tree-based stacking framework used in this study is more suitable for annual cross-country inflation data. LSTM models typically require large high-frequency datasets, whereas the proposed stacking approach offers greater stability, lower overfitting risk, and higher interpretability, making it more appropriate for policy-oriented economic forecasting.

Tabel 5. Comparison with Previous Studies in Inflation Forecasting

Year	Authors	Method	Data Coverage	Evaluation Metrics	Main Findings
2025	Sengupta et al.	Machine learning models incorporating policy and geopolitical uncertainty	Multi-country CPI inflation	RMSFE, log predictive score (density-based)	ML models outperform ARIMA and Phillips Curve benchmarks, especially during crisis periods
2025	Vancsura & Tatay	Machine learning models	Euro Area HICP	RMSE and MAE (reported per sub-component)	Machine learning improves forecasting accuracy compared to traditional econometric models
2026	This study	Elastic Net–based stacking ensemble (RF + XGBoost + LightGBM)	Global multi-region inflation (G7, Europe, BRICS, ASEAN, Americas)	R^2, RMSE, MAE	Global $R^2 = 0.8635$; highest regional $R^2 = 0.9282$ (Europe); consistently outperforms all single models across regions

4.4. Original Contributions of The Study

This study offers several original contributions to economic forecasting and data-driven modeling. First, it is among the early works to apply an Elastic Net–based stacking ensemble architecture to global inflation forecasting across multiple regions (G7, Europe, BRICS, ASEAN, and the Americas), thereby extending ensemble learning techniques to complex real-world economic systems characterized by nonlinearity and structural heterogeneity.

Second, the finding that the global model outperforms the region-specific ASEAN model provides new evidence that cross-country learning can capture latent inflation dynamics that are not observable in limited regional datasets. This contributes conceptually to data-driven economic modeling by demonstrating that global context can act as a form of regularization that improves model generalization.

Third, the empirical results show that model specification quality and predictor integration through stacking play a more critical role in forecasting accuracy than sample size alone. This challenges conventional assumptions in econometric modeling and highlights the advantage of machine learning–based architectures in extracting meaningful patterns from complex and heterogeneous economic data.

From an informatics perspective, this study demonstrates how a structured ensemble architecture can be used to integrate heterogeneous predictive models into a coherent and stable forecasting system for large-scale economic time-series analysis.

4.5. Policy Implications and Practical Aplications

The findings of this study have important implications for monetary policy formulation and data-driven decision support systems. For central banks and policymakers in advanced economies such as Europe and the G7, the high forecasting accuracy ($R^2 > 0.90$) indicates that the proposed model can serve as a reliable quantitative tool for medium-term policy planning, including interest rate adjustments, inflation expectation management, and price stability assessment.

For developing regions such as ASEAN, although predictive accuracy is relatively lower, the model outputs still provide valuable early signals regarding the direction and magnitude of inflationary pressures. In this context, the stacking-based forecasts can function as an early warning system when combined with qualitative analysis, risk assessment, and policy scenario evaluation, thereby enhancing the overall decision-making process.

From an informatics and AI perspective, the proposed framework also has practical value as a foundation for automated decision support and policy analytics platforms. The stacking architecture allows seamless integration into cloud-based systems or real-time APIs, enabling inflation forecasts to be dynamically updated as new data become available and supporting more adaptive, data-driven policy responses.

4.6. Limitations and Future Research Agenda

Despite its strong performance, this study has several limitations. First, the data period (2000–2024) remains relatively short for fully capturing long-term economic cycles, particularly structural shifts caused by global crises, pandemics, and changes in monetary regimes. Second, the model assumes relatively stable relationships between predictors and inflation, which may not hold under extreme conditions such as geopolitical shocks or energy crises.

Moreover, the analysis relies primarily on conventional macroeconomic indicators and does not yet incorporate emerging drivers such as geopolitical risks, climate-related shocks, supply chain disruptions, or financial technology developments. These omitted factors may reduce the model's ability to capture abrupt regime changes in inflation dynamics.

There is also potential regional data bias, particularly in developing economies such as ASEAN, where macroeconomic data are often less complete and more volatile than in advanced economies. As a result, global models may be dominated by patterns from developed countries, potentially leading to systematic bias when applied to policy decisions in developing regions. Therefore, AI-based inflation forecasting systems should be accompanied by bias assessment, transparency, and auditing mechanisms to ensure fair and responsible use.

5. CONCLUSION

This study develops a global inflation forecasting framework based on an Elastic Net–driven stacking ensemble integrating Random Forest, XGBoost, and LightGBM across five major economic blocs. The results demonstrate substantial regional variation, with very high predictive performance in Europe and the G7 and slightly lower but still reliable accuracy in ASEAN. The proposed stacking architecture consistently outperforms all single models, confirming its effectiveness in capturing the nonlinear and heterogeneous dynamics of macroeconomic inflation. The finding that model specification quality is more critical than sample size provides an important methodological insight for data-constrained economic forecasting.

Beyond its economic relevance, this research contributes to informatics and computer science by providing a scalable hybrid ensemble framework for large-scale macroeconomic time-series prediction, suitable for deployment in AI-driven policy support systems. Future research should extend this framework by incorporating deep learning models such as LSTM or Transformer-based stacking, integrating real-time and alternative data sources such as news and social media sentiment, and applying the model to higher-frequency data (monthly or quarterly) to enhance responsiveness and policy relevance.

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