

An Interpretable Machine Learning Approach for Inflation Forecasting in Indonesia Using Domestic Macroeconomic Indicators

Ahmad Maimunif, Evaristus Didik Madyatmadja

Information Systems Department, Bina Nusantara University, Jakarta, Indonesia

Abstract—Accurate inflation forecasting is essential for supporting forward-looking monetary policy, maintaining price stability, and preserving economic welfare. This study proposes an interpretable machine learning framework for inflation forecasting in Indonesia by integrating domestic macroeconomic indicators and seasonal variables. The study employs Random Forest, Extreme Gradient Boosting (XGBoost), and Artificial Neural Network (ANN) models using monthly data from 2008 to 2025. To systematically evaluate model performance, three experimental scenarios are implemented: baseline modeling, time-series feature augmentation, and hyperparameter optimization. Model performance is evaluated using RMSE, MAE, and R^2 metrics. The results consistently show that ensemble-based methods outperform ANN across all scenarios, with XGBoost achieving the best overall performance after temporal feature augmentation and hyperparameter optimization (RMSE = 0.4987, MAE = 0.3339, R^2 = 0.9517). The findings further indicate that temporal feature augmentation provides relatively limited improvement, whereas hyperparameter optimization substantially enhances forecasting accuracy. SHAP analysis identifies money supply (M2) and wages as the dominant contributors to inflation predictions, suggesting that monetary liquidity and labor-related factors play a more significant role than seasonal patterns in explaining inflation dynamics. Rather than contributing through algorithmic novelty, this study contributes through a systematic and interpretable forecasting framework that integrates predictive accuracy and explainable artificial intelligence to support transparent and policy-relevant inflation analysis in Indonesia and other emerging economies with similar economic structures.

Keywords—Inflation forecasting; machine learning; explainable AI; macroeconomic indicators; time-series analysis; monetary policy

I. INTRODUCTION

Inflation is one of the main indicators of macroeconomic stability, particularly in developing economies such as Indonesia that remain vulnerable to both global and domestic economic shocks. Commodity price volatility, exchange-rate fluctuations, capital flows, and monetary policy changes in developed economies may significantly influence inflation dynamics in emerging markets. In Indonesia, these conditions are further affected by the country's dependence on food and energy commodities, making inflation dynamics highly sensitive and complex. Maintaining price stability is, therefore, essential because inflation directly affects purchasing power, economic stability, and long-term economic growth [1], [2].

Bank Indonesia implements the Flexible Inflation Targeting Framework (FITF) as the primary monetary policy framework to maintain inflation stability. Since FITF is forward-looking, accurate inflation forecasting is important for supporting timely monetary policy decisions. From a monetary policy perspective, inflation in Indonesia may be driven by multiple interconnected factors, including exchange rates, interest rates, money supply, labor wages, external-sector conditions, and seasonal consumption patterns related to socio-cultural events [3], [4]. These variables interact through nonlinear transmission mechanisms, making inflation forecasting a challenging analytical task [5].

Traditional econometric approaches such as ARIMA and VAR have been widely used for inflation forecasting. Although these methods provide relatively strong interpretability, their reliance on linear assumptions limits their ability to capture complex nonlinear interactions among macroeconomic variables [6]. Recent developments in machine learning provide alternative forecasting approaches that are more suitable for modeling nonlinear and high-dimensional economic data [7]. In particular, ensemble-based methods such as Random Forest and Extreme Gradient Boosting (XGBoost) have demonstrated strong predictive performance in various economic forecasting applications [7], [8].

Despite their predictive capability, machine learning models are often criticized for limited interpretability because they operate as “black-box” systems. This limitation is particularly important in policy-relevant contexts where transparency and accountability are essential [9]. Explainable Artificial Intelligence (XAI) techniques, especially Shapley Additive Explanations (SHAP), provide a systematic approach to explain the contribution of predictor variables to model predictions and improve interpretability in machine learning analysis [10].

Although machine learning approaches for inflation forecasting have become increasingly common, several gaps remain in the literature. Many previous studies focus mainly on forecasting accuracy while providing limited explanation regarding the economic factors driving model predictions. In addition, prior studies often rely on limited macroeconomic indicators and rarely evaluate forecasting models under multiple experimental configurations involving feature augmentation and hyperparameter optimization.

Accordingly, this study proposes an interpretable machine learning framework for inflation forecasting in Indonesia by integrating domestic macroeconomic indicators and seasonal

variables. Rather than contributing through algorithmic novelty, this study contributes through a systematic forecasting framework that combines multiple machine learning models, time-series feature augmentation, hyperparameter optimization, and explainable artificial intelligence within a unified experimental setting. Specifically, this study compares Random Forest, XGBoost, and Artificial Neural Network (ANN) models using monthly data from 2008 to 2025 under three experimental scenarios: baseline modeling, time-series feature augmentation, and hyperparameter optimization. Model performance is evaluated using RMSE, MAE, and R^2 metrics, while model interpretability is assessed using SHAP analysis.

The findings of this study are expected to contribute both methodologically and practically. Methodologically, the study provides an interpretable machine learning framework that integrates predictive performance and explainable AI analysis for inflation forecasting. Practically, the proposed framework may support transparent and forward-looking monetary policy analysis in Indonesia and other emerging economies with similar economic structures.

II. LITERATURE REVIEW

This section outlines the theoretical foundations and relevant prior studies that support this study. These theories include the economic theory of inflation, machine learning methodology, the CRISP-DM framework, and related works on inflation forecasting.

A. Economic Theory

Inflation is an economic phenomenon characterized by a sustained increase in the general price level over a period of time. Price increases are caused by complex interactions between supply and demand conditions, monetary factors, and inflation expectations.

Demand-pull inflation is caused by an increase in aggregate demand that exceeds production capacity. This type of inflation is generally driven by consumption, credit expansion, government spending, and investment activity. Cost-push inflation is caused by an increase in production costs, such as energy and food prices, wages, and exchange rate depreciation.

From a monetary theory perspective, inflation is viewed as a long-term monetary phenomenon resulting from the growth of the money supply exceeding real output. Meanwhile, the credibility of monetary policy and central bank communication in shaping inflation expectations is essential in inflation dynamics. These two theories form the conceptual basis used in building inflation forecasting models.

In line with the concept, the dynamics of inflation in Indonesia are generally influenced by the main macroeconomic variables, such as the exchange rate, interest rates, money supply, gross domestic product, balance of payments conditions, foreign exchange reserves position, and labor wages [11].

Money supply is one of the main factors that drive inflation, as measured by monetary aggregates, either M1 or M2. The Quantity Theory of Money states that excessive growth in the money supply compared to real output will create inflationary pressures [12]. That is because an excessive supply of liquidity will stimulate and increase aggregate demand and trigger

inflation expectations. This ultimately leads to demand-pull inflation when productive capacity is limited [13], [14]. Empirical evidence from Indonesia indicates that M2 is positively associated with inflation [15].

The exchange rate, represented by the JISDOR, is one of the main determinants of inflation in Indonesia through exchange rate transmission. Exchange rate depreciation can increase import prices and production costs, resulting in cost-push inflation, while exchange rate appreciation reduces inflationary pressures [16].

Interest rates, as measured by the JIBOR, reflect short-term interbank liquidity conditions. JIBOR also serves as an important transmission channel for the transmission of monetary policy in Indonesia. Higher interest rates reduce investment and consumption, thereby reducing inflationary pressures. Conversely, lower interest rates tend to stimulate economic activity and potentially increase inflationary pressures [17], [18].

Labor wages are among the main determinants of inflation in Indonesia through cost-push inflation and demand-pull inflation. Higher wages increase production costs for firms and may be passed on to prices, thus generating cost-push inflation. On the other hand, higher wages also strengthen household purchasing power and stimulate aggregate demand, thus contributing to demand-pull inflation [4].

Foreign exchange reserves are important in influencing inflation by supporting exchange rate stability and controlling price levels. Adequate reserves allow the central bank to stabilize the rupiah, decreasing the risk of exchange rate depreciation and mitigating inflationary pressures. Conversely, insufficient reserves limit the central bank's ability to stabilize the rupiah, increasing the risk of exchange rate depreciation and increasing inflation [19].

Balance of payments is one of the main determinants of inflation in Indonesia through the exchange rate and capital flow. Current account deficits tend to weaken the rupiah and raise imported inflation. While surpluses can strengthen the exchange rate and contain inflationary pressures. Similarly, capital inflows support currency stability and inflation control, whereas capital outflows increase depreciation risks and inflationary pressures via higher import prices [20], [21].

GDP is one of the main factors that drive inflation through aggregate demand and supply. Economic growth caused by aggregate demand tends to increase inflationary pressures, especially in the absence of expansion of production capacity [22]. This mechanism is commonly explained by the short-run Phillips curve, which associates economic expansion with higher inflation and economic slowdowns with lower inflation.

B. Machine Learning Theory

Machine learning is a subfield of artificial intelligence that enables systems to learn patterns from data and improve prediction performance without explicit programming. Machine learning utilizes mathematical and statistical models to recognize patterns and relationships within historical data. These models are then used for analysis, classification, or prediction on new data. Evidence from the literature suggests

that machine learning is well-suited to complex prediction problems in non-linear data sets [23].

Machine learning approaches are generally classified into supervised and unsupervised learning. Supervised learning relies on labeled data to identify relationships between inputs and outputs, allowing outputs to be predicted or classified. Unsupervised learning will inspect unlabeled data to identify latent features or structures in the data. Both of these machine-learning techniques are complementary in nature. Supervised learning aims at making accurate predictions, and unsupervised learning is for understanding the nature of complex datasets through exploratory data analysis without prejudging what might be discovered.

In this study, a supervised machine learning approach based on Random Forest, XGBoost, and ANN is adopted. These models are selected because of their capability to capture nonlinear relationships and improve forecasting accuracy.

Random Forest is an ensemble learning algorithm introduced by Breiman [24], which constructs multiple decision trees using bootstrap sampling and random feature selection to improve prediction stability and reduce overfitting. RF is particularly effective for structured tabular data because it can capture nonlinear relationships and interactions among predictor variables.

For regression problems like inflation forecasting, the final RF prediction is obtained by averaging the outputs of all decision trees, formulated as:

$$\hat{y}(z) = \frac{1}{M} \sum_{m=1}^M T_m(z) \quad (1)$$

where, $\hat{y}(z)$ denotes the predicted inflation value, $T_m(z)$ represents the prediction of the m -th decision tree for the macroeconomic feature vector, and M is the total number of trees in the forest. This aggregation process reduces prediction variance and enhances forecast stability.

Furthermore, Farhadi et al. (2022) explain that each decision tree in the RF model is constructed by minimizing the residual sum of squares (RSS) at each node-splitting process [25], which is generally formulated as follows:

$$RSS(j, s) = \sum_{x_i \in R_1(j, s)} (y_i - \bar{y}r_1)^2 + \sum_{x_i \in R_2(j, s)} (y_i - \bar{y}r_2)^2 \quad (2)$$

where, $R_1(j, s)$ and $R_2(j, s)$ denote the two regions resulting from a split based on variable j and split point s , respectively. In the context of inflation forecasting, this mechanism enables the RF model to select optimal splits based on the most informative macroeconomic variables.

Extreme Gradient Boosting (XGBoost) is an optimized gradient boosting framework developed by Chen and Guestrin [26]. XGBoost sequentially improves prediction accuracy by iteratively minimizing the residual errors produced by previous models. This method allows the model to capture complex nonlinear relationships and high-order interactions, making it suitable for high-dimensional data and providing advantages over linear parametric methods [27].

Conceptually, XGBoost starts with a simple initial model (weak learner) and iteratively improves it by fitting subsequent models to the residuals of the previous prediction. The initial model can be formulated as:

$$y_i = F_1(X_i) + \varepsilon_i \quad (3)$$

where, $F_i(X_i)$ is the initial model and ε_i represents the residual. Since the initial model does not fully capture data variation, subsequent models are trained on these residuals, and the model is updated additively as:

$$F_M(X_i) = F_{M-1}(X_i) + h_{M-1}(X_i) \quad (4)$$

until iteration M [27].

Since the pseudo-residual is calculated using the negative gradient method from the change in the loss function relative to the current forecast, it can be seen as a measure of how much improvement remains relative to the current state. This pseudo-residual becomes the target for the training of weak learners, so each iteration focuses on the remaining improvement steps. The model is updated as :

$$F_m(X) = F_{m-1}(X) + \gamma_m h_m(X) \quad (5)$$

where, γ_m is the learning rate, which regulates the contribution of each weak learner and enhances model stability [27].

An ANN is a type of machine learning model that was inspired by biological neural systems and is the basis for deep learning architectures [28]. In an ANN, artificial neurons are connected and organized into layered forms that include input, hidden, and output layers. Input data X is passed through a series of weighted and biased linear combinations. Then, it is passed through an activation function, represented as $\sigma(WX + b)$, that introduces nonlinearity. Common activation functions include ReLU, Sigmoid, tanh, and Softmax, which enable ANNs to model complex and nonlinear relationships that arise in the data. The activation functions are formulated as follows:

$$\text{ReLU} \quad \sigma(z) = \max(0, z) \quad (6)$$

$$\text{Sigmoid} \quad \sigma(z) = \frac{1}{1 + e^{-z}} \quad (7)$$

$$\text{Tanh} \quad \sigma(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad (8)$$

$$\text{Softmax} \quad \sigma(z) = \frac{e^{z_i}}{\sum_{j=1}^z e^{z_j}} \quad (9)$$

The output layer represents the final numerical result obtained after the input data have been processed by the network and activation functions. It is the final result or prediction output by the neural network.

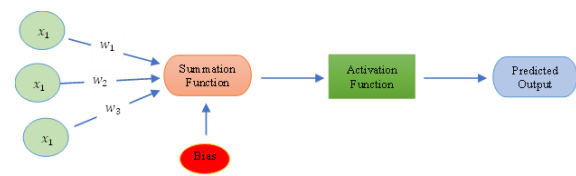


Fig. 1. Artificial neural network architecture

Fig. 1 illustrates the ANN architecture, where inputs (x_1, x_2, \dots, x_n) are linearly combined with weights (w_1, w_2, \dots, w_n) and a bias, then passed through an activation function to produce the model's prediction.

The ANN model is trained using forward propagation and backpropagation. Forward propagation sends input data through the network to generate output predictions. The predicted outputs are then compared with actual values using a loss function. In terms of regression cases, such as inflation forecasting, the mean squared error (MSE) is commonly employed as the loss function [28], defined as:

$$MSE = \frac{1}{2N} \sum_{i=1}^N (\hat{Y}_i - Y_i)^2 \quad (10)$$

where, Y_i and \hat{Y}_i denote the actual and predicted values, respectively.

Backpropagation then minimizes the loss function using gradient descent for updating model parameters. Weights and biases are iteratively adjusted as:

$$W^{(l)} \leftarrow W^{(l)} - \eta \frac{\partial L}{\partial W^{(l)}} \quad (11)$$

where, η is the learning rate controlling the convergence speed. This process is repeated until the network reaches an optimal solution with minimal prediction error.

SHAP (Shapley Additive Explanations) is an Explainable Artificial Intelligence (XAI) method introduced by Scott M. Lundberg and Su-In Lee to improve the interpretability of machine learning models by explaining the contribution of each predictor variable to a prediction. SHAP is based on Shapley values from cooperative game theory and provides a unified framework for additive feature attribution methods [29]. The SHAP explanation model is formulated as:

$$g(z') = \phi_0 + \sum_{i=1}^M \phi_i z'_i \quad (12)$$

where, ϕ_i represents the contribution of feature i to the prediction. SHAP explains both the magnitude and direction of variable influence on model predictions.

C. CRISP-DM Methodology

This study employs the Cross-Industry Standard Process for Data Mining (CRISP-DM) as the methodological framework to develop an inflation forecasting model. The selection of CRISP-DM is motivated by its systematic, standardized, and iterative structure, which has been extensively adopted in data mining and machine learning studies [30]. The framework comprises six interrelated phases that guide the end-to-end analytical process.

The Business Understanding phase establishes the study objectives and problem formulation, focusing on the development of an accurate and policy-relevant inflation forecasting model in the context of monetary analysis. The Data Understanding phase involves the collection of macroeconomic and seasonal data, followed by exploratory analysis and data quality assessment. The Data Preparation phase encompasses data cleaning, transformation, frequency harmonization, integration, and feature engineering, which are important for enhancing model performance. The Modeling phase applies selected machine learning algorithms, including Random Forest,

XGBoost, and ANN, within an iterative process that may require refinement of preceding stages. The Evaluation phase assesses model performance using quantitative metrics such as RMSE, MAE, and R^2 , while also ensuring alignment with the study objectives. Within an academic setting, the Deployment phase is realized through the presentation of forecasting results, model interpretability using explainable AI techniques, and the articulation of their implications for inflation analysis and policy support.

D. Related Works

Machine learning approaches have increasingly been applied to inflation forecasting because of their ability to capture nonlinear relationships and complex interactions among macroeconomic variables [7], [23]. Compared with traditional econometric models such as ARIMA and VAR, machine learning methods often demonstrate stronger predictive performance, particularly in volatile economic environments [31], [32], [33]. Algorithms such as Random Forest, XGBoost, and Artificial Neural Network (ANN) have been widely used in inflation forecasting studies across both developed and developing economies.

Several studies report that machine learning models outperform conventional forecasting approaches. Araujo and Gaglianone [33] show that machine learning methods improve inflation forecasting performance in Brazil, while Jouilil and Iaousse [34] demonstrate that machine learning approaches outperform classical time-series models in forecasting inflation in the United States. Similar improvements are also reported in studies conducted in Egypt and India [31], [32]. In developing economies, machine learning methods often achieve stronger forecasting gains because inflation dynamics are more strongly influenced by structural macroeconomic factors and volatility [31], [35].

Previous studies further indicate that forecasting performance depends not only on algorithm selection but also on feature engineering and model optimization. Li et al. [8] demonstrate that XGBoost combined with optimization techniques improves inflation forecasting accuracy, while Seo et al. [36] show that multivariate features and data augmentation significantly enhance forecasting performance. Ensemble-based methods such as Random Forest and XGBoost are also generally found to provide more stable performance than deep learning approaches for structured macroeconomic datasets with moderate sample sizes [34], [37].

Despite these advances, several limitations remain in the literature. Many previous studies focus mainly on predictive accuracy while providing limited explanation regarding the economic factors driving model predictions, resulting in machine learning models being criticized as black-box systems [9]. In addition, prior studies often rely on limited macroeconomic indicators and rarely integrate monetary, external-sector, labor, and seasonal variables simultaneously within a unified forecasting framework. However, inflation dynamics in Indonesia are influenced by complex interactions among money supply, exchange rates, wages, and external-sector conditions [3], [4], [11].

The application of Explainable Artificial Intelligence (XAI) to inflation forecasting remains relatively limited. SHAP-based approaches have recently gained attention because they improve transparency by explaining the contribution of predictor variables to machine learning predictions [9], [10]. Nevertheless, only a limited number of studies integrate SHAP analysis directly into a systematic inflation forecasting framework.

Accordingly, this study proposes an interpretable machine learning framework for inflation forecasting in Indonesia by integrating domestic macroeconomic and seasonal variables. Unlike many previous studies that mainly focus on predictive accuracy, this study combines multi-scenario experimentation, hyperparameter optimization, Diebold–Mariano statistical testing, and SHAP-based explainability within a unified forecasting framework. Therefore, the contribution of this study lies in integrating predictive performance, interpretability, and policy-relevant inflation analysis in Indonesia and emerging economies with similar economic structures.

III. METHODOLOGY

This study adopts the CRISP-DM methodology, which comprises six structured phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. Each phase is systematically described in the following sections. The implementation of each stage, particularly in data processing and modeling, is carried out using

the Python programming language and supporting machine learning libraries.

A. Business Understanding

The Business Understanding phase is aligned with Bank Indonesia’s Flexible Inflation Targeting Framework (FITF), an approach that maintains price stability as the primary objective of monetary policy. Due to its forward-looking nature, timely and accurate inflation predictions are critical to the soundness of policy choices. This study proposes a machine learning–based framework for inflation forecasting that aims to improve predictive accuracy while maintaining model interpretability.

B. Data Understanding

With the objectives set out in the Business Understanding phase, the Data Understanding phase seeks to identify relevant domestic macroeconomic and seasonal variables that impact inflation dynamics. In this phase, inflation-related time-series data are collected systematically and initially examined for their characteristics and suitability for modeling. Moreover, quality, accuracy, consistency, and temporal alignment are also tested for machine learning–based forecasting.

These variables are obtained officially from Bank Indonesia (BI), Badan Pusat Statistik (BPS), and official holiday calendars. The raw data initially provided in Microsoft Excel format has been converted to CSV format for faster processing.

TABLE I. DATA SOURCES AND INFORMATION

Indicators	Reference Source	Frequency	Publisher	Scale	Information	Fields
Inflation	TABLE8_1 in the SEKI Report sector real.	Monthly	BI	Percentage	Monthly observations	Publish date, inflation_yoy, Inflation_mtm
Money Supply	TABLE1_1 SEKI in the Report sector monetary	Monthly	BI	Trillion Rupiah	Monthly observations	Publish date, M2
Exchange Rate	Jakarta Interbank Spot Dollar Rate (JISDOR).	Daily	BI	Rupiah per US Dollar	The monthly value is calculated as the average of daily observations.	Publish date, JISDOR
Interest Rate	Jakarta Interbank Offered Rate (JIBOR).	Daily	BI	Percentage	The monthly value is calculated as the average of daily observations.	Publish date, JIBOR
Wages	Rata-rata upah tenaga kerja dalam satu bulan.	Semi-annual	BPS	Rupiah	Semi-annual observations	Publish date, wage
Foreign Reserve Asset	TABLE5_9 in the SEKI Report sector external.	Monthly	BI	Billion US Dollar	Monthly observations	Publish date, Foreign reserve
Balance of Payments	TABLE5_1 in the SEKI Report sector external.	Quarterly	BI	Billion US Dollar	Quarterly variables are transformed into monthly frequency.	Publish date, Balance of payments, export, import
Gross Domestic Product	TABEL7_1, TABEL7_2, and TABLE7_6 in the SEKI Report sector real.	Quarterly	BI	Trillion Rupiah	Quarterly variables are transformed into monthly frequency.	Publish date, GDP deflator, GDP Nominal
Seasonal event	Holiday calendars indicating cultural events.	Event-based	Holiday Calendar	“1” or “0”		Publish date, event tagging

Table I presents the data sources and characteristics of the macroeconomic and seasonal variables used in this study, including data frequency, measurement scale, and relevant information for machine learning–based inflation forecasting.

The dataset consists of heterogeneous temporal frequencies, including daily (exchange rate and interest rate), monthly (inflation, money supply, and foreign reserves), quarterly (balance of payments and GDP), and semi-annual (wages) observations. To ensure temporal consistency for machine

learning modeling, daily variables are aggregated into monthly averages, while quarterly variables are proportionally transformed into monthly frequency through time-series resampling techniques.

In addition, each variable is supported by structured fields such as publication date and relevant economic measures for easier tracking and integration. A temporal key is maintained with a variable “month”, which is generated from the publish date to ensure that all indicators can be aggregated as one

analytical dataset. Seasonal effects are represented using dummy variables (1 and 0) for calendar-related events that may affect inflation patterns. A high-level overview of this well-structured dataset serves as a brief foundation for data preparation and modeling.

C. Data Preparation

This phase involves preparing the dataset through data cleaning, frequency harmonization, feature engineering, data integration, and variable transformation for machine learning analysis. These processes are necessary to ensure temporal consistency, improve data quality, and enhance model performance.

Several anomalous observations, particularly zero values in the interest rate series, are identified as outliers and removed prior to analysis. Since the dataset consists of heterogeneous temporal frequencies, including daily, monthly, quarterly, and semi-annual observations, frequency harmonization is performed using time-series resampling techniques. All variables are transformed into a monthly frequency to maintain temporal alignment across predictors and support consistent forecasting analysis.

TABLE II. FREQUENCY HARMONIZATION TECHNIQUES

Variable	Conversion	Resampling Technique
Exchange Rate	Daily to Monthly	Monthly average
Interest Rate	Daily to Monthly	Monthly average
Wages	Semi-annual to Monthly	Interpolation
Balance of Payments	Quarterly to Monthly	Proportionally distributed across three months
GDP	Quarterly to Monthly	Proportionally distributed across three months

Table II presents the frequency harmonization process using time-series resampling techniques to convert variables into a consistent monthly frequency.

The wage variable requires particular attention because it is originally available at a semi-annual frequency and subsequently transformed into monthly observations using interpolation. This approach preserves temporal consistency with other macroeconomic indicators and maintains dataset completeness for machine learning modeling. However, the interpolation process may introduce smoother transitions than actual short-term wage fluctuations, potentially reducing volatility within the series and affecting the sensitivity of the models to labor-related inflation dynamics.

After harmonization, all macroeconomic and seasonal variables are integrated into a unified dataset using the month variable as the temporal key. Feature engineering is then performed to generate several derived variables relevant to inflation dynamics, including Broad Money (BM), Velocity of Money (VM), Exchange Rate Pass-Through (ERPT), and Import Cover Ratio (ICR). At this stage, all derived variables are standardized to maintain scale consistency.

1) *Broad Money (BM)*: Measures the level of liquidity in the economy by comparing money supply to annual nominal GDP. An excessively high liquidity ratio reflects money supply

expansion beyond real activity and may generate inflationary pressure when not supported by productive capacity growth [38]. BM is calculated as [38]:

$$BM = \frac{\text{Money supply (M2)}}{\text{Annual Nominal GDP}} \times 100 \quad (13)$$

2) *Velocity of Money (VM)*: It is a measure of how quickly money is circulating within an economy over a period of time, and it is derived from Fisher's quantity theory of money. When the velocity of money increases, inflation tends to increase, and decreases may even dampen inflation when the money supply expands [3]. Thus, inflation analysis must consider not only money supply but also the velocity of money circulation [3].

$$VM = \frac{\text{Annual Nominal GDP}}{\text{Money supply (M2)}} \quad (14)$$

3) *Exchange Rate Pass Through (ERPT)*: A metric of the extent to which the exchange rate changes are passed through to the domestic prices. A value of one indicates full transmission, and a value of less than one means incomplete passing through. ERPT consists of the ratio between changes in domestic prices and changes in the exchange rate expressed as elasticity.

$$ERPT = \frac{\% \Delta P(\text{Domestic price changes})}{\% \Delta ER(\text{Changes in exchange rates})} \quad (15)$$

4) *Import Cover Ratio (ICR)*: Measures the ability of foreign exchange reserves to finance a country's imports without additional inflows. A high ICR supports exchange rate stability and helps contain inflation by limiting increases in import prices, whereas a low ICR constrains reserve adequacy, increases depreciation risk, raises import costs, and amplifies inflationary pressures [39].

$$ICR = \frac{\text{Foreign Reserve Asset}}{\text{Monthly import value}} \quad (16)$$

In addition, temporal variables such as month, quarter, and year are constructed to capture potential time-series patterns and seasonal effects not fully represented by macroeconomic indicators alone.

The dataset is subsequently cleaned to ensure consistency and modeling compatibility. Missing values are handled selectively depending on the characteristics of each variable, while irrelevant attributes used during preprocessing are removed to improve modeling efficiency. Prior to modeling, the dataset is organized chronologically to preserve temporal order and avoid potential data leakage in the forecasting process.

D. Modeling

The modeling phase aims to develop an interpretable machine learning framework for inflation forecasting by implementing Random Forest, XGBoost, and Artificial Neural Network (ANN) algorithms. These algorithms are selected because of their capability to capture nonlinear relationships and complex interactions among macroeconomic variables that influence inflation dynamics.

To systematically evaluate forecasting performance, the models are assessed under three experimental scenarios: 1)

baseline modeling using macroeconomic and seasonal variables, 2) an extended model incorporating time-series features through the inclusion of quarter variables, and 3) an enhanced model combining time-series features with hyperparameter optimization to improve predictive performance. This multi-scenario framework evaluates the contribution of feature augmentation and model optimization within a unified experimental setting.

The baseline scenario employs domestic macroeconomic indicators, including exchange rate (JISDOR), interest rate (JIBOR), money supply (M2), foreign reserves, balance of payments, GDP deflator, wages, Broad Money, Velocity of Money, ERPT, and Import Cover Ratio. Seasonal variables such as Ramadan, Eid al-Fitr, Christmas and New Year, and back-to-school periods are also included as predictors. The target variable is annual inflation (Inflation_yoy).

To preserve temporal consistency and avoid data leakage in time-series forecasting, the dataset is divided chronologically, where the earlier 80% of observations are used for training and the remaining 20% are reserved for out-of-sample testing. This chronological split ensures that future observations are not used during model training.

The second scenario extends the baseline configuration by incorporating the quarter variable as an additional predictor to capture potential temporal and seasonal patterns not fully represented by macroeconomic variables. The third scenario further extends the second model by implementing hyperparameter optimization using GridSearchCV to improve predictive accuracy and model stability.

Fig. 2 presents the implementation code of the baseline Random Forest model using the RandomForestRegressor function with default parameter settings.

```
# Selecting all column as predictors
X=df[['JISDOR', 'JIBOR', 'M2', 'Foreign Reserve', 'Balance of Payment',
      'GDP Deflator', 'Wage', 'Back To School', 'Christmas and New Year', 'Ramadhan',
      'Idul Fitri', 'Broad Money', 'ERPT', 'Velocity of Money', 'Impor Cover Ratio']]

# Specify 'Inflation_yoy' column as 'y'
y=df['Inflation_yoy']

# Splitting the dataset into training and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train RandomForest model
model = rf.RandomForestRegressor(random_state=42)
model.fit(X_train, y_train)

# Making predictions on the test dataset
predictions = model.predict(X_test)
```

Fig. 2. Random Forest model in the baseline scenario.

Fig. 3 presents the Random Forest hyperparameter optimization using GridSearchCV with 5-fold cross-validation. Several parameters, including n_estimators, max_depth, min_samples_split, and min_samples_leaf, are systematically tuned to identify the optimal forecasting configuration. The best parameters obtained are n_estimators=300, max_depth=None, min_samples_split=2, and min_samples_leaf=1.

Fig. 4 presents the implementation code of the baseline XGBoost model using the XGBRegressor function with default parameter settings.

```
from sklearn.model_selection import GridSearchCV
param_tuning = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 15, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
rf_model = rf.RandomForestRegressor(random_state=42)
grid_search = GridSearchCV(estimator = rf_model,
                           param_grid = param_tuning,
                           cv=5,
                           n_jobs = -1,
                           verbose = 1)
grid_search.fit(X_train, y_train)
print("Best parameters for RandomForestRegressor:", grid_search.best_params_)

# Fitting 5 folds for each of 108 candidates, totalling 540 fits
# Best parameters for RandomForestRegressor: {'max_depth': None,
#      'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 300}
```

Fig. 3. Parameter optimization of Random Forest model.

```
# Selecting all column as predictors
X=df[['JISDOR', 'JIBOR', 'M2', 'Foreign Reserve', 'Balance of Payment',
      'GDP Deflator', 'Wage', 'Back To School', 'Christmas and New Year', 'Ramadhan',
      'Idul Fitri', 'Broad Money', 'ERPT', 'Velocity of Money', 'Impor Cover Ratio']]

# Specify 'Inflation_yoy' column as 'y'
y=df['Inflation_yoy']

# Splitting the dataset into training and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train XGBoost model
model = xgb.XGBRegressor()
model.fit(X_train, y_train)

# Making predictions on the test dataset
predictions = model.predict(X_test)
```

Fig. 4. XGBoost model in the baseline scenario.

Fig. 5 presents the XGBoost hyperparameter optimization using GridSearchCV with 5-fold cross-validation. Several parameters, including learning_rate, max_depth, min_child_weight, subsample, colsample_bytree, and n_estimators, are systematically tuned to identify the optimal forecasting configuration. The best parameters obtained are learning_rate=0.1, max_depth=5, min_child_weight=5, n_estimators=200, subsample=0.7, and colsample_bytree=0.5.

```
# Hyperparameter tuning
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV

param_tuning = {
    'learning_rate': [0.01, 0.1],
    'max_depth': [3, 5, 7, 10],
    'min_child_weight': [1, 3, 5],
    'subsample': [0.5, 0.7],
    'colsample_bytree': [0.5, 0.7],
    'n_estimators': [100, 200, 500],
    'objective': ['reg:squarederror']
}

xgb_model = XGBRegressor()
grid_search = GridSearchCV(estimator = xgb_model,
                           param_grid = param_tuning,
                           cv=5,
                           n_jobs = -1,
                           verbose = 1)
grid_search.fit(X_train, y_train)
print("Best parameters:", grid_search.best_params_)

# Fitting 5 folds for each of 288 candidates, totalling 1440 fits
# Best parameters: {'colsample_bytree': 0.5, 'learning_rate': 0.1, 'max_depth': 5,
#      'min_child_weight': 5, 'n_estimators': 200, 'objective': 'reg:squarederror', 'subsample': 0.7}
```

Fig. 5. Parameter optimization of XGBoost model.

The ANN model is implemented using the MLPRegressor function. Prior to training, feature normalization is performed using the Min-Max Scaling to transform all variables into the range [0,1]. This step is important for improving convergence stability and preventing variables with larger scales from dominating the learning process. Fig. 6 presents the implementation code of the ANN model in the baseline scenario.

```
# Selecting all column as predictors
X=df[['JISDOR', 'JIBOR', 'M2', 'Foreign Reserve', 'Balance of Payment',
      'GDP Deflator', 'Wage', 'Back To School', 'Christmas and New Year', 'Ramadhan',
      'Idul Fitri', 'Broad Money', 'ERPT', 'Velocity of Money', 'Impor Cover Ratio']]
# Specify 'Inflation_yoy' column as 'y'
y=df['Inflation_yoy']
# Splitting the dataset into training and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Normalize dataset
scaler = MinMaxScaler()
# Fit and transform
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Train model with default parameter
model = MLPRegressor(random_state=42)
model.fit(X_train, y_train)
# Making predictions on the test dataset
predictions = model.predict(X_test)
```

Fig. 6. ANN model in the baseline scenario.

Fig. 7 presents the ANN hyperparameter optimization using GridSearchCV with 3-fold cross-validation. Several parameters, including hidden_layer_sizes, activation, solver, and max_iter, are systematically tuned to identify the optimal forecasting configuration. The best parameters obtained are hidden_layer_sizes = (256, 128, 64), activation = tanh, solver = adam, and max_iter = 1000, indicating that deeper network architectures and sufficient training iterations improve the predictive performance of the ANN model.

```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid to search
param_grid = {
    'hidden_layer_sizes': [(100,), (50, 50), (256, 128, 64)],
    'activation': ['relu', 'tanh'],
    'solver': ['adam'],
    'max_iter': [500, 1000, 1500]
}
# Initialize MLPRegressor
mlp = MLPRegressor(random_state=42)
# Initialize GridSearchCV
grid_search = GridSearchCV(mlp, param_grid, cv=3,
                           scoring='neg_mean_squared_error', verbose=2, n_jobs=-1)
# Fit GridSearchCV to the training data
grid_search.fit(X_train, y_train)
# Print the best parameters and best score
print("Best parameters found: ", grid_search.best_params_)

# Fitting 3 folds for each of 18 candidates, totalling 54 fits
# Best parameters found: {'activation': 'tanh', 'hidden_layer_sizes': (256, 128, 64),
# 'max_iter': 1000, 'solver': 'adam'}
```

Fig. 7. Parameter optimization of ANN model.

E. Evaluation

The evaluation phase assesses the performance and reliability of the developed machine learning forecasting models. Model performance is evaluated on out-of-sample testing data using standard forecasting accuracy metrics, including RMSE, MAE, and R^2 .

Root Mean Squared Error (RMSE) is a widely used metric for evaluating predictive accuracy in statistical and machine learning models. It is defined as the square root of the average squared difference between actual and predicted values. A lower RMSE indicates better model performance, as larger errors are penalized more heavily.

Mean Absolute Error (MAE) measures the average magnitude of errors between actual and predicted values. A lower MAE indicates better predictive performance. Since it is

expressed in the same unit as the target variable, MAE is easy to interpret and suitable for model comparison.

Coefficient of determination (R^2) is a statistical metric used to evaluate regression model performance by measuring the proportion of variance in the dependent variable explained by the independent variables. The value of R^2 ranges from 0 to 1, where values closer to 1 indicate better explanatory power and model performance.

To further validate forecasting performance differences, statistical significance testing is conducted using the Diebold–Mariano (DM) test. The test evaluates whether forecast error differences between Random Forest, XGBoost, and ANN models are statistically significant.

In addition, XAI techniques are employed through SHAP (Shapley Additive Explanations) value analysis to quantify the contribution of each predictor variable, thereby ensuring that the forecasting framework is not only predictive but also economically interpretable.

F. Deployment

The Deployment phase represents the final stage in which the selected model is prepared for practical use. In this study, deployment is conducted within an analytical and decision-support context by utilizing the best-performing model for inflation forecasting and forward-looking monetary analysis. The deployment process includes presenting forecasting and interpretability outputs to support transparent inflation analysis. SHAP analysis is applied to explain the contribution of each predictor variable to forecasting outcomes. In addition, the proposed framework supports periodic updates using new data, enabling the model to remain adaptive to evolving macroeconomic conditions and inflation dynamics.

IV. RESULTS AND DISCUSSION

This section presents the performance evaluation results of the machine learning models across the three experimental scenarios, followed by interpretability analysis using SHAP and feature importance. SHAP analysis is applied to improve interpretability, while feature importance is used to support and validate the SHAP findings. The analysis evaluates forecasting performance, examines the effect of temporal feature augmentation and hyperparameter optimization, and identifies the macroeconomic variables that most strongly influence inflation predictions.

The regression performance of each model is evaluated using RMSE, MAE, and R^2 metrics to measure prediction accuracy, forecasting error, and explanatory power. Lower RMSE and MAE values indicate better forecasting performance, while higher R^2 values indicate stronger explanatory capability. In addition, Diebold–Mariano (DM) statistical testing is conducted to examine whether forecasting performance differences between models are statistically significant.

TABLE III. PERFORMANCE EVALUATION SUMMARY

Model	Scenario	RMSE	MAE	R ²
Random Forest	Baseline (macroeconomic indicators and seasonal variables)	0.5145	0.3619	0.9486
	Baseline Configuration with Time-Series Features	0.5287	0.3758	0.9457
	Baseline Configuration with Time-Series Features and Hyperparameter Tuning	0.5005	0.3469	0.9513
XGBoost	Baseline (macroeconomic indicators and seasonal variables)	0.6541	0.3664	0.9169
	Baseline Configuration with Time-Series Features	0.6245	0.3603	0.9242
	Baseline Configuration with Time-Series Features and Hyperparameter Tuning	0.4987	0.3339	0.9517
Artificial Neural Network	Baseline (macroeconomic indicators and seasonal variables)	1.7523	1.3153	0.4035
	Baseline Configuration with Time-Series Features	1.6543	1.2727	0.4683
	Baseline Configuration with Time-Series Features and Hyperparameter Tuning	1.0065	0.6503	0.8031

Table III presents the comparative performance of Random Forest, XGBoost, and ANN models across all scenarios using RMSE, MAE, and R² metrics.

The results consistently indicate that ensemble-based models outperform ANN across all experimental scenarios. In the baseline configuration, Random Forest achieves the strongest predictive performance, effectively capturing nonlinear relationships among macroeconomic and seasonal variables. XGBoost also performs relatively well, while ANN shows substantially weaker forecasting performance.

The weaker ANN performance in the baseline scenario may be associated with the sensitivity of neural networks to architecture configuration, parameter initialization, training iterations, and dataset size. Compared with ensemble-based models, ANN generally requires more extensive optimization to effectively learn nonlinear macroeconomic relationships. In contrast, tree-based ensemble methods are typically more robust for structured tabular economic data.

The inclusion of temporal variables in the second scenario produces mixed results. Random Forest shows a slight decline in performance, while XGBoost demonstrates moderate improvement after incorporating the quarter variable. ANN also shows limited improvement but remains below ensemble-based methods. These findings indicate that temporal feature augmentation is model-dependent rather than universally beneficial.

The best overall performance is achieved in the third scenario after hyperparameter optimization. XGBoost becomes the best-performing model with RMSE = 0.4987, MAE =

0.3339, and R² = 0.9517, closely followed by Random Forest with RMSE = 0.5005 and R² = 0.9513. ANN also improves substantially after optimization, confirming that neural network performance is highly dependent on architecture selection and parameter tuning. Overall, the findings indicate that hyperparameter optimization contributes more significantly to forecasting improvement than temporal feature augmentation.

To further validate forecasting performance differences between models, Diebold–Mariano (DM) testing is conducted using prediction errors from the testing dataset. The results indicate that the forecasting performance difference between XGBoost and Random Forest is not statistically significant (p-value > 0.05), suggesting that both ensemble-based models achieve relatively comparable predictive performance. However, both XGBoost and Random Forest significantly outperform ANN (p-value < 0.05), confirming the superior forecasting capability of ensemble-based methods for structured macroeconomic inflation data.

TABLE IV. DIEBOLD–MARIANO (DM) STATISTICAL TESTING

Comparison	DM Statistic	p-value	Result
XGBoost vs. RF	-1.7644	0.0851	Not Significant
XGBoost vs. ANN	-2.7265	0.0094	Significant
RF vs. ANN	-2.6407	0.0117	Significant

Table IV presents the results of the Diebold–Mariano (DM) statistical testing used to evaluate the statistical significance of forecasting performance differences between XGBoost, Random Forest, and ANN models.

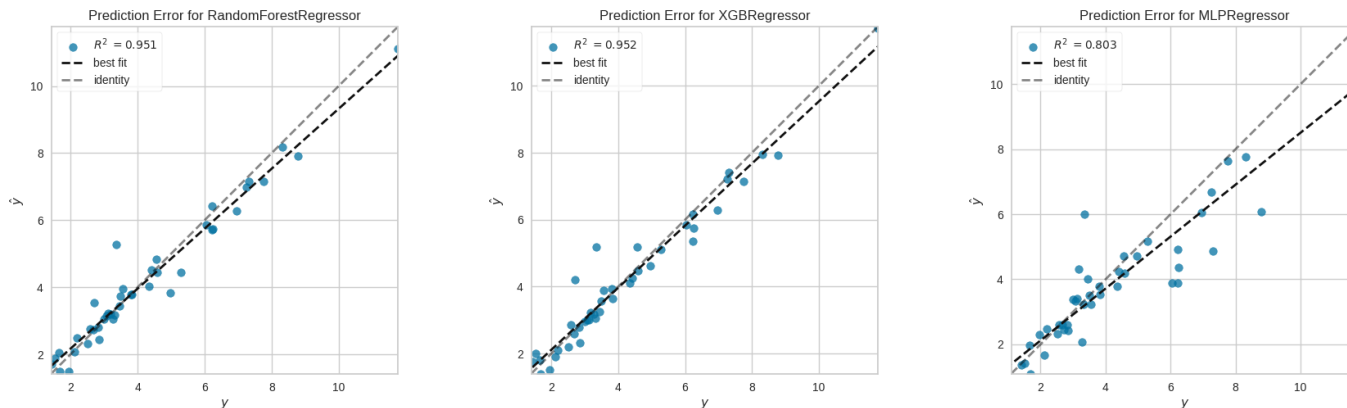


Fig. 8. Comparison of prediction error plots for Random Forest, XGBoost, and MLP (ANN) models in the third scenario.

Fig. 8 presents the prediction error plots for the three models in the third scenario. Random Forest and XGBoost show strong alignment between actual and predicted values, with most observations distributed near the identity line, indicating high predictive precision and limited systematic error. In contrast, ANN exhibits wider dispersion around the identity line, reflecting weaker predictive stability and larger forecasting errors.

To improve interpretability, SHAP analysis is applied only to the best-performing XGBoost model in the third scenario to provide transparent and policy-relevant insights into the contribution of macroeconomic variables to inflation forecasting. The analysis explains both the contribution and directional impact of each predictor variable on inflation forecasts, thereby helping to identify the key economic factors driving inflation.

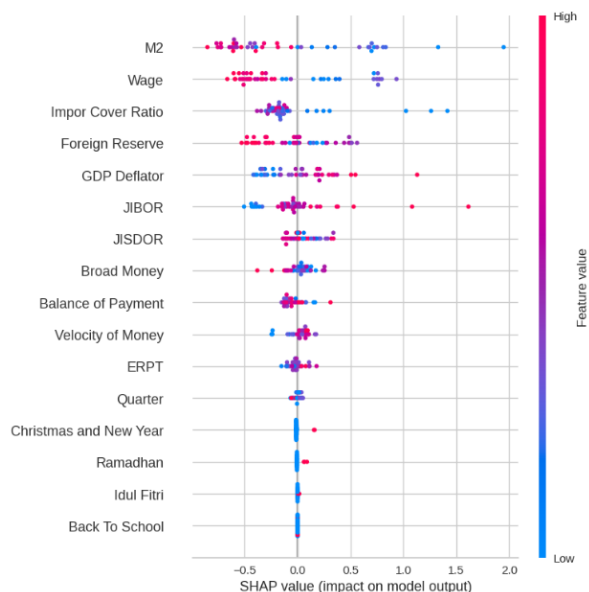


Fig. 9. SHAP summary for XGBoost model (third scenario).

Fig. 9 presents SHAP analysis for the XGBoost model (third scenario), showing that M2, Wage, and Import Cover Ratio are the main drivers, while other variables have moderate to low impact.

The dominance of M2 indicates the importance of monetary liquidity in influencing inflation dynamics, while Wage reflects labor-cost and purchasing-power effects. In addition, the relatively strong contribution of the Import Cover Ratio suggests that external-sector resilience and reserve adequacy also influence inflation stability through exchange-rate and import-price channels. Seasonal and temporal variables contribute relatively less, indicating that structural macroeconomic conditions play a more important role than calendar-based effects.

To support the SHAP results, feature importance analysis is subsequently performed for the best-performing XGBoost model. This additional analysis is intended to validate the consistency of the SHAP findings by identifying the variables that contribute most significantly to the forecasting process from the model perspective. The comparison between SHAP and

feature importance provides complementary interpretability insights and strengthens the reliability of the identified macroeconomic determinants of inflation.

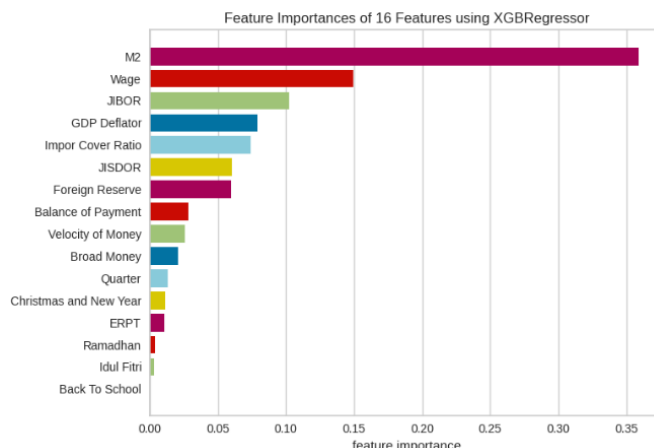


Fig. 10. Feature importance of XGBoost model (third scenario).

Fig. 10 presents the feature importance analysis for the best-performing XGBoost model in the third scenario. The results show that M2 is the most influential variable, indicating that monetary liquidity plays a dominant role in inflation forecasting. Wage emerges as the second most important variable, suggesting that labor-cost and purchasing-power effects also contribute significantly to inflation dynamics. Other variables, including JIBOR, GDP Deflator, and Import Cover Ratio, exhibit moderate importance, reflecting the influence of interest rate transmission, general price-level conditions, and external-sector resilience on inflation behavior.

Compared with the SHAP analysis of the best-performing XGBoost model, the feature importance results show a consistent pattern. Both analysis identify M2 and Wage as the dominant contributors to inflation forecasting, confirming the strong influence of monetary liquidity and labor-related factors on inflation dynamics in Indonesia. In addition, Import Cover Ratio also appears as an influential variable, highlighting the role of external-sector stability and reserve adequacy in influencing inflation through exchange-rate and import-price channels.

However, SHAP provides deeper interpretability than feature importance because it explains not only the magnitude but also the direction of each variable's contribution to inflation predictions. While feature importance identifies globally influential variables, SHAP further explains how variables such as M2 and Wage positively or negatively affect predictions across observations. The consistency between both analyses strengthens the reliability of the interpretability findings and confirms that inflation dynamics in Indonesia are primarily driven by structural macroeconomic conditions rather than seasonal effects.

V. CONCLUSION

This study proposes an interpretable machine learning framework for inflation forecasting in Indonesia using domestic macroeconomic and seasonal variables. The framework systematically evaluates Random Forest, XGBoost, and ANN

models under three experimental scenarios: baseline modeling, temporal feature augmentation, and hyperparameter optimization.

The results consistently show that ensemble-based methods outperform ANN across all scenarios, with XGBoost achieving the best overall performance after hyperparameter optimization (RMSE = 0.4987, MAE = 0.3339, $R^2 = 0.9517$), closely followed by Random Forest (RMSE = 0.5005, $R^2 = 0.9513$). Diebold–Mariano (DM) testing further indicates that the forecasting performance difference between XGBoost and Random Forest is not statistically significant, whereas both ensemble-based models significantly outperform ANN. These findings confirm the effectiveness of ensemble-based machine learning models for inflation forecasting.

To improve interpretability, SHAP analysis is applied to the best-performing XGBoost model. The results identify M2, Wage, and Import Cover Ratio as the dominant contributors to inflation forecasting, indicating that monetary liquidity, labor-related factors, and external-sector resilience play important roles in explaining inflation dynamics in Indonesia.

Overall, this study contributes through a systematic forecasting framework that integrates predictive accuracy, temporal feature evaluation, hyperparameter optimization, statistical validation, and explainable artificial intelligence within a unified experimental setting. From a practical perspective, the proposed framework may support more transparent and forward-looking monetary policy analysis in Indonesia and other emerging economies with similar economic structures.

Nevertheless, this study has several limitations. It focuses primarily on domestic macroeconomic indicators and does not yet incorporate broader external variables. In addition, the harmonization of lower-frequency variables into monthly frequency may simplify some short-term dynamics. Future studies may incorporate developed-country interest rates and global commodity prices to better capture external monetary influences and global shocks affecting inflation dynamics.

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