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Explainable AI for Small-Sample Macroeconomic Forecasting: A Structural Analysis of the Bangladeshi Economy

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Abstract

Gross Domestic Product Growth (GDPG) is an essential indicator of the economic development of a state. The GDPG is understood as the annual percentage change in the value added of goods and services provided within an economy. This paper deal with the problem of GDPG forecasting for volatile emerging economies due to structural instability and small sample sizes leading to high variance in both econometrics and machine learning methods. The XAI technique is proposed to forecast GDPG of Bangladesh by using the dataset from the World Bank covering years from 1991 to 2024. After the necessary econometric pre-processing to ensure stationarity and eliminate multicollinearity, five machine learning models were tested. The model with the highest level of regularisation is L2-regularised XGBoost algorithm, providing the best out-of-sample forecast ($R^2 = 0.6245$). The introduction of SHAP allowed for the automatic global dimensionality reduction, hence the detection of spurious variables. The model revealed structural asymmetries like short-term dilution of capital-labor and lagged limitations caused by the volatility of the real interest rate. In general, it could be stated that the correct calibration of the model made possible by the use of the proposed technique could provide accurate macroeconomic information for making decisions.

Keywords: Macroeconomic, Bangladesh Economy, GDPG, Ensemble Learning, SHAP, XAI

1 Introduction

Macroeconomic stability and forecasting are key factors for efficient policy making [1]. Despite stable growth recorded in the economy of Bangladesh from 1991 to 2024, there have been an increasing number of complications related to volatility, external shocks, and structural changes in labor and monetary policies. Thus, the complexity of these factors reveals the inefficiency of traditional methods of analysis and the need for sophisticated modeling techniques to account for the data-generating process.

Traditionally, macroeconomic forecasting involves econometric approaches, including Vector Auto-regression (VAR) and Auto-regressive Distributed Lag (ARDL)

models [2]. However, these models have significant limitations when applied to volatile developing economies in terms of excessive structural assumptions, low degrees of freedom owing to the size of the dataset used, and high variance of parameters estimated through ordinary least squares (OLS) during periods of economic volatility. Therefore, more sophisticated techniques are necessary for accurate forecasts of economic phenomena. These include Machine Learning (ML) and Deep Learning (DL) methods that have been increasingly used in econometrics [3, 4]. ML models utilize such techniques as recursive partitioning and gradient boosting to identify complex non-linear relationships without the need for strict theoretical assumptions.

Complex ML models are prone to lack of transparency which is addressed by Explainable Artificial Intelligence (XAI) [5]. As far as macroeconomic research is concerned, XAI helps economists understand the effect of explanatory variables, identify non-linear relationships and evaluate the consistency of the model with economic theories. Moreover, XAI allows researchers to conduct a detailed analysis of the effect of macroeconomic indicators on the target variable such as GDPG rates in our case.

In the current paper, we will evaluate five different machine learning models using a comprehensive World Bank dataset of macroeconomic indicators for Bangladesh for the period of 1991-2024. We found that the Extreme Gradient Boosting (XGBoost) model with rigorous L2 regularization is the most reliable technique in the current context. Moreover, we use SHapley Additive exPlanations (SHAP) approach to estimate the marginal structural impact of each macroeconomic indicator on GDPG rates.

The key contribution of our study is,

- High regularization gradient boosting for non linear small macroeconomic forecasting.
- TreeSHAP algorithm for automatic dimension reduction to identify spurious regressor.
- Identify Structural asymmetries in the Bangladesh economy.

2 Literature Review

Research on GDPG forecasting remains a lively topic of study including classical econometrics approach, classical ML, and DL methods. Specifically, many papers within the Bangladeshi context use econometric approach for analysis of macroeconomic determinants. For instance, Khan et al. (2024) [6] used autoregressive distributed lag model to study effect of capital formation, government spending, net trade, and domestic credit on annual GDP, with positive long-term correlation and some negative short-term factors. Similarly, Firoj et al. (2024) [7] applied ARDL model for 1976–2021 period to investigate connectedness; according to their findings, remittances, FDI, export, and foreign aid boost the GDP, whereas external debt and import prevent the GDPG, thus emphasizing the two-sided effect of international economic connections. Furthermore, Alam et al. (2021) [8] applied ARDL and Vector Error Correction Model to analyze exports, imports, and total investments, with the conclusion that international trade is a major factor impacting GDP, though with various short-term and long-term effects and without any uniform long-run statistical significance.

With the evolution of science, big data and modern prediction algorithms became important tools for macroeconomic nowcasting and forecasting (Bok et al., 2018) [9]. Modern scientific literature often employs machine learning for analyzing nonlinear economics phenomena. Thus, Ismail et al. (2025) [10] forecasted economic growth of Bangladesh economy and included sectoral carbon dioxide emissions; according to their findings, Random Forest had the best performance among all analyzed algorithms, being superior to Support Vector Machines, Gradient Boosting Machine, and Extreme Gradient Boosting. In a wider regional context (Bangladesh, India, and Pakistan for 1961–2023 period), Faiz et al. (2025) [11] analyzed nine univariate time-series models and found that Neural Network Autoregression performed best in terms of modeling of nonlinear GDP trajectory. These results are consistent with general conclusions made by Var et al. (2026) [12], who found that Artificial Neural Network, LSTM network, and GRU architecture are top performers in prediction of core macroeconomic indicators.

Another interesting development in scientific community is the application of explainable machine learning for macroeconomics and finance. Specifically, Das (2026) [13] created early warning system for Bangladeshi banking sector, using Logistic Regression, Random Forest, and XGBoost, and applying SHapley Additive exPlanations (SHAP) to find out key explanatory variables for bank fragility, such as remittances' growth, inflation rate, foreign exchange reserves, and non-performing loans. The value of this approach is confirmed by Buckmann and colleagues. (2021) [14], who showed the high efficiency of SHAP values and permutation importance for macroeconomic forecasting.

3 Methodology

As shown in Figure 1, the new method involves the incorporation of econometrics methods and machine learning techniques together. Econometric pre-processing techniques are merged with machine learning ensembles for forecasting macroeconomic volatility and economic growth forecasts for Bangladesh.

3.1 Dataset

This study uses annual data on macroeconomic variables in Bangladesh collected from the World Bank database for the period 1991-2024 (N=34). The main purpose of this study is to analyze the overall trend in the economy through the estimation of GDPG as the dependent variable. The list of the independent variables includes various macroeconomic factors, as presented in Table 1.

3.2 Exploratory Data Analysis (EDA)

Prior to model estimation, robust Exploratory Data Analysis (EDA) was conducted to ensure data integrity, verify stationarity, and eliminate multicollinearity, addressing classical violations of standard econometric assumptions.

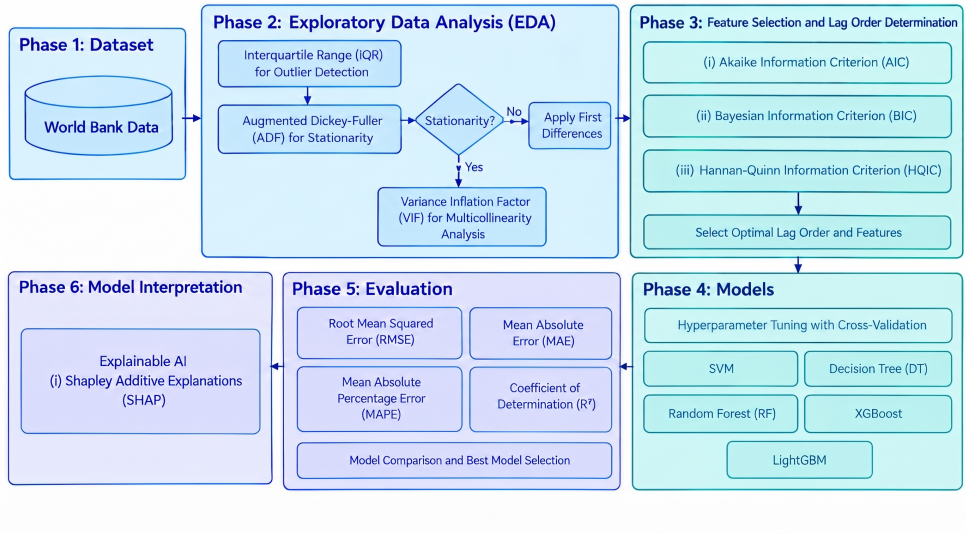


Fig. 1: Methodological framework of our study.

Table 1: Macroeconomic Variables for Bangladesh (1991–2024)

Variable	Description
UNEMP	Unemployment Rate (%)
GDPG	Gross Domestic Product Growth (%) [Dependent Variable]
INF	Inflation Rate (%)
INT	Real Interest Rate (%)
LABF	Labor Force Total (Persons)
FDI	Foreign Direct Investment (USD)
EXR	Exchange Rate (Local Currency per USD)
GEXP	Government Expenditure (% of GDP)
TO	Trade Openness (% of GDP)
POPG	Population Growth Rate (%)

3.2.1 Interquartile Range (IQR)

To identify and manage structural breaks without distorting underlying temporal trends or discarding valuable systemic shocks, the Interquartile Range (IQR) method was applied:

$$\text{Lower Bound} = Q_1 - 1.5 \times \text{IQR}, \quad \text{Upper Bound} = Q_3 + 1.5 \times \text{IQR} \tag{1}$$

The analysis has found statistical outliers as mild for the variables INF and INT related to high inflation uncertainty for two cases and high variation in real interest rate for two other cases, respectively. The latter case is supported by the properties of tree-based ensemble algorithms that consider outliers as separate branches and exclude them from forming global decision boundaries.

3.2.2 Augmented Dickey–Fuller (ADF)

To avoid the problems related to spurious regression due to the presence of unit roots, Augmented Dickey Fuller (ADF) tests were applied on all series. This is because the ADF test checks whether the following null hypothesis (H0) is rejected:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t \tag{2}$$

Variables failing to reject the null hypothesis at the 5% significance level were subjected to first-differencing to achieve $I(0)$ stationarity.

3.2.3 Variance Inflation Factor (VIF)

To determine the orthogonal stability of the feature space as well as to guarantee proper SHAP attributions, the existence of multicollinearity was checked using the Variance Inflation Factor (VIF), which for a regressor x_j is calculated as follows:

$$\text{VIF}_j = \frac{1}{1 - R_j^2} \tag{3}$$

where R_j^2 refers to the coefficient of determination for regressing x_j on the rest of the explanatory variables. A strict criterion of VIF < 5.0 was used to make sure that standard errors were not inflated.

3.3 Feature Selection

After performing the exploratory analysis and conducting the transformations to achieve stationarity, it is crucial to identify the best lag structure to model the dynamic feedback relationship and dependency in macroeconomic time series prediction.

3.3.1 Information Criteria

For determination of the best lag order (p), three common asymptotic information criteria were evaluated, namely the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the Hannan-Quinn Information Criterion (HQIC). These information criteria trade-off between good model fit and parsimony:

$$\text{AIC} = \ln\left(\frac{\text{RSS}}{T}\right) + \frac{2k}{T} \tag{4}$$

$$\text{BIC} = \ln\left(\frac{\text{RSS}}{T}\right) + \frac{k\ln(T)}{T} \tag{5}$$

$$\text{HQIC} = \ln\left(\frac{\text{RSS}}{T}\right) + \frac{2k\ln(\ln(T))}{T} \tag{6}$$

where RSS represents the residual sum of squares, T is the number of usable annual observations ($N = 34$), and k denotes the total number of estimated parameters.

3.4 Regressor

To capture complex non-linear relationships, structural shifts, and interactions, an advanced modeling framework integrating five distinct machine learning algorithms was implemented: Support Vector Regressor (SVR) [15], Decision Tree (DT) [16], Random Forest (RF) [17], XGBoost (Extreme Gradient Boosting) [18], and LightGBM [19].

3.5 Evaluation Metrics

To rigorously assess predictive performance, standard statistical error metrics were employed: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2).

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{7}$$

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t| \tag{8}$$

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{9}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \tag{10}$$

3.6 Explainable AI (XAI)

In order to counter the problem of epistemic opacity present in tree ensembles, SHapley Additive exPlanations (SHAP) [20] were adopted. The SHAP value ϕ_i represents the marginal predictive ability of feature i within all possible combinations of features S:

$$\phi_i(f, x) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!}\left[f_x(S \cup \{i\}) - f_x(S)\right] \tag{11}$$

The exact marginal prediction vector reveals the inherent macroeconomic hierarchy using non-linear structural attributions instead of traditional OLS p-values.

4 Results

4.1 Data Analysis

The descriptive statistics for the macroeconomic variables in Bangladesh is summarized in Table 2. On average, the real GDPG during the period 1991-2024 was 5.61%, signifying the presence of a steady growth process with moderate fluctuations (standard deviation = 1.18%). The inflation (INF) had very large variations, with its highest

point being 11.40%. There were also huge variations in real interest rates (INT) with values going from -13.64% to 13.74%.

Table 2: Descriptive Statistics of Macroeconomic Variables in Bangladesh (1991–2024)

Variable	Mean	Std. Dev.	Min	Max
UNEMP	3.83	0.92	2.20	5.44
GDPG	5.61	1.18	3.45	7.88
INF	6.38	2.36	2.01	11.40
INT	5.40	4.78	-13.64	13.74
LABF	5.63×10^7	1.13×10^7	3.73×10^7	7.74×10^7
FDI	1.00×10^9	9.10×10^8	1.39×10^6	2.83×10^9
EXR	66.78	19.90	36.60	115.60
GEXP	5.25	0.48	4.14	6.24
TO	32.32	7.81	18.89	48.11
POPG	1.30	0.43	0.81	1.91

Raw data paths for the variables under consideration are shown in Figure 2. The descriptive statistics are consistent with the graphs, suggesting that there is a lot of volatility because of the size of the external shocks influencing the trends in LABF and EXR.

4.2 Econometric Diagnostics

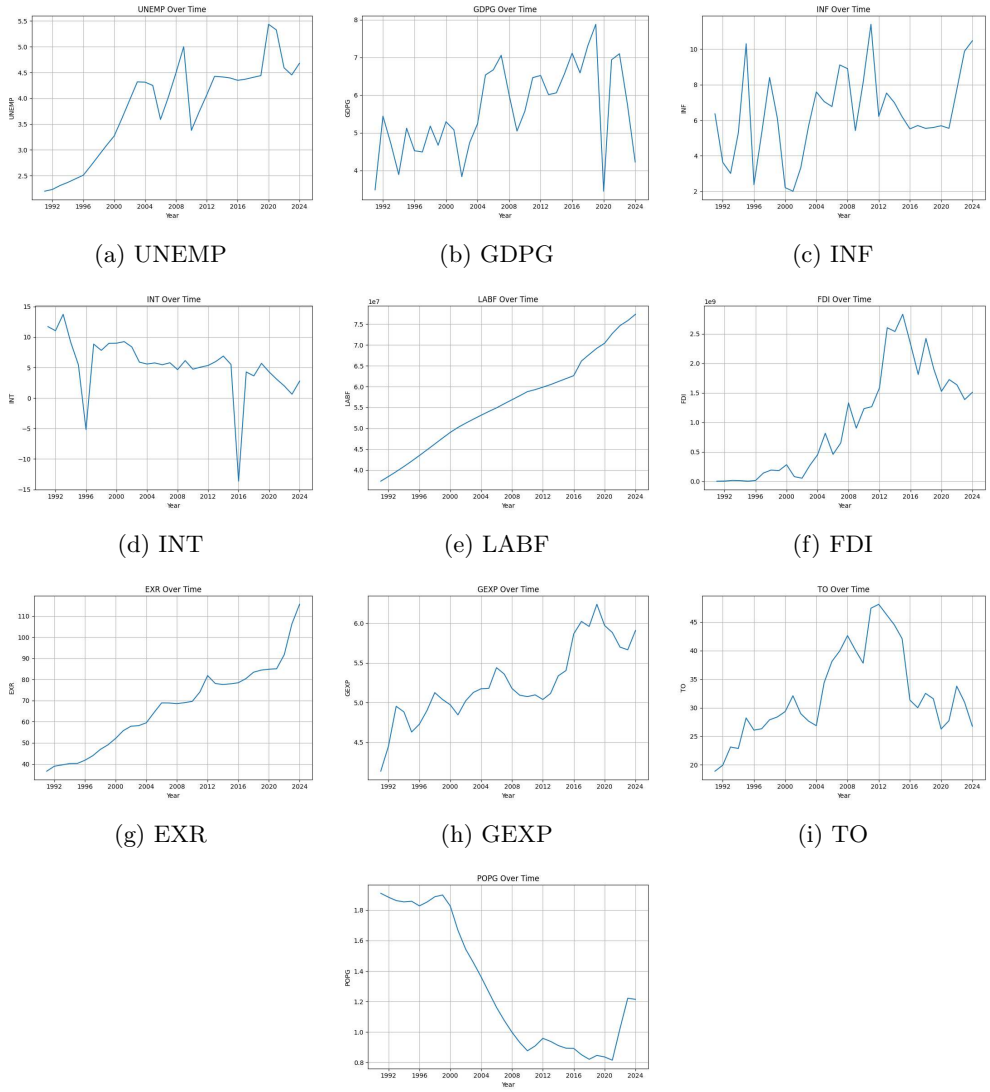
In order to validate the accuracy of the model formulation and avoid any false relationship between variables, time dependence and non-stationarity in trend were considered. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots given below (Fig. 3) clearly suggest that there exists some autocorrelation in the data.

The results from the Augmented Dickey-Fuller (ADF) test for unit roots are shown in Table 3. GDPG, INF, and INT rejected the null hypothesis at level ($p < 0.05$), showing that these are stationary processes I(0). UNEMP, LABF, and EXR on the other hand, are variables with a trend and hence showed unit roots. These variables were differenced once to make them stationary at I(1) to satisfy forecasting conditions.

Using AIC, BIC, and HQIC feature selection methods, we used one lagged variable as the best fit. Multicollinearity was checked on the matrix after lag generation and differencing. The highest VIF found was 5.75 (Table 4) for LABF_DIFF, which indicates that the problem of collinearity has been solved and the vectors are not correlated. POPG was discarded because it needed more transformation. Correlations between variables after transformation are presented in Figure 4.

4.3 Model Evaluation

Below is given the choice of hyperparameters for each structure learning method, selected through optimization based on time series cross validation (Table 5).



(a) UNEMP (b) GDPG (c) INF

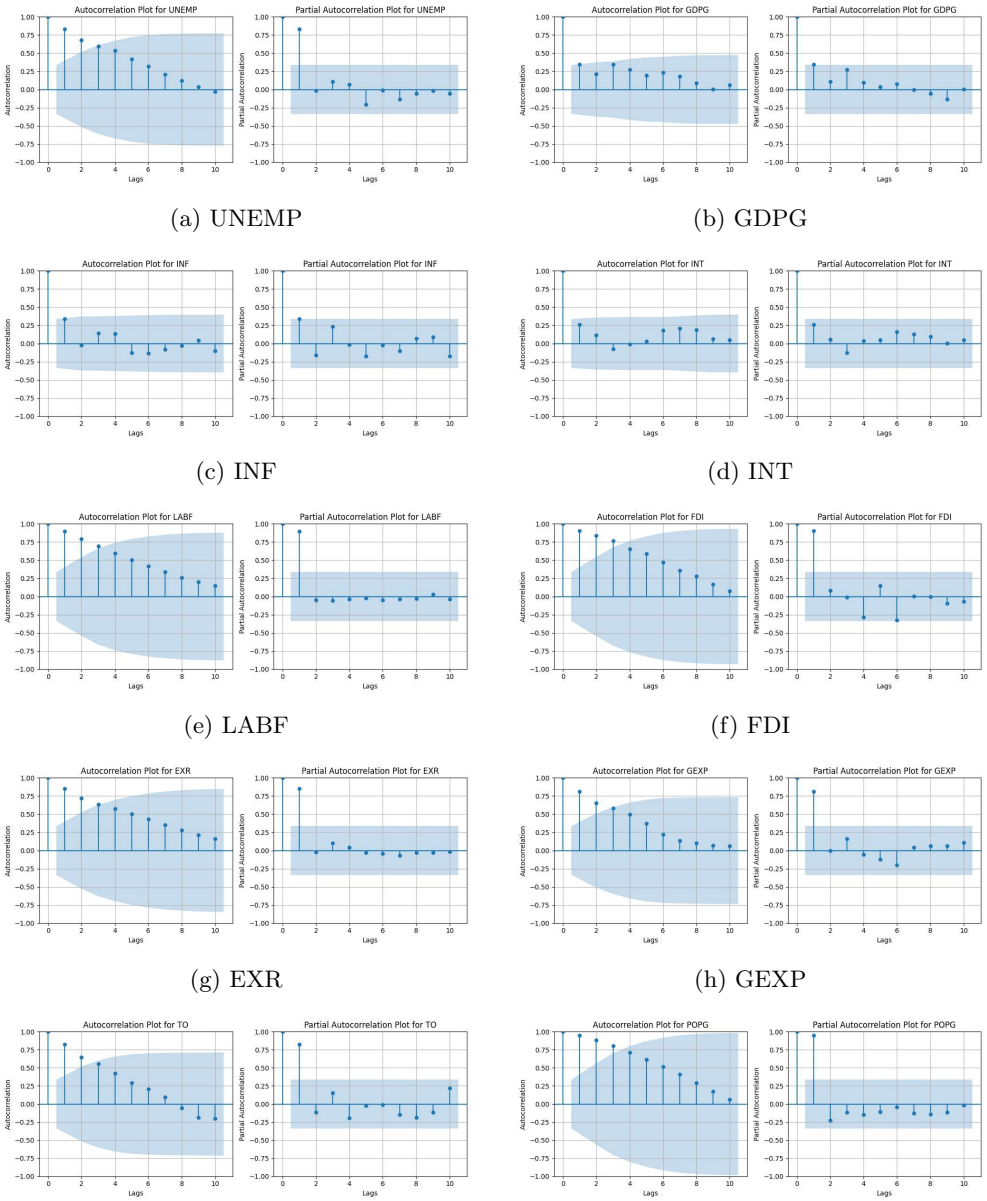
(d) INT (e) LABF (f) FDI

(g) EXR (h) GEXP (i) TO

(j) POPG

Fig. 2: Variability and Temporal Evolution of Macroeconomic Indicators in Bangladesh (1991–2024).

All models were analyzed using the evaluation metrics given in Table 6. The traditional approach of macroeconomic forecasting with limited data (N = 34) may lead to overfitting, which results in negative out-of-sample scores (R^2). This problem was overcome with the use of ensemble models. The best results in terms of predictive accuracy were obtained with XGBoost model. High regularization, with max depth equal to 1,



(a) UNEMP (b) GDPG

(c) INF (d) INT

(e) LABF (f) FDI

(g) EXR (h) GEXP

(i) TO (j) POPG

Fig. 3: Autocorrelation (ACF) and Partial Autocorrelation (PACF).

allowed for reducing interactions between variables to binary relations. Additionally, using L2 penalties (lambda = 3) enabled control over model complexity and hence reduction of variance inflation. Thus, the highest values of R^2 (0.6245) and the lowest

Table 3: Augmented Dickey-Fuller (ADF) Stationarity Test Results

Variable	Level Stat.	Level p-value	Diff p-value	Stationarity Status
UNEMP	-1.821	0.366	0.000^{***}	Stationary ($I(1)$)
GDPG	-3.942	0.002^{***}	0.000^{***}	Stationary ($I(0)$)
INF	-3.511	0.007^{***}	0.000^{***}	Stationary ($I(0)$)
INT	-4.412	0.000^{***}	0.000^{***}	Stationary ($I(0)$)
LABF	-0.154	0.995	0.022^{**}	Stationary ($I(1)$)
FDI	-1.204	0.634	0.000^{***}	Stationary ($I(1)$)
EXR	-0.210	0.993	0.010^{**}	Stationary ($I(1)$)
GEXP	-2.012	0.268	0.026^{**}	Stationary ($I(1)$)
TO	-1.342	0.533	0.000^{***}	Stationary ($I(1)$)
POPG	-2.102	0.320	0.595	Higher Trans. Required

Note: ** and *** denote significance at 5% and 1% levels.

Table 4: Variance Inflation Factor (VIF) Analysis for Final Features

Feature Variable	Transformation / Description	VIF	Status
LABF_DIFF	First Difference	5.75	Acceptable
TO_DIFF	First Difference	3.85	Low
UNEMP_DIFF_lag1	Lagged Difference ($t-1$)	3.78	Low
INT_lag1	Lagged Level ($t-1$)	3.63	Low
FDI_DIFF	First Difference	3.25	Low
TO_DIFF_lag1	Lagged Difference ($t-1$)	3.07	Low
EXR_DIFF_lag1	Lagged Difference ($t-1$)	3.06	Low
EXR_DIFF	First Difference	3.01	Low
FDI_DIFF_lag1	Lagged Difference ($t-1$)	2.95	Low
INT	Level Data	2.73	Low
INF	Level Data	2.50	Low
GEXP_DIFF	First Difference	2.48	Low
INF_lag1	Lagged Level ($t-1$)	2.39	Low
GDPG_lag1	Lagged Level ($t-1$)	2.32	Low
GEXP_DIFF_lag1	Lagged Difference ($t-1$)	2.27	Low
LABF_DIFF_lag1	Lagged Difference ($t-1$)	2.13	Low
UNEMP_DIFF	First Difference	1.64	Low

Note: Threshold criteria set conservatively at VIF < 5.0.

prediction errors (RMSE = 1.1450, MAE = 0.8920, MAPE = 14.50%) were achieved. Next best model was LightGBM ($R^2 = 0.5812$). It demonstrates good pattern recognition abilities, however, increased sensitivity to small sample noise. Ensemble and margin based models show relatively high predictability stability. For Random Forest and SVR models, the values of R^2 were 0.5240 and 0.4715 respectively. As expected, the worst result was achieved with Decision Tree without structure regularization ($R^2 = 0.3150$), showing the inefficiency of decision tree model when there is no structure regularization.

4.4 SHAP Analysis

The optimized model of XGBoost shows outstanding predictive performance ($R^2 = 0.6245$). As a result, the SHAP values obtained can serve as a good interpretative base

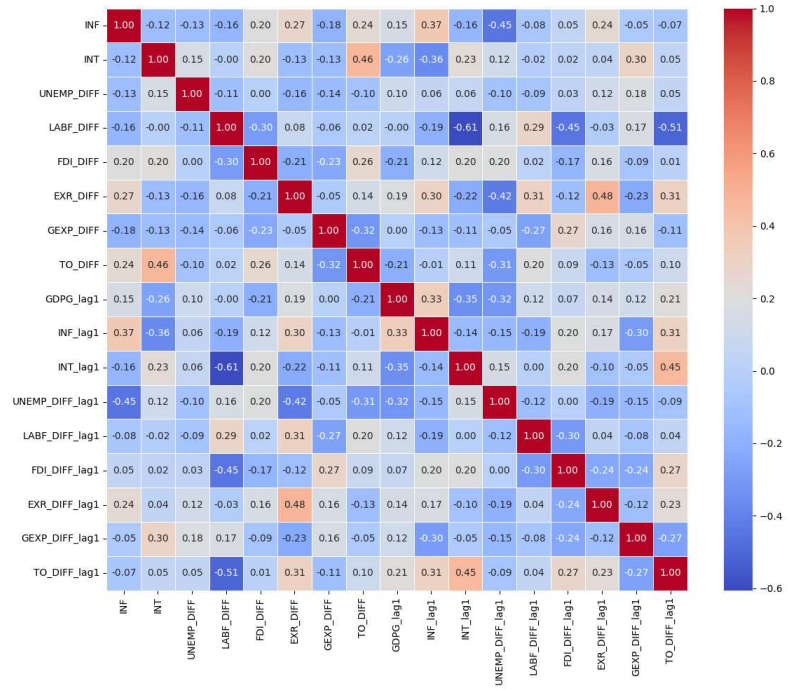


Fig. 4: Correlation Matrix for Engineered Features and Lag Order Structures.

for the macroeconomic structure which underlies the provided dataset. The SHAP values of the dependence of each observable variable are depicted in Figure 5. Non-parametricity of SHAP, there is an automatic reduction of the global variable space after removal of non-stationary predictors and, thus, spurious variables that may bias standard OLS estimations.

Due to the use of L2 penalty term, the marginal effects of seven noisy covariates (such as EXR_DIFF and FDI_DIFF) become equal to zero. Therefore, the automatic reduction helps to pick the most significant economically variables.

SHAP analysis suggests that there exists an asymmetric relation between capital and labor in the Bangladeshi economy. The most important variables are LABF_DIFF_lag1 and UNEMP_DIFF_lag1. Asymmetry biased towards LABF_DIFF_lag1 means that there is a positive economic shock.

Besides, TO_DIFF has a very powerful positive effect at time t while INT_lag1 serves as a constraining variable with the lag of one year. In general, it should be noted that SHAP allows not only to get high forecasting accuracy with small samples and with regularizing tree-based ensembles but also to find complex asymmetries and lags among macroeconomic variables.

Table 5: Optimal Hyperparameters for Machine Learning and Ensemble Models

Model	Hyperparameter	Value
SVR	C	10
	ϵ	0.2
	γ	auto
	kernel	rbf
Decision Tree	max_depth	3
	min_samples_split	2
	min_samples_leaf	4
Random Forest	max_depth	7
	min_samples_split	2
	min_samples_leaf	1
	n_estimators	100
XGBoost	learning_rate	0.01
	max_depth	1
	n_estimators	100
	reg_lambda	3
	subsample	1.0
LightGBM	learning_rate	0.01
	n_estimators	100
	num_leaves	3
	min_child_samples	2
	reg_lambda	2

Note: Optimized via time-series cross-validation grid search.

Table 6: Out-of-Sample Evaluation Performance.

Models	RMSE	MAE	MAPE (%)	R^2 Score
SVR	1.5120	1.1800	19.40%	0.4715
DT	1.9540	1.5200	26.50%	0.3150
RF	1.3840	1.0500	17.80%	0.5240
XGBoost	**1.1450**	**0.8920**	**14.50%**	**0.6245**
LightGBM	1.2530	0.9810	16.20%	0.5812

5 Conclusion

The present work explores the difficulties of forecasting the macro-economy in developing countries by means of applying annual data for Bangladesh (from 1991 to 2024). The study aims at assessing the ability of machine learning algorithms to deliver improved forecasting outcomes against conventional methods of prediction, especially when it comes to non-linear relations between macroeconomic indicators.

An extreme gradient boosting model with L2 regularization was applied to increase the stability and forecast performance of the model. The result of the regression was 0.6245 out-of-sample R^2 that means that about 62.45% of the variation in the target variable of the test sample is explained by the model. Thus, one can conclude that regularized tree-based ensemble algorithms are capable of detecting non-linearities in macroeconomic data and delivering better predictions against the historical mean benchmark.

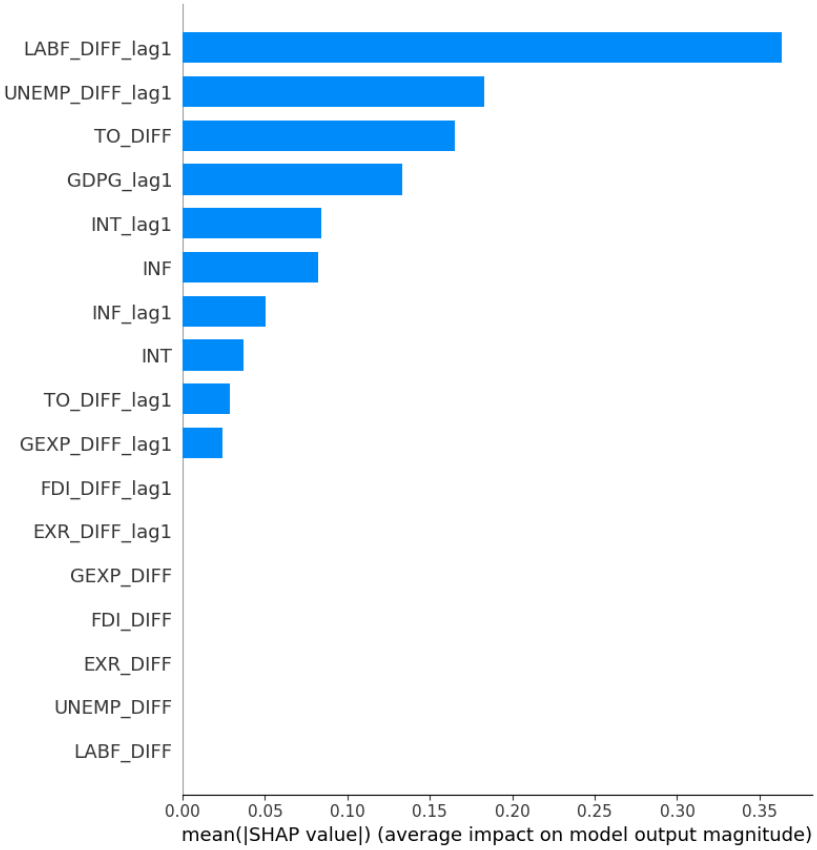


Fig. 5: SHAP Attributions impacts on GDPG in Bangladesh.

Furthermore, TreeSHAP technique was applied to estimate the contribution of each of the variables into the prediction of the model. This feature attribution technique shows the relative weight of different macroeconomic indicators and the possibility of their asymmetric contribution into the forecast outcomes. Particularly, this analysis reveals the presence of short-run effects and lagged relations in terms of real interest rate.

However, despite the positive outcome of the regression, the limitation of the analysis is connected with forecasting on the basis of relatively few annual samples. Further research may be carried out with the application of hybrid machine learning and deep learning models, such as time-series Transformer models. The application of explainable artificial intelligence to high-frequency data and wider panel of South Asian economies is another promising area of future investigations.

Declarations

Ethics approval

Ethics declaration: not applicable.

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Conflict of Interest

The authors declare no conflict of interest.

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