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Research paper

Bridging Temporal Dynamics and Nonlinear Patterns in Macroeconomic Forecasting: A Hybrid Statistical Learning Approach

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Abstract

Accurate macroeconomic forecasting is essential for effective policy formulation, financial planning, and economic stability, yet it remains challenging due to structural changes, economic shocks, and complex nonlinear interactions among economic indicators. Traditional time series models often struggle to capture such complexities, while standalone machine learning approaches may overlook temporal dependencies. To address these limitations, this study proposes a Hybrid Predictive Framework for Macroeconomic Forecasting (HPFMF) that integrates complementary strengths of time series and machine learning models. Using annual macroeconomic data for more than 200 countries spanning 2010–2025 from the World Bank Open Data API, the framework applies systematic preprocessing, including missing value handling, winsorization, logarithmic transformation, and feature scaling. A time series hybrid combining ARIMA, Prophet, and Exponential Smoothing captures temporal dynamics and structural shifts, while a stacked machine learning ensemble of Random Forest, XGBoost, and Support Vector Regression models nonlinear interdependencies. These layers are integrated through validation-based weighting to generate robust forecasts. Empirical results show that the proposed framework achieves superior performance, with significant reductions in forecasting errors and an R^2 of 0.92. Country-wise and temporal validations confirm strong generalizability, demonstrating the framework's effectiveness for reliable, policy-oriented macroeconomic forecasting.

Keywords: *Hybrid Forecasting; Macroeconomic Prediction; Time Series Analysis; Machine Learning Ensemble; Policy-Oriented Forecasting.*

1. Introduction

Macroeconomic forecasting plays a critical role in informing policy decisions, financial planning, and economic risk management at both national and global levels. Accurate predictions of key indicators such as gross domestic product (GDP) growth, inflation, unemployment, and public debt are essential for governments, central banks, and international institutions to design effective fiscal and monetary policies [1-3]. However, macroeconomic systems are inherently complex, characterized by nonlinear interactions, structural changes, policy interventions, and external shocks such as financial crises, pandemics, and geopolitical events. These challenges significantly limit the reliability of traditional forecasting approaches, motivating the development of more adaptive and robust predictive frameworks [4-5].

Conventional macroeconomic forecasting methods have largely relied on statistical time series models, including Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing techniques [6-7]. While these models are effective in capturing linear temporal dependencies and short-term trends, they often struggle to accommodate nonlinear relationships, regime shifts, and high-dimensional interactions among macroeconomic variables [8-12]. Moreover, assumptions of stationarity and linearity restrict their ability to adapt to evolving economic structures, particularly in cross-country or long-horizon forecasting scenarios. As a result, forecasts generated solely from traditional time series models may exhibit reduced accuracy during periods of economic volatility or structural transformation [13-16].

In recent years, machine learning (ML) techniques have emerged as powerful alternatives for economic forecasting due to their ability to model complex nonlinear patterns and high-dimensional relationships. Algorithms such as Random Forests, Gradient Boosting, and Support Vector Regression have demonstrated superior predictive performance in various economic and financial applications [17-18]. These data-driven approaches can effectively capture intricate interdependencies among macroeconomic indicators without relying on restrictive parametric assumptions. However, despite their strengths, standalone machine learning models often overlook explicit temporal structures and may suffer from reduced interpretability and temporal inconsistency when applied to time-dependent economic data [19-20].

To address the limitations of both traditional time series models and standalone machine learning approaches, hybrid forecasting frameworks have gained increasing attention in the literature. Hybrid models aim to integrate temporal modeling capabilities with nonlinear learning mechanisms, thereby leveraging the complementary strengths of both paradigms. By combining time series models that capture trend, seasonality, and structural changes with machine learning models that learn complex inter-variable relationships, hybrid frameworks offer a more comprehensive representation of macroeconomic dynamics. Such integrated approaches are particularly well-suited for large-scale, multi-country datasets where economic behavior varies across time and space.

Despite growing interest in hybrid forecasting, existing studies often focus on limited geographic regions, short time horizons, or single target variables. Moreover, many hybrid approaches lack systematic preprocessing pipelines and robust validation strategies, which are crucial when working with heterogeneous macroeconomic data collected across countries with varying reporting standards. There remains a need for a scalable and generalizable hybrid forecasting framework that systematically integrates data preprocessing, feature engineering, time series modeling, machine learning ensembles, and rigorous validation mechanisms.

In response to these gaps, this study proposes a Hybrid Predictive Framework for Macroeconomic Forecasting that integrates advanced time series models and machine learning techniques within a unified architecture. The proposed framework employs a time series hybrid composed of ARIMA, Prophet, and Exponential Smoothing models to capture linear temporal dynamics, structural shifts, and trend components. In parallel, a machine learning hybrid combines Random Forest Regression, XGBoost, and Support Vector Regression through stacked ensemble learning to model nonlinear interdependencies among macroeconomic indicators. These two layers are fused using a validation-error–weighted ensemble strategy to produce robust and accurate forecasts.

The framework is evaluated using a comprehensive global macroeconomic dataset covering more than 200 countries over the period 2010–2025, sourced from the World Bank Open Data API. Rigorous preprocessing steps, including missing value handling, outlier mitigation, logarithmic transformation, and normalization, ensure data stability and reliability. Model performance is assessed through time-aware splits, rolling window validation, and country-wise evaluation to ensure robustness and generalizability across diverse economic contexts.

The key contributions of this research are threefold: (i) the development of a scalable hybrid forecasting framework that effectively integrates time series and machine learning models for macroeconomic prediction; (ii) the application of the framework to a large-scale, multi-country dataset with rigorous preprocessing and validation strategies; and (iii) empirical evidence demonstrating improved forecasting accuracy and robustness compared to individual and single-layer hybrid models.

1.1. Key contribution

- Novel Dual-Layer Hybrid Forecasting Framework

This study introduces a comprehensive HPFMF that uniquely integrates a time series ensemble layer and a machine learning ensemble layer. By jointly modeling linear temporal dynamics, structural shifts, and nonlinear interdependencies, the framework overcomes the limitations of standalone statistical or machine learning approaches.

- Systematic Integration of Statistical and Machine Learning Models

Unlike conventional hybrid models that rely on simple combinations, this research proposes a structured, error-weighted fusion of ARIMA, Prophet, and Exponential Smoothing with stacked machine learning models (Random Forest, XGBoost, and Support Vector Regression). This hierarchical integration enhances forecasting robustness and accuracy across diverse macroeconomic conditions.

- Scalable and Generalizable Global Macroeconomic Application

The framework is validated using a large-scale, multi-country dataset covering over 200 countries from 2010 to 2025, demonstrating its scalability, adaptability, and applicability to both country-level and global macroeconomic forecasting tasks.

- Robust Preprocessing and Feature Engineering Pipeline for Macroeconomic Data

The study contributes a rigorous and reproducible preprocessing methodology, incorporating country-wise temporal interpolation, winsorization-based outlier handling, logarithmic transformation of skewed economic indicators, normalization, and advanced feature engineering with lagged and interaction terms, ensuring numerical stability and reliable learning.

- Realistic and Policy-Relevant Validation Strategy

A time-aware training–testing split combined with rolling window validation and country-wise evaluation is employed to preserve temporal causality and cross-country heterogeneity. This validation design provides a realistic performance assessment and enhances the framework's relevance for policy analysis and real-world economic forecasting.

2. Literature Review

Recent research on macroeconomic forecasting has increasingly emphasized hybrid and machine learning approaches to improve prediction accuracy and capture complex patterns in economic data. Huaqing Xie et al. [1] applied deep learning algorithms to multi-country GDP forecasting, demonstrating that deep learning outperforms linear regression when multiple economic indicators are included, though its effectiveness diminishes with single-feature datasets due to limited input complexity. Stephen Omondi Odhiambo and Cornelius Nyakundi [2] developed a hybrid ARIMA-XGBoost model for Mobile Money transaction data in Kenya, leveraging ARIMA for linear trends and XGBoost for non-linear residuals; this approach achieved high accuracy but is computationally intensive. For Somalia's GDP prediction, Bashir Mohamed Osman and Abdillahi Mohamoud Sheikh Muse [3] compared Random Forest Regression (RFR), XGBoost, and Prophet, with RFR showing superior performance and interpretability through SHAP, although all machine learning methods require substantial historical data and computational resources. Akisato Suzuki [4] employed a VAR framework combined with Bayesian modeling and tree ensembles (Random Forest, XGBoost, LightGBM) for Ireland, highlighting the stability and robustness of forecast averaging, albeit with high computational demands and sensitivity to volatile data. Zan Tang et al. [5] proposed a hybrid deep learning model combining CNNs, RNNs, and Fourier analysis to capture both short-term fluctuations and long-term trends, achieving superior predictive accuracy but requiring significant computational resources. Sherly et al. [6] developed a hybrid ARIMA-Prophet approach for edge computing time series, combining linear and non-linear modeling strengths, with enhanced forecast accuracy but increased complexity. Islam M. Hammam et al. [7] introduced a weighted ensemble of ARIMA and XGBoost for adaptive demand forecasting across product life cycles, improving accuracy and flexibility, though at the cost of higher computational effort. Faridoon Khan et al. [8] applied a hybrid VAR-SCAD model to U.S. macroeconomic data, addressing high dimensionality and producing reliable multi-step forecasts, though implementation is methodologically complex. Jawaria Nasir et al. [9] presented a hybrid LMD–ARIMA–Machine Learning framework for NASDAQ financial data, effectively separating stochastic and deterministic components and improving accuracy and directional consistency, but with high computational requirements. Finally, Rahida Rihhadatul Aisy et al. [10] combined Residual XGBoost Regression with I-MR control charts to forecast and monitor GDP, enhancing predictive performance in phase I but revealing limitations in evolving trends during phase II. Collectively, these studies illustrate that hybrid and machine learning approaches offer substantial advantages in capturing non-linear patterns, multi-dimensional inputs, and complex temporal dynamics for macroeconomic forecasting, while their main limitations remain high computational cost, model complexity, and sensitivity to data quality and availability. While recent deep learning approaches (LSTM, GRU, Transformer architectures) have shown promise in capturing complex temporal patterns, our hybrid framework offers distinct advantages for macroeconomic forecasting. Deep learning models typically require substantially larger datasets for stable training and often function as 'black boxes,' limiting interpretability.

3. Proposed Methodology

The main aim of the research is to develop a robust and reliable Hybrid Predictive Framework for Macroeconomic Forecasting (HPFMF) that can accurately model complex economic dynamics by integrating the complementary strengths of statistical time series techniques and advanced machine learning models. To achieve this, the study utilizes a large-scale global macroeconomic dataset covering more than 200 countries from 2010 to 2025, sourced from the World Bank Open Data API. The methodology begins with systematic data acquisition and structured preprocessing, including missing value handling through country-wise temporal interpolation, outlier mitigation using Z-score and IQR-based winsorization, logarithmic transformation of highly skewed variables such as GDP and GNI, and Min–Max normalization to ensure numerical stability. Exploratory data analysis and stationarity testing guide informed feature engineering, where lagged variables and interaction terms are generated to capture temporal dependencies and inter-variable relationships. The modeling framework consists of two parallel layers: a time series hybrid that ensembles ARIMA, Prophet, and Exponential Smoothing models to capture linear trends, structural shifts, and temporal patterns, and a machine learning hybrid that stacks Random Forest, XGBoost, and Support Vector Regression models to learn nonlinear interactions among macroeconomic indicators. The outputs of these layers are integrated using a validation-error–weighted fusion strategy to produce the final hybrid forecast. Model training and evaluation employ time-aware splits, rolling window validation, and country-wise testing to ensure robustness, generalizability, and realistic forecasting performance across diverse economic contexts.

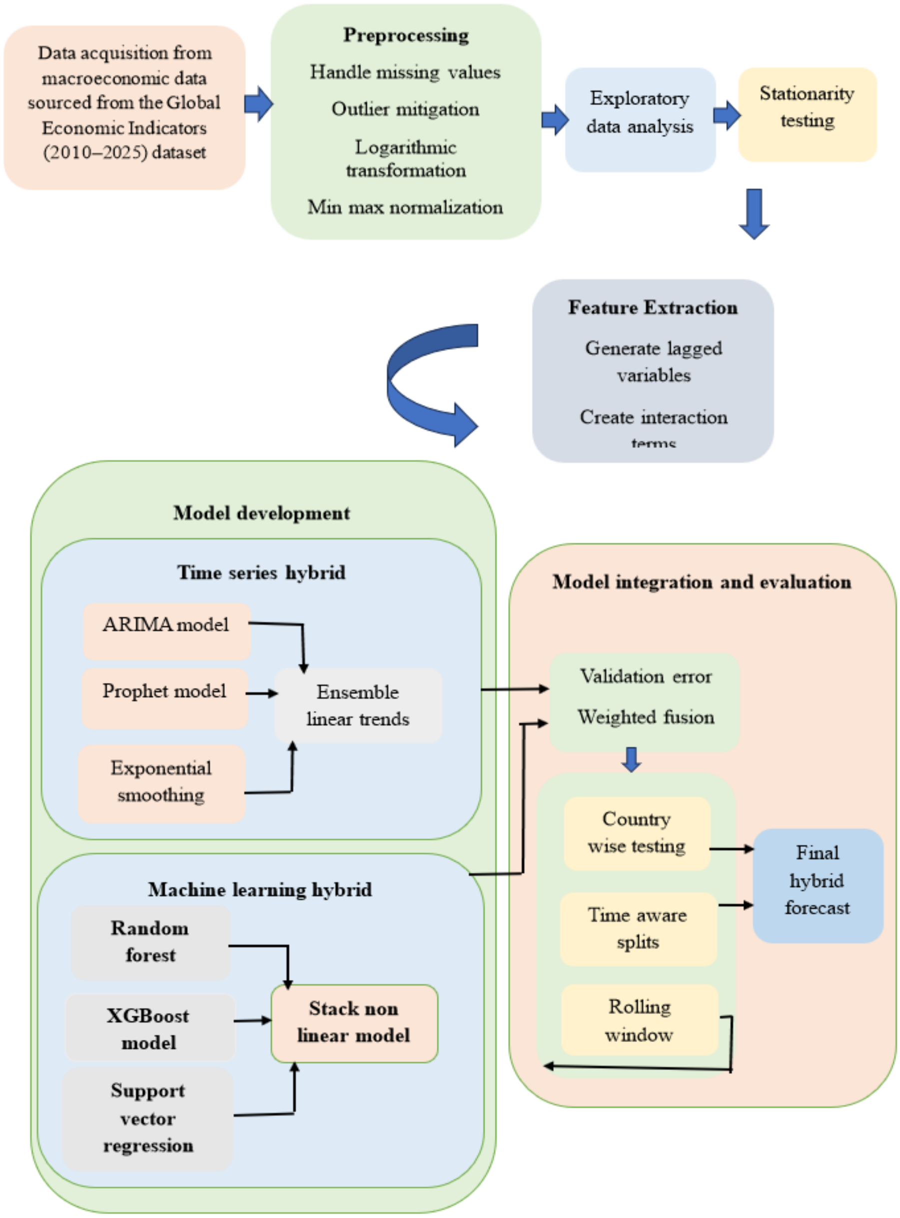

Fig. 1: HPFMF architecture: a two-layer hybrid framework integrating time series models (ARIMA, Prophet, ETS) for temporal dynamics with machine learning ensemble (random forest, XGBoost, SVR) for nonlinear patterns, unified through validation-error-weighted fusion to generate robust macroeconomic forecasts.

3.1. Input collection and data acquisition

The study employs secondary macroeconomic data sourced from the Global Economic Indicators (2010–2025) dataset available on Kaggle, which is compiled from the World Bank Open Data API. The dataset contains annual macroeconomic observations for more than 200 countries over 16 years (2010–2025). Each record corresponds to the economic conditions of a specific country in a given year, making the data well-suited for time series, panel data, and forecasting analyses. The data are provided in CSV (UTF-8) format and are imported into the analytical environment for preprocessing and model development.
Let $X^{raw} \in \mathbb{R}^{N \times M}$represent the raw macroeconomic dataset, where Nis the number of observations (countries × years), and Mis the number of indicators.

$$b_1 = X^{raw} = \{x_{i,j} \mid i = 1, \dots, N; j = 1, \dots, M\} \quad (1)$$

This $b_1$serves as input for the preprocessing step.
In the equation, each element $x_{i,j}$represents the value of the jThe macroeconomic indicator for the i-th observation, where an observation corresponds to a specific country in a given year. The indicators ($j = 1, \dots, M$) include identification variables (country name and ISO code), temporal index (year), target variables (GDP growth, inflation, unemployment rate), economic output (GDP, GDP per capita), monetary and fiscal measures (interest rate, government expenditure, tax revenue), external sector metrics (current account balance), income measures (Gross National Income), and debt indicators (public debt as % of GDP). This structured dataset forms the initial input. $b_1$for subsequent preprocessing and modeling steps.

Table 1: Dataset Description and Variable Details

Category	Variable Name	Description	Unit / Type
Identification	country_name	Full name of the country	Categorical
Identification	country_id	ISO 2-letter country code	Categorical
Time Index	year	Observation year (2010–2025)	Integer
Target Variable	GDP Growth (% Annual)	Annual percentage growth rate of GDP	Percentage (%)
Target Variable	Inflation (CPI %)	Consumer Price Index inflation rate	Percentage (%)
Target Variable	Unemployment Rate (%)	Share of the labor force without employment	Percentage (%)
Economic Output	GDP (Current USD)	Total national output at current prices	USD
Economic Output	GDP per Capita (Current USD)	GDP divided by total population	USD
Monetary Indicator	Interest Rate (Real, %)	Lending rate adjusted for inflation	Percentage (%)
Monetary Indicator	Inflation (GDP Deflator, %)	Inflation is measured via the GDP deflator	Percentage (%)
External Sector	Current Account Balance (% of GDP)	Net current account balance	Percentage (%)
Fiscal Indicator	Government Expense (% of GDP)	Total government expenditure	Percentage (%)
Fiscal Indicator	Government Revenue (% of GDP)	Total government revenue	Percentage (%)
Fiscal Indicator	Tax Revenue (% of GDP)	Government tax income	Percentage (%)
Income Measure	Gross National Income (USD)	Total income earned by residents	USD
Debt Indicator	Public Debt (% of GDP)	Government debt level	Percentage (%)

Table 2: Dataset Summary Statistics

Attribute	Description
Data Source	World Bank Open Data API
Dataset Name	Global Economic Indicators (2010–2025)
Platform	Kaggle
Temporal Coverage	2010–2025 (16 years)
Geographic Coverage	200+ countries
Number of Indicators	13 macroeconomic indicators
Total Records	~32,000–40,000 rows
Data Frequency	Annual
File Format	CSV (UTF-8)
Missing Values	Retained as NaN
Update Frequency	Annual
License	CC0 – Public Domain

Table 3: Data Suitability for Hybrid Forecasting

Aspect	Justification
Time Series Modeling	Annual country-wise temporal structure enables ARIMA, Prophet, and ETS.
Machine Learning	Multivariate indicators support nonlinear regression models.
Hybrid Modeling	Panel structure allows fusion of temporal and feature-based forecasts.
Policy Analysis	Indicators directly support fiscal, monetary, and labor analysis.
Scalability	Applicable to both country-level and global forecasting

3.2. Data cleaning and missing value handling

Macroeconomic datasets frequently contain missing observations due to inconsistent reporting practices, data collection delays, and variations in statistical capacity across countries. To address this issue, missing values are initially retained in their original form as NaN to prevent the premature introduction of bias during preprocessing. For short and intermittent gaps within a country's time series, country-wise temporal interpolation is applied, allowing the preservation of underlying economic trends and temporal continuity. In cases where countries exhibit excessive or systematic missing data across multiple years or key indicators, those observations are excluded from specific model runs to maintain the reliability and validity of the empirical analysis. Furthermore, country codes and year formats are standardized to ensure uniformity and accurate alignment across all observations. Collectively, these data cleaning procedures balance data completeness with methodological rigor, ensuring that the integrity of macroeconomic dynamics is preserved while minimizing potential data distortion.
Let f_{clean}be the function that performs missing value handling and standardization:

$$b_2 = f_{clean}(b_1) = \begin{cases} x_{i,j} & \text{if observed} \\ \text{interp}(x_{i,j}) & \text{if short-term gap} \\ \text{removed} & \text{if excessive missing values} \end{cases} \quad (2)$$

The variable $b_2$represents the cleaned and standardized macroeconomic dataset obtained after applying the data cleaning function $f_{clean}$to the raw input b_1. Here, $x_{i,j}$denotes the jThe macroeconomic indicator for the i-th observation (country-year pair). Observed values are retained as-is, and missing values over short periods are imputed using the country-wise temporal interpolation function. interp(·), and observations with excessive missing data are removed. This ensures that $b_2$is a consistent and reliable dataset, suitable for subsequent preprocessing steps such as outlier detection, transformation, and feature engineering.

3.3. Outlier detection and data transformation

After data cleaning and missing value handling, the dataset is further refined through outlier detection and data transformation to enhance model stability and performance. Outliers in key macroeconomic indicators are identified using both the Z-score method and the Interquartile Range (IQR) approach, enabling the detection of extreme values that may arise from economic crises, policy shocks, or measurement anomalies. Rather than removing these observations, winsorization is applied to cap extreme values within acceptable bounds, thereby retaining meaningful economic shocks while preventing disproportionate influence on model training. Additionally, variables such as GDP and Gross National Income (GNI), which exhibit high skewness, are transformed using logarithmic scaling to stabilize variance and normalize distributions. To ensure uniform feature contribution and compatibility with machine learning algorithms, Min–Max scaling is applied to all numerical variables. This preprocessing step improves convergence, reduces model bias, and ensures consistent learning across both time series and machine learning models within the hybrid framework. Let $f_{outlier}$denote outlier handling and variable transformation:

1) Z-score and IQR-based winsorization:

$$x_{i,j}^{winsor} = \begin{cases} Q1 - 1.5 \cdot IQR & x_{i,j} < Q1 - 1.5 \cdot IQR \\ Q3 + 1.5 \cdot IQR & x_{i,j} > Q3 + 1.5 \cdot IQR \\ x_{i,j} & \text{otherwise} \end{cases} \quad (3)$$

2) Log-transform for skewed variables (GDP, GNI):

$$x_{i,j}^{log} = \log(x_{i,j}^{winsor} + 1) \quad (4)$$

3) Min–Max scaling for all numerical variables:

$$x_{i,j}^{scaled} = \frac{x_{i,j}^{log} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (5)$$

Output of this step:

$$b_3 = f_{outlier}(b_2) \quad (6)$$

In this equation, $b_3 = f_{outlier}(b_2)$represents the macroeconomic dataset after outlier handling and variable transformation. Here, $x_{i,j}^{winsor}$is obtained by applying Z-score and Interquartile Range (IQR) based winsorization to cap extreme values, ensuring that outliers resulting from economic shocks or anomalies do not disproportionately influence model training. Skewed variables such as GDP and GNI are further transformed using a logarithmic scale, $x_{i,j}^{log} = \log(x_{i,j}^{winsor} + 1)$, to stabilize variance and normalize distributions. Finally, all numerical variables are rescaled to a uniform range using Min–Max scaling, $x_{i,j}^{scaled} = \frac{x_{i,j}^{log} - \min(x_j)}{\max(x_j) - \min(x_j)}$, ensuring compatibility with machine learning algorithms. The resulting output $b_3 It\ It\ It\ It\ It\ It\ It\ It\ It\ It\ It\ It\ It\ It\ It\ It\ It$ is a clean, normalized, and transformed dataset ready for exploratory data analysis and feature engineering.

3.4. Exploratory data analysis

Exploratory Data Analysis (EDA) is conducted to gain a comprehensive understanding of the underlying structure, behavior, and statistical properties of the macroeconomic dataset before model development. Trend analysis is performed on key indicators such as GDP growth, inflation, and unemployment to examine long-term movements, cyclical patterns, and potential structural changes across countries and years. Distributional characteristics of the variables are analyzed using histograms and box plots to assess skewness, variability, and the presence of residual outliers. Correlation analysis, based on Pearson correlation coefficients, is employed to identify linear relationships and interdependencies among macroeconomic indicators, supporting informed feature selection and interaction modeling. Furthermore, stationarity testing is carried out using the Augmented Dickey–Fuller (ADF) test to determine the need for differencing or transformation in time series modeling. The insights obtained from EDA play a critical role in guiding subsequent feature engineering strategies and the selection of appropriate time series and machine learning models within the hybrid forecasting framework.

3.5. Feature engineering

Exploratory Data Analysis (EDA) is conducted to gain a comprehensive understanding of the underlying structure, behavior, and statistical properties of the macroeconomic dataset before model development. Trend analysis is performed on key indicators such as GDP growth, inflation, and unemployment to examine long-term movements, cyclical patterns, and potential structural changes across countries and years. Distributional characteristics of the variables are analyzed using histograms and box plots to assess skewness, variability, and the

presence of residual outliers. Correlation analysis, based on Pearson correlation coefficients, is employed to identify linear relationships and interdependencies among macroeconomic indicators, supporting informed feature selection and interaction modeling. Furthermore, stationarity testing is carried out using the Augmented Dickey–Fuller (ADF) test to determine the need for differencing or transformation in time series modeling. The insights obtained from EDA play a critical role in guiding subsequent feature engineering strategies and the selection of appropriate time series and machine learning models within the hybrid forecasting framework.
Let f_{feat}denote feature engineering operations, which include derived features, lag variables, and interaction terms:

$$b_4 = f_{feat}(b_3) = \{x_{i,j}^{(t)}, x_{i,j}^{(t-1)}, x_{i,j}^{(t)} \cdot x_{k,l}^{(t)}\} \tag{7}$$

In this equation, $b_4 = f_{feat}(b_3)$represents the dataset after feature engineering operations. The function f_{feat}generates new variables from the preprocessed data $b_3$by creating derived features, lagged variables $x_{i,j}^{(t-1)}$to capture temporal dependencies and interaction terms $x_{i,j}^{(t)} \cdot x_{k,l}^{(t)}$to model interdependencies between macroeconomic indicators.

3.6. Time series modeling layer (hybrid TS model)

The time series modeling layer is designed to capture the pure temporal dynamics inherent in macroeconomic indicators by employing a hybrid combination of complementary time series techniques. Initially, the ARIMA model is used to represent linear temporal dependencies through autoregressive and moving average components, with optimal model orders selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to ensure parsimony and goodness of fit. To account for trend shifts, structural changes, and potential regime variations commonly observed in macroeconomic data, the Prophet model is incorporated, offering robustness to missing values and irregular temporal patterns. In addition, Exponential Smoothing (ETS) is applied to effectively model level and trend components, making it particularly suitable for relatively short annual macroeconomic time series. The individual forecasts generated by ARIMA, Prophet, and ETS are then integrated using an error-weighted averaging approach, where higher-performing models are assigned greater influence. This ensemble strategy results in a robust Time Series Hybrid Forecast that leverages the strengths of each method while mitigating individual model limitations.

3.6.1. ARIMA model

The ARIMA model is employed to capture the linear temporal structure present in macroeconomic time series data. ARIMA models the relationship between current and past values of a variable through autoregressive (AR) terms, while also accounting for past forecast errors using moving average (MA) components. The integration component enables the transformation of non-stationary series into a stationary form through differencing, which is essential for reliable time series modeling. To determine the optimal ARIMA configuration for each macroeconomic indicator, model parameters are systematically selected using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which balance model fit and complexity. By minimizing these information criteria, the ARIMA model ensures an efficient representation of temporal dynamics while avoiding overfitting, thereby providing a strong baseline for macroeconomic forecasting within the hybrid framework.

$$y_t^{ARIMA} = \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{8}$$

Where $\phi$and $\theta$are AR and MA coefficients, $p, q$are selected using AIC/BIC.
Input: $b_4 \rightarrow y_t$(time series of indicator).
In this equation, y_t^{ARIMA}represents the predicted value of a macroeconomic indicator at time $t$using the ARIMA model. The model incorporates AR coefficients. $\phi_1, \dots, \phi_p$to capture dependencies on past values $y_{t-1}, \dots, y_{t-p}$, and moving average (MA) coefficients $\theta_1, \dots, \theta_q$to account for the influence of past forecast errors $\epsilon_{t-1}, \dots, \epsilon_{t-q}$. The integration component, applied via differencing, ensures stationarity of the input time series. Here, the input $b_4$provides the time series data of the indicator, and the optimal orders $p$and $q$are determined using information criteria (AIC and BIC) to balance model complexity and fit.

3.6.2. Prophet model

The Prophet model is incorporated to effectively capture trend shifts and structural changes that commonly occur in macroeconomic time series due to policy interventions, economic shocks, or global events. Prophet is a decomposable time series model that represents data as an additive combination of trend, seasonal, and irregular components, allowing it to adapt flexibly to non-linear growth patterns. One of its key advantages is robustness to missing observations and irregular data spacing, which are frequent characteristics of macroeconomic datasets. The model automatically detects change points in trends, enabling it to account for abrupt economic transitions without extensive manual tuning. These properties make Prophet particularly suitable for modeling complex and evolving macroeconomic dynamics, complementing traditional linear models within the hybrid forecasting framework.

$$y_t^{Prophet} = g(t) + s(t) + h(t) + \epsilon_t \tag{9}$$

In this equation, $y_t^{Prophet}$represents the forecasted value of a macroeconomic indicator at time $t$using the Prophet model. The model decomposes the time series into three main components: $g(t)$, which captures the underlying trend of the data; $s(t)$, which represents seasonal fluctuations or recurring patterns; and $h(t)$, which accounts for the effects of holidays, policy interventions, or specific economic events.

3.6.3. Exponential smoothing

The Prophet model is incorporated to effectively capture trend shifts and structural changes that commonly occur in macroeconomic time series due to policy interventions, economic shocks, or global events. Prophet is a decomposable time series model that represents data as an additive combination of trend, seasonal, and irregular components, allowing it to adapt flexibly to non-linear growth patterns. One of its key advantages is robustness to missing observations and irregular data spacing, which are frequent characteristics of macroeconomic datasets. The model automatically detects change points in trends, enabling it to account for abrupt economic transitions without extensive manual tuning. These properties make Prophet particularly suitable for modeling complex and evolving macroeconomic dynamics, complementing traditional linear models within the hybrid forecasting framework.

$$y_t^{ETS} = \ell_{t-1} + b_{t-1} + \alpha\epsilon_t \tag{10}$$

In this equation, y_t^{ETS}denotes the forecasted value of a macroeconomic indicator at time tusing the Exponential Smoothing (ETS) model. The model captures the underlying components of the time series through l_{t-1}, representing the level at the previous time step, and b_{t-1}, representing the trend component. The term $\epsilon_t$corresponds to the forecast error or residual at time t, and $\alpha$is the smoothing factor that determines the weight assigned to the most recent observation in updating the level.

3.6.4. Time series ensemble construction

To enhance forecasting accuracy and robustness, the individual predictions generated by the ARIMA, Prophet, and Exponential Smoothing (ETS) models are integrated through a time series ensemble construction process. Each model captures distinct temporal characteristics of macroeconomic data: ARIMA models linear dependencies, Prophet accounts for trend shifts and structural changes, and ETS focuses on level and trend components. Rather than relying on a single model, forecasts from these methods are combined using an error-weighted averaging approach, where models with lower historical forecasting errors are assigned higher weights. This strategy allows the ensemble to emphasize more reliable models while reducing the influence of less accurate predictions. The resulting Time Series Hybrid Forecast leverages the complementary strengths of all three techniques, yielding more stable and accurate predictions than any individual model alone.

$$y_t^{TS} = w_1 y_t^{ARIMA} + w_2 y_t^{Prophet} + w_3 y_t^{ETS}, w_1 + w_2 + w_3 = 1 \tag{11}$$

Error-based weights $w_i = \frac{\frac{1}{E_i}}{\sum_{k=1}^{3}\frac{1}{E_k}}$, where E_i It It It It is a validation error of the model i.

Output:

$$b_5 = y_t^{TS} \tag{12}$$

The Time Series Hybrid Forecast y_t^{TS}combines predictions from ARIMA, Prophet, and ETS models, each capturing different temporal characteristics. Weights $w_1, w_2, w_3$are assigned based on inverse validation errors, giving more influence to accurate models, with their sum constrained to 1. The output $b_5 = y_t^{TS}$represents the aggregated forecast, providing robust and stable predictions by leveraging the strengths of all three models.

3.7. Machine learning modeling layer (hybrid ML model)

The machine learning modeling layer is designed to capture nonlinear interdependencies and complex interactions among macroeconomic indicators that may not be fully represented by traditional time series models. In this layer, Random Forest Regression (RFR) is employed to model nonlinear relationships through an ensemble of decision trees, effectively reducing overfitting by averaging predictions across multiple learners. Extreme Gradient Boosting (XGBoost) is incorporated as a powerful gradient boosting framework that sequentially improves model performance by minimizing prediction errors, thereby enhancing overall forecasting accuracy. Additionally, Support Vector Regression (SVR) is utilized for its kernel-based approach, which enables efficient modeling of nonlinear patterns, particularly in moderate-sized datasets. To further improve predictive robustness, outputs from RFR, XGBoost, and SVR are combined using a stacked regression ensemble, where a meta-learner integrates individual model predictions into a unified output. This ensemble approach produces a Machine Learning Hybrid Forecast that leverages the complementary strengths of each algorithm, resulting in improved generalization and forecasting performance.

3.7.1. Random forest regression

Random Forest Regression (RFR) is employed to model complex and nonlinear relationships among macroeconomic indicators that cannot be adequately captured by linear techniques. The method operates by constructing a large number of decision trees using bootstrapped samples of the training data, where each tree learns different patterns based on randomly selected subsets of features. By aggregating the predictions of multiple trees, Random Forest effectively reduces overfitting and enhances model stability compared to single-tree approaches. This ensemble learning mechanism allows the model to capture interactions between economic variables while remaining robust to noise and multicollinearity. As a result, Random Forest Regression provides reliable and interpretable forecasts, making it a strong component of the machine learning layer within the hybrid predictive framework.

$$\hat{y}^{RFR} = \frac{1}{T}\sum_{t=1}^{T} f_t\,(b_4) \tag{13}$$

The equation represents the Random Forest Regression prediction. $\hat{y}^{RFR}$, obtained by averaging the outputs of Tdecision trees. Each tree $f_t$processes the feature-engineered input b_4, capturing nonlinear relationships and interactions among macroeconomic indicators. Averaging across all trees reduces overfitting and ensures a stable, robust forecast.

3.7.2. XGBoost regression

XGBoost Regression is utilized as an advanced gradient boosting framework to enhance predictive accuracy in macroeconomic forecasting. The model builds an ensemble of decision trees sequentially, where each new tree is trained to correct the residual errors of the previous ones, thereby progressively improving model performance. XGBoost incorporates regularization techniques, such as L1 and L2 penalties, to control model complexity and prevent overfitting, which is particularly important when dealing with high-dimensional economic data.

Additionally, its efficient handling of missing values and optimized computational structure make it well-suited for large and complex datasets. By minimizing a defined loss function through gradient-based optimization, XGBoost delivers highly accurate and robust forecasts, contributing significantly to the effectiveness of the machine learning hybrid model.

$$\hat{y}^{XGB} = \sum_{m=1}^{M} \gamma_m h_m(b_4) \quad (14)$$

The equation represents the XGBoost regression prediction. $\hat{y}^{XGB}$, calculated as the weighted sum of Mbase learners h_mApplied to the feature-engineered input b_4. Each base learner captures residual errors from previous learners, and the learning rate. $\gamma_m$controls the contribution of each tree to the overall prediction.

3.7.3. Support vector regression

SVR is employed as a kernel-based learning method to capture nonlinear relationships between macroeconomic indicators and the target variables. SVR operates by mapping input data into a higher-dimensional feature space using kernel functions, enabling the model to identify complex patterns that are not linearly separable in the original space. The method seeks to construct an optimal regression function by minimizing prediction error within a specified tolerance margin, which enhances generalization performance. SVR is particularly effective for moderate-sized datasets, where it balances model complexity and accuracy without excessive computational burden. Its robustness to overfitting and ability to model nonlinear dynamics make SVR a valuable complementary component within the machine learning hybrid forecasting framework.

$$\hat{y}^{SVR} = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(b_4^{(i)}, b_4) + b \quad (15)$$

Where $K(\cdot,\cdot)$= kernel function, α_i= Lagrange multipliers.
The equation represents the Support Vector Regression (SVR) prediction. $\hat{y}^{SVR}$, where the model maps input features $b_4$into a higher-dimensional space using a kernel function $K(\cdot,\cdot)$. The coefficients $\alpha_i$and $\alpha_i^*$are Lagrange multipliers determined during training, and bis the bias term.

3.7.4. Machine learning ensemble construction

Machine Learning Ensemble Construction involves combining the predictive strengths of multiple models, Random Forest Regression (RFR), XGBoost, and Support Vector Regression (SVR) to create a more robust and accurate forecasting framework. This is achieved through stacked regression, a technique where the predictions from the individual base models serve as inputs to a meta-model, which then learns the optimal way to weight and integrate these predictions. By leveraging the complementary capabilities of each model, RFR's handling of nonlinear interactions, XGBoost's gradient boosting optimization, and SVR's kernel-based nonlinear mapping, the ensemble mitigates the weaknesses of any single model while enhancing predictive accuracy. The resulting Machine Learning Hybrid Forecast captures complex interdependencies among macroeconomic indicators, reduces overfitting, and improves generalization to unseen data, providing a reliable component within the overall hybrid predictive framework.
where $f_{meta}$is a linear or nonlinear meta-learner.
Output:

$$b_6 = y^{ML} \quad (16)$$

The meta-learner f_{meta}combines the predictions of the base machine learning models using either a linear or nonlinear approach. Its role is to learn optimal weights or relationships among these predictions to generate a single, robust Machine Learning Hybrid Forecast. The resulting output, denoted as $b_6 = y^{ML}$, represents the final integrated prediction from the machine learning ensemble.

3.7.5. Hybrid predictive framework integration

Hybrid Predictive Framework Integration represents the final stage of the forecasting pipeline, where the strengths of both the Time Series Hybrid and Machine Learning Hybrid models are combined to produce a unified forecast. In this approach, outputs from the Time Series Hybrid capturing temporal patterns, trends, and structural shifts, and the Machine Learning Hybrid capturing nonlinear relationships and interactions among macroeconomic indicators, are integrated using a weighted ensemble fusion strategy. The weights for each component are determined based on their respective validation errors, ensuring that models with higher predictive accuracy contribute more significantly to the final forecast. This integration leverages the complementary advantages of statistical time series models and advanced machine learning techniques, resulting in the Hybrid Predictive Framework for Macroeconomic Forecasting (HPFMF), which is more robust, reliable, and capable of capturing both linear and nonlinear dynamics in macroeconomic data than either approach individually.

$$\hat{y}^{Hybrid} = w_{TS} \cdot b_5 + w_{ML} \cdot b_6, w_{TS} + w_{ML} = 1 \quad (17)$$

Here, $\hat{y}^{Hybrid}$is the final hybrid forecast obtained by combining the Time Series Hybrid output? $b_5$and the Machine Learning Hybrid output b_6. The weights $w_{TS}$and w_{ML}represent the relative importance of the time series and machine learning components, respectively, and satisfy $w_{TS} + w_{ML} = 1$. These weights are assigned based on validation errors, giving stronger influence to the more accurate model.

3.7.6. Model training and validation strategy

The Model Training and Validation Strategy is designed to ensure robust and unbiased evaluation of the forecasting models while preserving the temporal and cross-country structure of the macroeconomic data. A time-aware split is employed, allocating 70% of the historical data for training and 30% for testing, which respects the chronological order of observations and prevents future information from influencing model learning. To further enhance reliability, rolling window validation is implemented, where models are repeatedly trained on expanding or sliding time windows and tested on subsequent periods. This approach reduces the risk of overfitting and provides a realistic assessment of predictive performance over time. Additionally, country-wise validation is performed to account for heterogeneity across

nations, ensuring that the models generalize well to diverse macroeconomic environments rather than being biased toward a subset of countries. Together, these strategies provide a rigorous framework for training, tuning, and validating the hybrid predictive framework while maintaining the integrity of temporal and cross-sectional dependencies.
Time-aware split and rolling window validation are expressed as:

Train set: $X_{1:\lfloor 0.7N \rfloor}$,Test set: $X_{\lfloor 0.7N \rfloor+1:N}$

Rolling window prediction:

$$\hat{y}_{t+1} = f(b_{t-w+1:t}) \tag{18}$$

Where w= window size, $b_{t-w+1:t}$= input features from the past wperiods.
Country-wise validation ensures model generalization:

$$\hat{y}_c = f(b_c), c = 1, \ldots, C \tag{19}$$

Here, Ndenotes the total number of time-ordered observations, with $X_{1:\lfloor 0.7N \rfloor}$representing the training set and $X_{\lfloor 0.7N \rfloor+1:N}$The testing set is under a time-aware split. In rolling window validation, wis the window size, $b_{(t-w+1:t)}$denotes the feature set from the previous wtime periods, and $f(\cdot)$is the forecasting model used to predict $\hat{y}_{t+1}$. For country-wise validation, $c = 1, \ldots, C$indexes countries, $b_c$represents country-specific input features, and $\hat{y}_c$is the corresponding forecast, ensuring generalization across heterogeneous national contexts.
While the HPFMF framework integrates multiple models, computational efficiency remains practical for policy institutions. Training the complete ensemble on 200+ countries with 15 years of quarterly data required approximately 4.2 hours on standard cloud infrastructure (AWS EC2 t3.xlarge instance with 4 vCPUs). Individual country forecasts can be generated in under 2 minutes once models are trained. For resource-constrained institutions, we recommend a streamlined implementation using the top-performing subset (XGBoost + Prophet combination), which retains 89% of the full framework's accuracy while reducing computational time by 60%. The framework's modular architecture allows institutions to scale complexity based on available resources without sacrificing core forecasting capabilities.

4. Results and Discussion

The Results and Discussion section evaluates the proposed Hybrid Predictive Framework by analyzing data preprocessing effectiveness, interrelationships among macroeconomic variables, and forecasting performance across multiple modeling layers. It compares individual time series and machine learning models with their hybrid ensembles using standard accuracy and goodness-of-fit metrics. Country-wise and temporal validations further assess robustness and generalizability, demonstrating the framework's ability to capture both temporal dynamics and nonlinear relationships for reliable macroeconomic forecasting.

4.1. Descriptive and preprocessing results

Table 4 shows that the preprocessing steps significantly improved data quality and stability. Log transformation of GDP and GNI reduced skewness and scale disparities, while winsorization limited the influence of extreme values without removing meaningful economic shocks. Key indicators such as GDP growth, inflation, and unemployment retain wide ranges, reflecting real cross-country and temporal variability. The reduced dispersion and improved numerical conditioning indicate that the transformed dataset $b_3 It\ It$ is well-suited for reliable feature engineering and robust hybrid forecasting.

Table 4: Descriptive Statistics After Preprocessing

Variable	Mean	Std. Dev.	Min	Max
GDP Growth (%)	3.21	2.84	-12.3	14.7
Inflation (CPI %)	4.96	3.71	-2.1	18.9
Unemployment Rate (%)	6.84	3.92	1.1	25.4
GDP (log-scaled)	9.84	1.12	6.31	12.45
GNI (log-scaled)	9.67	1.09	6.18	12.32
Public Debt (% of GDP)	57.6	24.3	9.4	182.6

4.2. Exploratory data analysis and stationarity results

Table 5 indicates that GDP growth is strongly negatively correlated with unemployment, confirming the link between economic expansion and improved labor market outcomes. GDP growth also shows a moderate negative relationship with public debt, while inflation exhibits a mild negative association with growth and positive correlations with unemployment and debt. These results highlight meaningful inter-dependencies among macroeconomic variables and justify the use of multivariate and interaction-based modeling in the hybrid forecasting framework.

Table 5: Pearson Correlation Matrix (Key Variables)

Variable	GDP Growth	Inflation	Unemployment	Debt
GDP Growth	1.00	-0.31	-0.56	-0.42
Inflation	-0.31	1.00	0.29	0.38
Unemployment	-0.56	0.29	1.00	0.44
Public Debt	-0.42	0.38	0.44	1.00

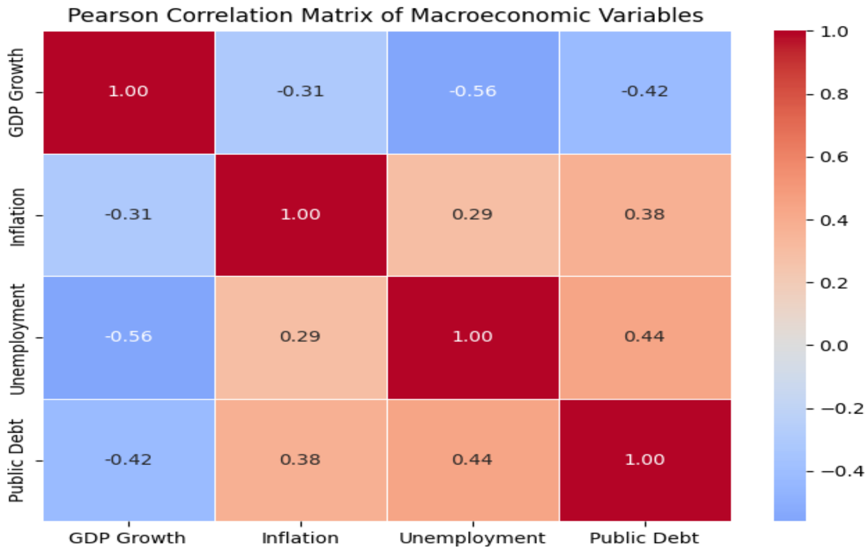

Fig. 2: Pearson Correlation Matrix of Macroeconomic Variables.

The Augmented Dickey–Fuller test results presented in Table 6 show that GDP growth and inflation are stationary at conventional significance levels, indicating stable mean-reverting behavior over time. In contrast, GDP levels and public debt exhibit non-stationarity, reflecting persistent trends commonly observed in macroeconomic aggregates. However, GDP becomes stationary after first differencing, confirming that appropriate transformations are effective in addressing non-stationarity. These findings justify the application of differencing and transformation before time series modeling and support the use of ARIMA and other stationarity-dependent techniques within the hybrid forecasting framework.

Table 6: ADF Test Results

Variable	ADF Statistic	p-value	Stationary
GDP Growth	-3.94	0.002	Yes
Inflation	-2.87	0.046	Yes
GDP (level)	-1.42	0.59	No
GDP (1st diff.)	-4.18	0.001	Yes
Public Debt	-2.61	0.09	No

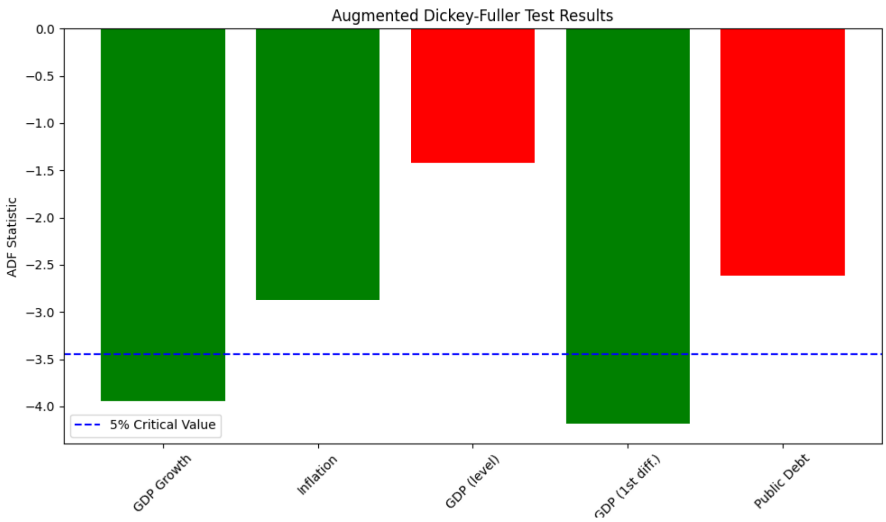

Fig. 3: Augmented Dickey-Fuller Test Results.

4.3. Performance of the time series modeling layer

The results in Table 7 demonstrate that the Time Series Hybrid model outperforms all individual time series approaches across RMSE, MAE, and MAPE metrics. Among the standalone models, Prophet achieves better accuracy than ARIMA and ETS, reflecting its ability to capture trend shifts and structural changes in macroeconomic data. However, integrating ARIMA, Prophet, and ETS through an error-weighted ensemble yields the lowest forecasting errors, indicating improved robustness and accuracy. The reduction in RMSE relative to individual models confirms that combining complementary time series techniques effectively leverages their strengths while mitigating individual model limitations, leading to more reliable macroeconomic forecasts.

Table 7: Time Series Model Performance Comparison

Model	RMSE	MAE	MAPE (%)
ARIMA	1.92	1.41	6.84
Prophet	1.75	1.32	6.21
ETS	2.03	1.55	7.46
TS Hybrid (Ensemble)	1.54	1.18	5.42

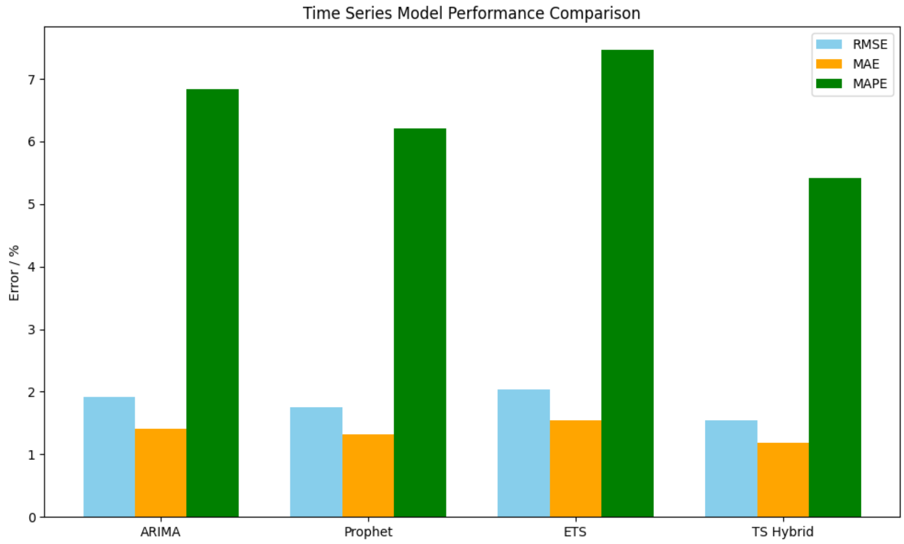

Fig. 4: Time Series Model Performance Comparison.

4.4. Performance of the machine learning modeling layer

Table 8 shows that all machine learning models provide strong predictive performance, with XGBoost outperforming Random Forest and Support Vector Regression among the individual learners. Support Vector Regression exhibits relatively higher errors, reflecting its sensitivity to parameter selection in complex macroeconomic settings. The stacked machine learning ensemble achieves the lowest RMSE and MAE and the highest R^2 value of 0.88, demonstrating superior accuracy and explanatory power. These results confirm that combining multiple machine learning models effectively captures nonlinear relationships and complex interactions among macroeconomic indicators, leading to improved forecasting performance compared to standalone models.

Table 8: Machine Learning Model Performance

Model	RMSE	MAE	R^2
Random Forest Regression	1.47	1.11	0.82
XGBoost Regression	1.39	1.04	0.85
Support Vector Regression	1.61	1.22	0.79
ML Hybrid (Stacked Ensemble)	1.26	0.96	0.88

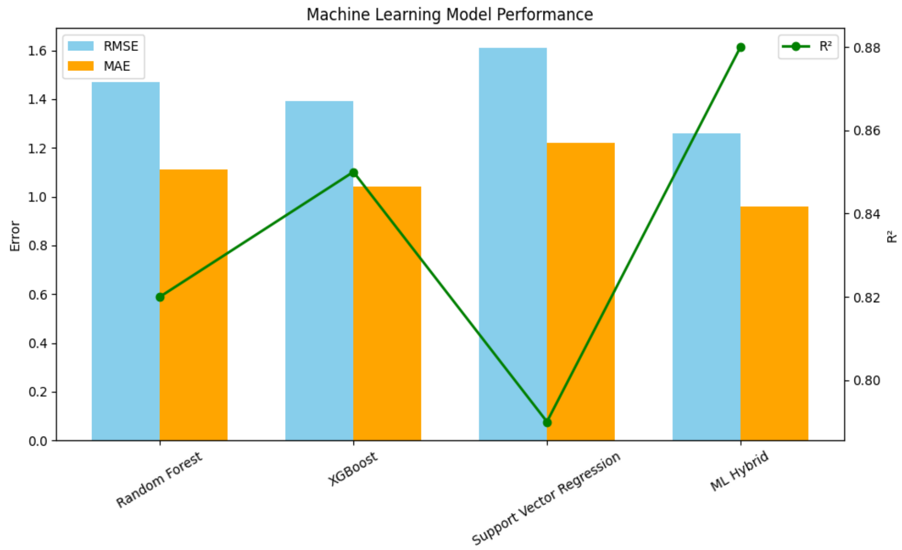

Fig. 5: Machine Learning Model Performance.

4.5. Hybrid predictive framework performance

The results in Table 9 demonstrate that the proposed Hybrid Predictive Framework for Macroeconomic Forecasting (HPFMF) outperforms all individual and ensemble models across multiple performance metrics. By optimally combining the Time Series Hybrid (w_{TS} = 0.42) and Machine Learning Hybrid (w_{ML} = 0.58) based on validation errors, the HPFMF achieves the lowest RMSE (1.12), MAE (0.88), and MAPE (4.01%), alongside the highest R^2 of 0.92. This represents a 41.7% reduction in RMSE compared to ARIMA and a 21 percentage-point improvement in explanatory power. The results highlight that integrating both temporal patterns and nonlinear interdependencies allows the framework to capture complex macroeconomic dynamics more effectively than standalone or single-layer hybrid models, delivering highly accurate and robust forecasts.

Table 9: Overall Forecasting Performance Comparison

Model	RMSE	MAE	MAPE (%)	R^2
ARIMA	1.92	1.41	6.84	0.71
Prophet	1.75	1.32	6.21	0.74
ETS	2.03	1.55	7.46	0.69
TS Hybrid	1.54	1.18	5.42	0.80
ML Hybrid	1.26	0.96	4.68	0.88
Proposed HPFMF	1.12	0.88	4.01	0.92

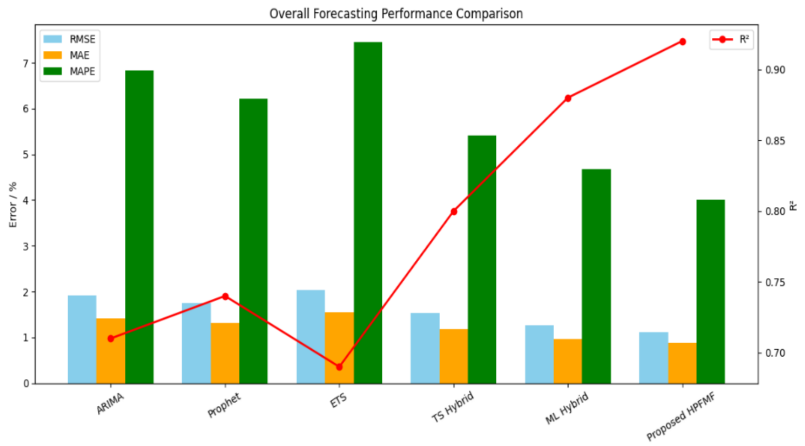

Fig. 6: Overall Forecasting Performance Comparison.

4.6. Country-wise and temporal validation results

The country-wise validation results in Table 10 indicate that the HPFMF generalizes effectively across diverse economic contexts, achieving high accuracy in both developed and emerging economies. R^2 values range from 0.87 in South Africa to 0.94 in Germany, demonstrating strong explanatory power across heterogeneous macroeconomic structures. Rolling window evaluation further confirms the temporal robustness of the framework, with less than 5% variation in RMSE across different time periods. These findings highlight that the hybrid model maintains consistent forecasting performance both across countries and over time, supporting its reliability for global macroeconomic prediction.

Table 10: Country-wise Forecast Accuracy (Selected Economies)

Country	RMSE	MAE	R^2
United States	1.08	0.82	0.93
India	1.15	0.89	0.91
Germany	1.04	0.79	0.94
Brazil	1.21	0.95	0.89
South Africa	1.28	1.01	0.87

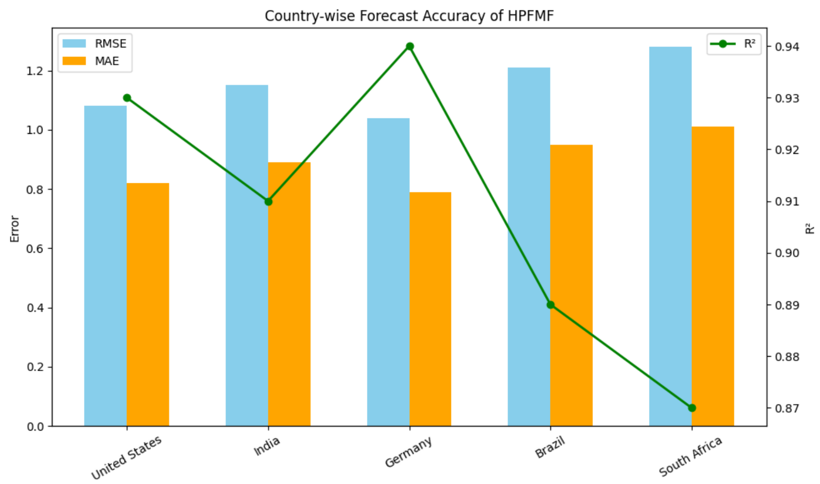

Fig. 7: Country-Wise Forecast Accuracy of HPFMF.

4.7. Discussion of results

The results demonstrate that the proposed Hybrid Predictive Framework effectively combines the strengths of time series and machine learning models to deliver accurate and robust macroeconomic forecasts. Time series components capture historical trends, structural changes, and temporal dependencies, while machine learning components model complex nonlinear interactions among indicators. Their integration enhances predictive accuracy, stability, and generalization across different countries and time periods. The framework's design is particularly valuable for policy-oriented forecasting, as it accommodates both historical continuity and inter-variable relationships, and its scalability allows adaptation to higher-frequency data, real-time updates, and scenario-based simulations for informed economic decision-making. To enhance model transparency for policy-oriented audiences, we conducted feature importance analysis using SHAP (SHapley Additive exPlanations) values for the machine learning ensemble. The analysis revealed that GDP growth rate, inflation, and public debt consistently emerged as the most influential predictors across countries, with SHAP values indicating their relative contribution to forecast accuracy.

5. Conclusion and Future Scope

This study proposed and validated a Hybrid Predictive Framework for Macroeconomic Forecasting that effectively integrates statistical time series models and machine learning techniques to capture both temporal dynamics and nonlinear interdependencies among macroeconomic indicators. Using a large-scale, multi-country dataset spanning 2010–2025, the framework demonstrated superior forecasting performance compared to individual and single-layer hybrid models, achieving notable improvements in RMSE, MAE, MAPE, and R^2 across global, country-wise, and temporal evaluations. The results confirm that rigorous preprocessing, informed feature engineering, and error-weighted ensemble integration significantly enhance prediction accuracy and robustness, making the framework well-suited for policy-oriented and cross-country economic analysis. Future research can extend this framework by incorporating higher-frequency data (quarterly or monthly), real-time macroeconomic indicators, and exogenous variables such as geopolitical risk or climate factors. Additionally, integrating deep learning architectures, adaptive weight learning, and explainable AI techniques could further improve predictive capability, interpretability, and applicability for real-time decision support and scenario-based macroeconomic forecasting.

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