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Predicting financial cycles with dynamic ensemble selection frameworks using leading, coincident and lagging indicators

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ABSTRACT

This paper develops a model for predicting financial cycles in India, and defines leading, coincident, and lagging indicators to achieve the research objective. The dependent variable is binary, and Synthetic Minority Oversampling Technique (SMOTE) is used for correcting imbalances in the dataset. The study utilizes six distinct Dynamic Ensemble Selection (DES) models, and five different pools of classifiers. Explainable Artificial Intelligence (XAI) is used to identify feature importance. The predictive framework is applied to different time periods with distinct characteristics, and all the DES frameworks yield efficient forecasts. The importance and role of the indicators, however, differ among phases. Our results show, that while during CYCLE phases, exchange rate fluctuations play a significant role in explaining financial cycles, in an UPWARD expansionary phase, expansion in bank credit, capital formation, and realty growth are significant factors. During a DOWNWARD phase and a bearish environment, VIX and oil prices emerge significant.

1. Introduction

The 2008 global financial crisis (GFC) led to surging academic interests in exploring the contributions of financial cycles (med-term divergences of financial markets from their longer-term pattern of movements) (Magubane, 2024) to the inherent dynamics of financial sector growth with real sector growth and economic development (King and Levine, 1993; Levine, 1997; Aghion et al., 2004; Rajan and Zingales, 1998; Samargandi et al., 2015; Dell'Ariccia, Marquez, 2006). These cycles promulgate economic shocks (Bernanke and Gertler, 1989; Gertler and Karadi, 2011), and affect business cycles, triggering financial disruptions that often end with great recessions (Borio, 2014; Oman, 2019). Further, financial cycles possess the power of forecasting systematic financial crises relative to other macroeconomic cycles, e.g., business cycles, due to its close nexus with the fluctuations in the financial system (e.g., financial booms and busts) (Borio, 2014; Oman, 2019). Moreover, it is considered important to review how the domestic macroeconomic environment will take shape in the future, and how the financial sector and the real sector will interact to impact future outcomes in the increasingly globalised world (Yadav et al., 2023). At present, shocks in various parts of the world have domestic ripple effects in other

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economies. For instance, a change in the US Fed Rate affects inflow or outflow of foreign exchange in the developing world (Abedin et al., 2023). Recently, around September 2024, in response to US policies, India observed large scale financial capital outflow which led to stock market crash. In the past, change in the US Fed Rate has caused financial capital outflow. Further, the ongoing Russia-Ukraine and Israel-Iran conflicts have had adverse effects on oil prices, goods movements and also international air traffic (Bouteska et al., 2025). As India is a large importer of crude oil, and more than eighty percent of its import bill consists of payment for crude oil, these ongoing conflicts have caused concerns regarding availability of oil in the country, and also in its pricing. These events are having significant effects on the Indian financial market. In the context of identifying and predicting business cycles, OECD (as cited in Ha et al., 2024) defined composite leading indicators (CLIs), and the construction of CLIs depends on leading, coincident, and lagging indicators.

In light of the above backdrop, this paper defines leading, coincident and lagging indicators, using stock market indices of the National Stock Exchange (NSE), and develops a model for predicting financial cycles in India. While predictions using coincident and lagged indicators only assume that the future can be explained by past events, they remain sensitive to unexpected events. Use of leading indicators minimizes this surprise element, and this paper defines some indicators that give some insight into the future macroeconomic environment of the economy. Methodologically, this study utilises six distinct Dynamic Ensemble Selection (DES) models, namely, K- Nearest Oracle Elimination (KNORAE), K-Nearest Oracle Union (KNORAU), Meta-Learning for Dynamic Ensemble Selection (METADES), Dynamic Ensemble Selection Performance (DESP), Dynamic Ensemble Selection-K Nearest Neighbor (DESKNN), and Dynamic Ensemble Selection Randomized Reference Classifier (DESRRC) for predicting financial cycles. For implementing the DES models, the homogeneous pool of classifiers considered for modelling are Random Forest (RF), Bagging (BG), Gradient Boosting (GB), and Extreme Gradient Boosting (XGB). The heterogeneous pools are simulated through pooling framework combing Support Vector Machine (SVM), K Nearest Neighbor (KNN), Decision Tree (DT), and Logistic Regression (LR). Despite the recent surge and traction toward DES frameworks in resolving predictive analytics tasks (De Carvalho et al., 2025), their financial time series modeling applications are scarce. The different DES methodologies are built to be immune to data bias, which makes them robust for deployment in solving regression and classification tasks. The present study contributes to the said strand of literature by leveraging the capability of DES models in predicting financial cycle states in India.

The overall findings of the paper duly rationalize the efficacy of the DES methodologies in accurately predicting the dynamics of financial cycle in Indian context. The accuracy differs across different time regimes. Among the explanatory features, coincident and lagging indicators transpire to be relatively more prudent in predicting the financial cycles in classification frameworks. This present paper will help in policy intervention, as it defines appropriate variables that need to be monitored. Further, the predictive methodology will help in early detection of symptoms of distress.

This study has at least three novel aspects. First, we develop a model for predicting financial cycles using stock market indices of the NSU (India). This approach is useful as stock market constructs represent financial and real sector variables well, as Bouteska et al. (2025) demonstrated. The associated indicators for the study will be defined and explained in a separate section in the paper, and this is a novel aspect of the paper. The second novel aspect is the definition of a financial cycle. The literature on business cycles has focused on the difference between actual output and potential output to identify the phase of a cycle. To define potential output, they have used the Beveridge and Nelson (1981) method, the Hodrick and Prescott (1997) filter, and methods proposed by Baxter and King (1999) and Christiano and Fitzgerald (2003). Beveridge and Nelson (1981) leveraged econometric modelling for defining financial cycles. Hodrick and Prescott (1997) also presented a time series decomposition framework for disentangling trends and cyclical components to define financial cycle movements. Baxter and King (1999) developed an approximate band-pass filter for extracting business cycles. Christiano and Fitzgerald (2003) also developed an alternative model for a band-pass filter and extended the same to unveil business cycles. The underlying work leverages a classification framework for defining and estimating the financial cycle in the Indian context. The third novel aspect is the application of DES-based methodologies to model financial cycles in India. Unlike orthodox ensemble machine learning algorithms, DES methods dynamically selects and combines a subset of homogeneous or heterogeneous base classifiers to suitably conduct complex pattern recognition problems. The capacity to choose and realign the base classifiers based on different criteria provides an additional edge to DES tools over the conventional ones. Considering the research problem under consideration, proper usage of DES will be highly beneficial to detect the movements of financial cycles in turbulent external environments.

The remainder of this paper proceeds as follows. A literature survey is presented in Section 2 to position the paper and identify the gaps. The variables used to understand a financial cycle and their determinants are defined and discussed Section 3. Section 4 discusses in detail the different components of the integrated classification framework, and the methodological lens of Artificial Intelligence (XAI). Section 5 presents the results and Section 6 discusses the key findings and practical implications of the present work. Section 7 draws conclusions.

2. Literature review

This section presents a literature review to position the present research work and relate it to the ideas that have been explored in the area of predicting financial cycles and business cycles. Further, research work using the proposed methodology is discussed.

2.1. Financial cycles

As one of the pioneering works, Bernanke and Gertler (1989) developed a dynamic general equilibrium model that incorporates the role of credit market frictions in business fluctuations. Their framework shows that developments in credit markets amplify and induce shocks to the macroeconomy. They propose that asymmetric information and financial distress among firms can cause real cycles to deepen. In the present paper, firm performance is incorporated through the sectoral indices, and financial distress among firms will have an impact on these indices. Incorporating the banking sector index represents credit market conditions and firm performance. However, the importance of financial cycles and their interaction with the macroeconomy has gained increased attention since the 2007–08 financial crisis (Liu et al., 2024; Mahmood et al., 2024). Domanski and Ng (2011) related financial cycles to swings in credit growth, asset prices, liquidity, financing constraints, and other financial indicators. Borio (2014) stated that understanding financial cycles is essential to understanding business cycles and emphasizes on specific characteristics of financial cycles. These include movement in credit and property prices, peaks in financial cycles being associated with banking crisis, and movement in property prices away from the norm. It is also postulated that a financial cycle works through market participants' perceptions of risk and financing constraints. Claessens et al. (2010), (2012) emphasize on credit, equity and housing cycles. The present research work includes variables representing the banking sector and the realty sector. Rey, (2018) argued that the global financial cycle co-moves with the VIX index, which resembles aggregate market risk perceptions and uncertainty. In the present research, credit growth and risk perception indicators like VIX are included. Findings by Ma and Zhang (2016) suggested that the financial cycle exerted a significant influence on business cycle dynamics and macroeconomic fluctuations during financially unstable periods. The role of the financial cycle in predicting foreign exchange rates has been acknowledged by Raheem and Vo (2022).

Menden and Proaño (2017) aimed to develop a measure of the financial cycle based on a broad set of macro-financial indicators using the dynamic factor model approach. The explanatory variables include interest rate spreads, VIX, consumer survey indices, consumer credit outstanding as a percentage of GDP, and a measure of money supply. In this paper, the explanatory variables considered include VIX, stock market indices on the consumption basket, bank credit, and capacity utilization. Through a large sample of advanced and emerging economies, Beirne (2020) found that equity market cycles in emerging market economies may be more useful in identifying financial cycles, as compared to cycles in credit and property markets. Thus, the use of stock market indices in this paper to analyze and predict financial cycles, finds support. Škare and Porada-Rochoń (2020) used spectral Granger causality to analyze the synchronization between business and financial cycles in the UK. For identifying real cycles, real GDP at market prices is considered. For identifying financial cycles, the variables considered are the real house price index, credit, and credit to GDP ratio in England. Multi-channel singular-spectrum Analysis (MSSA) is used to reconstruct the time series on the three variables to get financial cycles. Their approach allows robust identification of oscillatory patterns (cycles) in the house price index, credit, and credit to GDP ratio. Further, these cycles vary over time. The present research work incorporates realty index and bank index as explanatory variables. Adarov, (2022) integrated dynamic factor model and state space techniques to extract regional and financial cycles for several advanced and developing countries, integrating variables manifesting conveying price, quantity, and risk dynamics in credit, housing, bond, and equity markets. The said cycles appeared to be indicative of major financial distress episodes. Lv et al. (2023) explored the relationship between financial cycles and economic development. In today's globalization era, where financial markets of different economies have become interconnected, it is important to study the extent of the persistence of financial cycles. Using a nonlinear smoothing transition autoregressive (STAR) model, they find that national financial cycles exhibit more prolonged expansions and faster contraction trends. Tian et al. (2024) utilized the dynamic factor model to advance alternative models for global financial cycles for emerging and developing economies. It was also observed that global financial cycles shared strong similarities and synchronization in asset price and capital flows. In particular, with respect to forecasting financial crisis, Kostanyan et al. (2023) developed a model for estimating financial cycle output gaps (FCMOD). They propose that high asset prices and excessive credit need to be monitored, and safe levels of debt need to be assessed. In the present paper, both the bank index and the realty index are included for financial cycle forecasting.

2.2. *Business cycles*

Uncovering the dynamics and impact of business cycle has been duly acknowledged in literature (Abosedra et al., 2021; Ghiaie et al., 2020; Hingley and Park, 2017; Vithessonthi and Tongurai, 2016). Rose (1967) proposed a theory of the business cycle through the introduction of a nonlinear Philip's curve. The responsiveness of the rate of wage inflation to the unemployment rate was infinitely high for lower and higher values of unemployment, which were associated with booms and depressions, respectively. However, the rate of wage inflation was low for intermediate values, as the effects of lay-offs and hiring cancelled each other out. Dua and Banerji (2006) developed models that describe business cycles and growth rate cycles for the Indian economy. They develop coincident indicators and leading indicators for the purpose. Along with firm performance, their leading indicators include capacity expansion and availability of bank credit. These variables, among others, have been included in the present paper. Vetlov et al. (2011) discussed the importance of New-Keynesian Dynamic Stochastic General Equilibrium (NK DSGE) for estimating potential output. This provides a benchmark for predicting business cycles. The paper has three definitions of potential output, namely efficient output, natural output, and trend output. While the trend output gap (deviation of actual output from trend output) measures the business cycle, other output gaps represent economic inefficiencies due to imperfect competition and price-setting frictions. OECD (2012) defined composite leading indicators (CLIs) for predicting cycles. Business cycles are defined as fluctuations in the output gap, and the latter is the difference between potential and observed output. Potential output is determined using the Phase Average Trend (PAT) Method, while the structure of the Hodrick-Prescott (HP) Filter and the Christiano-Fidgerald (CF) filter are also discussed. The construction of CLIs depends on leading, coincident, and lagging indicators. In their paper, they define the long-term trend as the 75-month moving average of the actual series. In the present research, 200 DMA is used, which is equivalent to 12 calendar months. In their literature survey paper on business cycles, Pu et al. (2023) brought out the use of the Dynamic Factor (DF) model, Markov switching (MS) model, and Real business cycle (RBC) model for detecting business cycles. For detrending the output series, they discuss the use of the Hodrick and Prescott (1997) filter, the Beveridge and Nelson (1981) method, VAR models, and methods proposed by Baxter and King (1999) and

Christiano and Fitzgerald (2003). Andersson et al. (2018) and Vetlov et al. (2011) also developed models for estimating potential output. This paper proposes an alternative definition of a phase of a cycle. Bhadury et al. (2021) provided a framework for estimating business cycles in India using explanatory variables from industry and construction, the index number of industrial production (IIP) for consumer goods, auto sales, credit, and the stock market sentiment index (Sensex). In this research paper, these variables are represented by their Indian stock market counterparts. In addition, many other variables like VIX, crude oil prices, capacity expansion and business confidence index are included. Andersson et al. (2018) described the difference between potential output and actual output and provide an alternative measure of potential output. Bodnár et al. (2020) discuss the movements in potential output during the COVID-19 phase, considering both the demand side and supply side effects. Choudhry et al. (2020) established the existence of a causal influence of US economic uncertainty on the business cycles of 12 European countries on a short-term time scale. The literature on the relationship between financial and real cycles has emphasized the role of credit and housing prices. Further, recessions associated with financial disruptions tend to be longer and deeper than other recessions. Yan and Huang (2020) use macro-financial variables like private credit, private credit-to-GDP ratio, house prices, and share prices to construct financial cycles, and then they use wavelet analysis to measure the duration of the financial cycle. They use wavelet coherence to analyze the relationship between the financial cycle and the business cycle. Odasseril and Shanmugam (2023) developed a Markov Switching Auto-regressive model to analyze the nature of business cycles in India using quarterly GDP growth data from 1998 to 2022. This present expands on the aforementioned literature in terms of an alternative definition of a financial cycle, and also in the choice of explanatory variables.

2.3. Dynamic ensemble selection (DES)

DES methodologies have seen considerable traction in the literature in areas of complex classification tasks (Wei et al., 2024, Zulfira et al., 2021). Muhammed and Thiyagarajan (2021) extensively used several DES methodologies for systematically modelling Alzheimer's classification. The DES framework on pool of classifiers emerged to attain highest classification accuracy. Feng et al. (2022) integrated METADES and binary multi-objective non-dominated sorting based genetic algorithm (NSGA-II) for predicting bank telemarketing sales. The NSGA-II tool was used to select base classifiers from a pool of classifiers, namely, logistic regression (LR), decision trees (DT), random forests (RF), gradient boosting decision trees (GBDT), extreme gradient boosting (XGB) and light gradient boosting machine (LightGBM). The findings duly rationalized the robustness and efficiency of the proposed modelling. Zheng et al. (2022) leveraged DES methodology-driven random forest framework for precisely carrying out fault classification modelling in industrial processes. The framework outshined several conventional approaches. Davtalab et al. (2024) propounded a novel fuzzy hyperboxes-driven DES methodology, which outshined conventional DES techniques for classification problems. The proposed framework utilized the fuzzy set theory for generating a competence map in the said DES approach. Zeng et al. (2024) proposed a drift-aware dynamic ensemble framework to adaptively select and aggregate models for predicting Carbon prices to tackle Carbon neutrality and Carbon peaking. The predictive outcome substantiated the robustness and efficacy of the model. Despite the advantages and superiority of the DES algorithms, financial time series classification has primarily been confined to conventional ensemble learning and deep learning methodologies (Cho and Kim, 2025; Manian and Kayal, 2025; Su et al., 2025). DES-driven classification modelling has not been applied for financial cycle predictions. The present work strives to address this gap.

The existing strand of cognate literature on financial and business cycle modelling is relatively tilted toward macroeconomic indicators for defining cycles and resorts to econometric frameworks for drawing deeper insights, which necessitates the assumption of several data distribution aspects. On the other hand, it is of utmost relevance to analyze the dynamics of the financial cycle through the lens of financial market proxies for facilitating strategic interventions by unveiling the influence structures of relevant explanatory indicators. Additionally, the majority of the past research is primarily confined to a specific time regime. Proper analyses of financial cycles in different market states can reveal deeper insights and enable comparative evaluation. The present research aims to bridge the gaps by advancing a novel methodological framework to define and anticipate financial cycles based on financial market information in the Indian context. A careful and systematic approach has been adopted to understand the pattern and dependence of the financial cycle in varying market conditions, which significantly underscores the contribution of the current endeavor. On the predictive methodology front, review of pertinent literature on DES-driven ensemble machine learning exemplifies the true potential of the same in offering a robust solution to complex pattern recognition tasks. Its advantages over the traditional ensemble machine learning models in thwarting overfitting and fetching superior predictions have been acknowledged. The present study leverages the DES methodologies systematically to unveil the temporal dynamics of financial cycles in the Indian market through the lens of classification. The DES methodology is used with a homogeneous and heterogeneous pool of classifiers extensively to enable a comparative evaluation in a balanced orientation.

3. Data and variables

3.1. Defining cycle

This paper defines a cycle, and its phases by Eqs. (1) and (2).

$$Financial\ Cycle = NIFTY_{60Day\ Forward} - \frac{\sum_{t=1}^{200} NIFTY_t}{200} \tag{1}$$

where NIFTY, defined by the National Stock Exchange in India, is an indicator of overall stock market sentiment.

The phase of a financial cycle is defined as

$$Class_{Financial\ Cycle} = \begin{cases} 1 & (Upswing) if\ Financial\ Cycle > 0 \\ 0 & (Downswing) Otherwise \end{cases} \tag{2}$$

Financial cycle is the dependent variable and is binary in nature. NIFTY, defined by the National Stock Exchange in India, is an indicator of overall stock market sentiment. It is based on the stock prices of the top fifty companies in India, their market capitalization, and market turnover. The level of NIFTY and its movement over time is a reflection of the macroeconomic environment of the country. Being a stock market indicator, it will be affected by short-term speculative play. However, its 200 DMA (Day Moving Average) will smoothen these random movements. The difference between Nifty and its 200 DMA is taken as a proxy for the difference between actual and potential values respectively. To identify turning points, its 60-day forward value is what will be predicted. This 60-day forward value is almost equivalent to a three-month calendar period. That is, the proposed framework intends to forecast turning points nearly 90 days into the future. The said formulation of predicting financial cycle is a binary classification task. The following defines the independent variables, which have been classified under leading, coincident, and lagging indicators.

3.2. Defining indicators

3.2.1. Leading indicators

NIFTYDMA: It is computed as follows:

$$NIFTYDMA = NIFTY_t - \frac{\sum_{t=1}^{200} NIFTY_t}{200} \tag{3}$$

A positive value of this indicator represents buoyant market sentiment and indicates positive mood with expectations of future growth.

BANKDMA: It is computed as follows:

$$BANKDMA = NIFTY\ BANK_t - \frac{\sum_{t=1}^{200} NIFTY\ BANK_t}{200} \tag{4}$$

Stock market sentiment with respect to the banking sector is measured by NIFTY BANK and is a reflection of the health of the banking system. This variable defined in (4) is an indicator of credit growth, and its positive value generates expectations of future growth.

DELMETAL: It is calculated as follows:

$$DELMETAL = NIFTY\ METAL_t - \frac{\sum_{t=1}^{30} NIFTY\ METAL_t}{30} \tag{5}$$

The NIFTY METAL index is composed of stock prices of leading companies in India in the steel, aluminium, copper, zinc and other metal sectors. Metal enters all manufacturing activities, and a positive value of the variable given in (5) reflects an increase in capacity utilization and expectations of further growth.

DELREALTY: It is expressed as:

$$DELREALTY = NIFTY\ REALTY_t - \frac{\sum_{t=1}^{30} NIFTY\ REALTY_t}{30} \tag{6}$$

A positive value of this variable reflects growth in the real estate sector, which has been cited as an important factor representing upswing in business cycles. The NIFTY Realty index (NIFTY REALTY) can increase if the stock prices of most of the constituent companies' stock prices rise. A positive difference over a 30-day period reflects buoyant mood of the economy.

DELCOM: It is estimated as:

$$DELCOM = NIFTY\ COMMODITY_t - \frac{\sum_{t=1}^{30} NIFTY\ COMMODITY_t}{30} \tag{7}$$

In the literature, Menden and Proaño (2017) and Aguiar-Conraria and Soares (2011) consider consumer survey and industrial production indices as factors explaining financial cycles. In this paper, DELCOM is used as a proxy for purchasing managers index (PMI) and business confidence index. It is designed by NSE to reflect fundamental performance of a diversified set of companies from the commodities segment including sectors such as Oil, Petroleum Products, Cement, and Power. Its increase over a 30-day trading period signifies increasing demand for commodities, generating business confidence.

DELCG: It is determined as,

$$DELCG = BSE\ CAPITAL\ GOODS_t - \frac{\sum_{t=1}^{30} BSE\ CAPITAL\ GOODS_t}{30} \tag{8}$$

The BSE Capital Goods Index is composed of stock prices of leading capital goods producers in India that are listed on the Bombay Stock Exchange (BSE), the other leading stock exchange in India. The companies included are ABB India, Bharat Forge, BHEL, HAL, Carborandum Universal and many more. These companies contribute significantly to India's economic growth. A positive value of this variable is used in this paper as a proxy for increase in demand for capital goods, which implies capacity expansion. As capacity expansion generates output in the future, it is a forward-looking indicator.

VIX: This is an implied volatility indicator and moves inversely with the market sentiment index, NIFTY. It is not historic volatility based on past values, but forward-looking and signifies expected volatility. When market players expect the market to turn bearish, they rush to cover their positions by buying puts. This raises VIX.

P/E (PE): The P/E multiple for a company is a forward-looking measure and indicates future prospects. A high P/E ratio for the market as a whole is indicative of good future business prospects.

3.2.2. *Coincident indicators*

Crude Oil Price: Along with sectoral performance, for a large crude oil importing country like India, crude oil prices play a significant role in driving inflation and also production activities. Its recent prices are included as a coincident factor. The current day price (OIL) and one-day lagged (OILLAG1) prices are deployed as coincident indicators.

Exchange Rate: The exchange rate is a macroeconomic indicator which reflects the balance of payments position of an economy. In this work, we have considered the present-day value of Rupee-US Dollar exchange rate (EX) and one-day lagged figure (EXLAG1) of the same as coincident indicators.

NIFTY: Recent values of overall market sentiment are included in this set. It reflects the current macroeconomic environment. The present day (NIFTY) and one-day lagged (NIFTYLAG1) values are used as coincident indicators.

NIFTY Consumption: It is designed by NSE to reflect fundamental performance of a diversified set of companies from the domestic consumption sector which includes Consumer Non-durables, Healthcare, Auto, Telecom Services, Pharmaceuticals, Hotels, Media & Entertainment. This index, and its movement reflect the current macroeconomic state of the economy. The present day (CONS) and one-day lagged (CONSLAG1) values of the index are utilized as coincident constructs.

NIFTY Infrastructure and NIFTY FMCG: Recent values of these indices reflect current performance of the infrastructure and fast-moving consumer goods (FMCG) sectors, which is a reflection of the performance of the economy as a whole. Similar to the earlier indicators, the present day and one-day lagged values of these sectoral indices (INFRA, INFRALAG1, FMCG, FMCGLAG1) are incorporated in the underlying research.

3.2.3. *Lagged Indicators*

As lagged indictors, the same variables used as coincident indicators, but with higher lags, are included. To be precise, five-day and ten-day lagged values crude oil price (OILLAG5, OILALG10), foreign exchange rate (EXLAG5, EXLAG10), NIFTY (NIFTYLAG5,

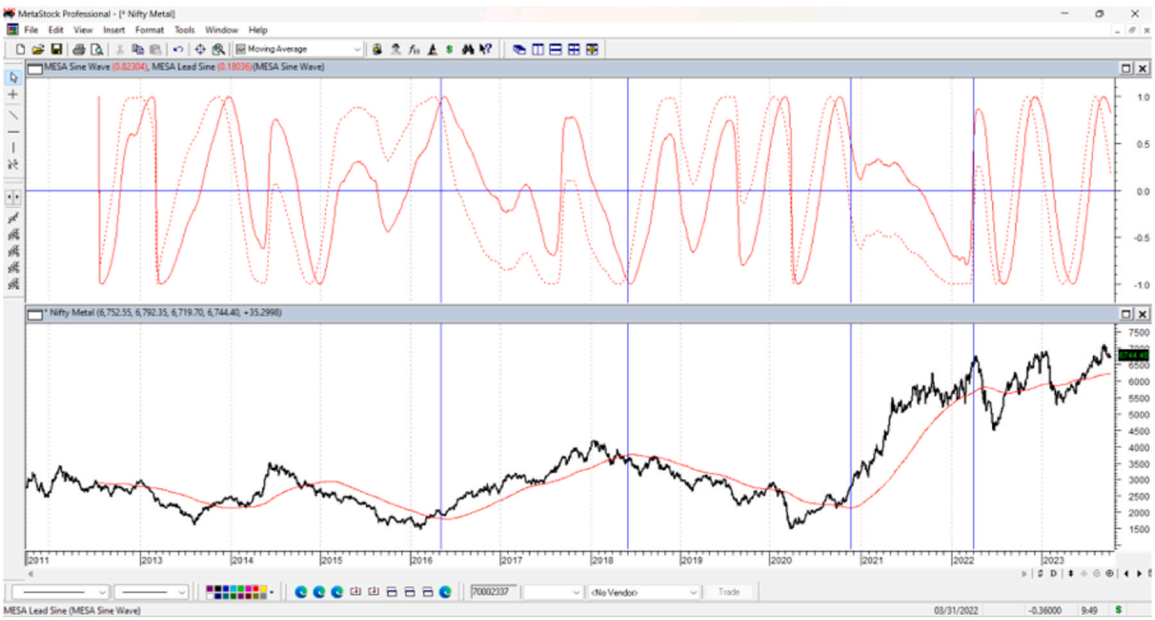

Fig. 1. Temporal Evolutionary Pattern of NIFTY.

NIFTYLAG10), NIFTY Consumption (CONSLAG5, CONSLAG10), NIFTY Infrastructure (INFRALAG5, INFRALAG10), and NIFTY FMCG (FMCGLAG5, FMCGLAG10).

The explanatory variables discussed above cover many of the variables considered in the literature like GDP growth, expansion in bank credit, expansion in the realty sector, VIX, and the exchange rate. Sectoral indices like NIFTY Metal, NIFTY Infrastructure, NIFTY Consumption and NIFTY FMCG reflect business confidence index, capacity utilization and purchasing managers' confidence index.

3.3. Data compilation and regime definition

For the present research, the data has been compiled from the Bloomberg data repository from January 3, 2011, to December 31, 2023. The following Fig. 1 depicts the evolutionary pattern of NIFTY over this period.

For executing the predictive framework, the entire time period is segregated into four time zones. The daily closing values of NIFTY from January 3, 2011, to December 30, 2016, exhibits strong cyclical movements. We define this timeline as CYCLE phase. From January 4, 2016, to mid-2018 (June 29, 2018), NIFTY demonstrates an upward trend pattern, which is referred to as UPWARD TREND regime. A gradual downward trend pattern in NIFTY can be observed from Mid-2018 (July 2, 2018) to December 31, 2020. The same has been denoted as DOWNWARD TREND regime. January 3, 2021 to December 29, 2023, indicates cyclical movement in NIFTY, and is referred to as CYCLE 2 regime. We carry out predictive modelling of directional changes of financial cycle across the four regimes. Table 1 reports key statistical characteristics of NIFTY. The select time regimes overlap with several geo-political and unprecedented events like Russia-Ukraine war, Israel-Palestine conflict, and COVID-19 pandemic. This will help in evaluating the robustness of the proposed predictive framework in forecasting financial cycles in the Indian context.

The movement in the Mesa Sine Wave indicator in the upper panel of Fig. 1, and the statistical properties of NIFTY closing values, suggest presence of cycles. The outcome of the Shapiro and AD tests rejects normal distribution patterns across the five regimes. The ADF test statistics reveal that movement in NIFTY in the select time regimes strongly exhibit nonstationary behaviour. Terasvirta's NN test indicates significant nonlinear patterns. The values of Hurst exponent of NIFTY, in all five regimes, have emerged to be substantially greater than 0.5, indicating presence of long memory dependence (Jana et al., 2021). Thus, the presence of nonparametric, nonstationary, and nonlinear traits rationalizes the use of advanced ensemble machine learning modeling. On the other hand, the long memory dependence justifies the incorporation of lagged information of several explanatory variables in building the classification framework.

4. Methodology

In this section, we elucidate in detail the different components of the integrated research architecture. Building classification frameworks on imbalanced dataset is a challenging task, which has been duly acknowledged in the literature. The class imbalance for binary classification largely arises from the skewed or biased distribution of the underlying datasets (Khan et al., 2023). As financial markets often exhibit high volatility and sensitivity to external chaos, delving into the directional changes of the financial market through the lens of classification-based modelling is likely to encounter class imbalance issue. Resampling is the most commonly used tool to resolve the same by increasing the proportion of minority class to rebalance the ratios. In this paper, Synthetic Minority Oversampling Technique (SMOTE) is used to balance the imbalance in the datasets, and the following section explains the procedural steps.

4.1. Synthetic minority oversampling technique (SMOTE)

Proposed by Chawla et al., (2002), SMOTE enables classification algorithms to augment its generalization by creating new minority instances. The basis of the generation process lies in an interpolation framework among neighboring minority class instances. The

Table 1
Empirical Characteristics of NIFTY.

Properties	CYCLE	UPWARD TREND	DOWNWARD TREND	CYCLE 2
Minimum	4544	6971	7610	13635
Maximum	8996	11130	12362	21779
Mean	6717	9191	11085	17388
Median	6187	9144	11235	17531
SD	1320.672	1090.913	855.372	1605.45
Skewness	0.1834	−0.1069	−1.270	0.0107
Kurtosis	−1.5460	−1.2347	1.7694	−0.3296
Shapiro Test	0.8925***	0.9493***	0.9030***	0.9840***
AD Test	64.623***	10.381***	44.081***	3.6722***
ADF Test	0.5404#	1.5295#	1.5672#	1.113#
Terasvirta's NN Test	438.74***	505.43***	828.35***	587.66***
Hurst Exponent	0.8952***	0.8728***	0.8763***	0.8429***

[*Note*: The table summarizes the values of measures of central tendency, dispersion, and some time series features of daily closing prices of NIFTY during different regimes. AD Test: Anderson-Darling Test, ADF Test: Augmented Dickey-Fuller Test, Terasvirta's NN Test: Terasvirta's Neural Network Test, # Not Significant, *** Significant at 1 % Level of Significance, ** Significant at 5 % Level of Significance.]

procedural steps involved in SMOTE are outlined below:

Step 1. For a sample, x_i belonging to the minority class, SMOTE choses a sample, x_p from its k-nearest neighbors

Step 2: The new synthetic sample, x_n is generated as a linear combination of x_i and x_p as:

$$x_n = x_i + u \times (x_p - x_i) \tag{9}$$

where u represents a random interpolation parameter, lies between 0 and 1.

Step 3: The process is repeated for all samples in the minority class, and for each, k-nearest neighbors are chosen to produce multiple synthetic samples, yielding a more balanced dataset.

Thus, by generating new data samples, which are typically similar but not identical to existing minority data points, the SMOTE framework alleviates the chances of overfitting. The respective classifiers, therefore, receive sufficient exposure to minority class characteristics in imbalanced datasets and, thereby, are subjected to robust training. The current work utilizes SMOTE across the chosen periods separately to balance the datasets before proceeding with actual classification exercises. It should be noted that literature reports a plethora of procedures to combat the data imbalance issue, viz. Adaptive Synthetic Sampling Approach (ADASYN), SMOTE-Tomek Links, SMOTE-Edited Nearest Neighbor Rule (ENN), SMOTE-Locally Linear Embedding (LLE), etc. (Kovács, 2019). However, the original SMOTE is relatively fast and computationally less resource intensive than the other hybrid mechanisms. Considering the large number of predictor variables, chosen for building the model, it is important to rely upon a relatively low resource intensive framework for resolving the problem.

4.2. Dynamic ensemble selection (DES)

DES is an advanced ensemble machine learning framework designed to improve classification performance by dynamically selecting the most competent subset of base classifiers for individual instances (Cruz et al., 2018). Unlike traditional ensemble methods, which combine and aggregate the outcome from all base classifiers in an ensemble, DES systematically gauges the competence of each classifier in the local region of the feature space where the test instance resides, thereby choosing only those classifiers that are most likely to yield highly precise predictions. The said approach is meant to adapt the selected classifiers to the specific characteristics of each instance. In the context of DES, the local region, commonly referred to as the region of competence, is a local neighborhood around a test instance where the competence of each classifier in the ensemble is ascertained. The region ideally covers a set of similar instances from the training sample identified by the standard K-nearest neighbors (KNN) method. By critically evaluating classifier performance within the region of competence, the DES framework can determine which classifiers are most competent for predicting the label of the test instance based on their success in classifying nearby, similar instances.

Mathematically, given an ensemble of classifiers $C = \{C_1, C_2, \ldots, C_N\}$, where N is the total number of classifiers, the endeavour of DES framework is to dynamically identify a subset of classifiers $C^* \subseteq C$ for every test instance, x_{test} based on the performance of the classifiers in the region of competence, $R(x_{test})$. feature space surrounding x_{test}. The competence of each classifier $c_j \in C$ is calculated as:

$$Competence(c_j, x_{test}) = \frac{1}{k}\sum\nolimits_{x_i \in R(x_{test})} \delta(c_j(x_i), y_i) \tag{10}$$

where y_i is the true level of instance, x_i and δ is an indicator function

$$\delta(c_j(x_i), y_i) = \begin{cases} 1 if c_j(x_i) = y_i \\ 0 Otherwise \end{cases} \tag{11}$$

DES uses different methodological approaches for estimating and finally selecting the base classifiers. The present study utilizes 6 distinct DES models, namely, *K*- Nearest Oracle Elimination (KNORAE), *K*-Nearest Oracle Union (KNORAU), Meta-Learning for Dynamic Ensemble Selection (METADES), Dynamic Ensemble Selection Performance (DESP), Dynamic Ensemble Selection-*K* Nearest Neighbor (DESKNN), and Dynamic Ensemble Selection Randomized Reference Classifier (DESRRC) for predicting financial cycles. KNORAE traverses for a local Oracle, indicating a base classifier that accurately classify all data samples lying in the region of competence of the test sample (Ko et al., 2008; Britto et al., 2014). All classifiers with a perfect performance in the region of competence are selected (local Oracles). The final outcome is estimated by the majority voting scheme. Basically, the framework effectively removes classifiers, which incorrectly classify any one of the samples in the neighborhood of the test segment. If the availability of competent classifiers becomes scarce, then the number of the nearest neighbors is regulated to discover at least one competent classifier. KNORAU aggregates classifiers that accurately classify a minimum of one sample belonging to the localized region (Britto et al., 2014). All classifiers that accurately discern the label of at least one instance from the training dataset within the K nearest neighbors of the test data are amalgamated to create an ensemble for the specified test data. The number of votes of select classifier is equal to the number of correctly classified samples in the region of competence. The final ensemble output is obtained by aggregating the votes of all base classifiers. The METADES framework is driven by a meta-learning framework to solve meta-problem, which imbibes a meta-feature extraction process to train meta-classifiers (Cruz et al., 2015). The resolution of this meta-problem primarily encompasses two fundamental stages: 1. The identification of meta-features pertinent to all classifiers within the designated pool: This process involves four distinct categories of meta-features, specifically, (a) the posterior probability associated with each label (which denotes the likelihood that the training instances within the defined region of competence correspond to the specified output label), (b) the comprehensive Local Accuracy of the classifier within the defined region of competence, (c) Neighbors hard classification (a vector of dimension ‘n’ is generated, where n represents the total number of training samples within the region of competence, such that if the classifier accurately classifies the sample within this region, the vector element is assigned a value of 1, and if not, a value of 0, thereby yielding a vector of dimension 'n'), (d) The confidence of the classifier (which is measured as the perpendicular distance from the input sample to the classifier's decision boundary), 2. The meta classifiers are employed to forecast the capability of the given classifier to provide an accurate prediction for the specified test data based on the identified meta-features. DESP methodology dynamically chooses a subset of classifiers from the ensemble that significantly outclass a random classifier in the competence region, thereby eliminating weak classifiers (Woloszynski et al., 2012). The dynamic selection process of classifiers is executed for each sample of test data by evaluating the efficacy of the classifiers against that of a random classifier within the predetermined vicinity of the test data. Should the performance metrics of a classifier exceed those of the random classifier, it becomes qualified for inclusion in the ensemble of classifiers pertinent to the specified test data. If no classifier from the pool is selected, then the whole pool of classifiers is chosen for the given test data. On the other hand, the DESKNN methodology (Soares et al., 2006) leverages both the diversity and accuracy of classifiers for constituting the ensembles. At first, the top 'a' accurate classifiers as per the performance manifested in the region of competence are selected. Subsequently, the most 'b' diverse among the top 'a' classifiers are sorted and selected as the ensemble of classifiers for a given test sample. Usually, a double-fault measure metric that counts the misclassification instances of the classifier is used to address the diversity aspect. DESRRC, on the other hand, gauges the competence of the classifiers utilizing a randomized reference classifier, whose class supports are reflected in random variables exhibiting beta probability distributions (Woloszynski and Kurzynski, 2011). The initial step involves the construction of a randomized reference classifier (RRC) whose class supports are defined as realizations of random variables governed by beta probability distributions. Utilizing the developed classifier, three distinct systems were constructed, which integrate dynamic classifier selection alongside dynamic ensemble selection (DES). In a nutshell KNORAE and KNORAU are relatively faster owing to comparatively less operational procedures, while METADES and DESRRC are more computationally expensive. Nonetheless, all six models of DES methodology are built upon solid technological bedrock to eliminate overfitting and underfitting issues in a seamless manner.

The current study resorts to homogeneous and heterogeneous pools of classifiers for implementing the DES models. The homogeneous pool of classifiers considered for modeling are Random Forest (RF), Bagging (BG), Gradient Boosting (GB), and Extreme Gradient Boosting (XGB). The heterogenous pools are simulated through pooling framework combing Support Vector Machine (SVM), *K*-Nearest Neighbor (KNN), Decision Tree (DT), and Logistic Regression (LR). From the individual base of classifiers, different DES mechanisms, i.e., KNORAE, KNORAU, etc. systematically identify and dynamically combine the constituent models by evaluating the performance in region of competence

To sum up, the present work uses six DES frameworks, KNORAE, KNORAU, METADES, DESP, DESKNN, and DESRRC on five different sets of classifiers, namely, RF, BG, GB, XGB, and pooling. The pooling framework comprises of SVM, KNN, DT, and LR. The said configurations result in 30 classification trials in each time regime.

4.3. Performance indicators

To systematically gauge the accuracy of the DES models-driven respective classification frameworks, the present research deploys six quantitative indicators, as follows.

The well-known Balanced Classification Accuracy (BCA) has been adopted in this work. The BCA metric is highly effective in measuring the classifier performance specifically for imbalanced datasets. It is basically the arithmetic mean of the sensitivity and specificity figures of the respective labels. The BCA of a specific label, i is computed as:

$$BCA_i = \frac{1}{2} \times \left[\left(\frac{TP}{TP + FN} \right) + \left(\frac{TN}{TN + FP} \right) \right] \tag{12}$$

The aggregate BCA is estimated as:

$$BCA = \frac{1}{L} \times \sum_{i=1}^{L} BCA_i \tag{13}$$

Similar to BCA metric, two additional metrics, Mathew's correlation coefficient (MCC), and F1 score (F1) are computed, which are calculated at aggregate level as:

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{14}$$

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{15}$$

The values of BCA, MCC, and F1 metrics should be close to 1 to infer accurate classification performance. The underlying work also utilizes two conventional classification evaluators, namely, Sensitivity and Specificity as defined in Eqs. 16 and 17.

$$Sensitivity = \frac{TP}{TP + FN} \tag{16}$$

$$Specificity = \frac{TN}{TN + FP} \tag{17}$$

Higher values of both metrics, ideally close to 1, are desirable for precise classification outcomes.

Additionally, we have also used the Receiver Operating Characteristic (ROC) Curve for determining the classification accuracy. The ROC curve depicts a visualization of sensitivity represented by vertical axis and 1-specificity represented by horizontal axis. It ascertains the probability of correctly specifying a random pair of positive and negative instances. To get quantitative information from ROC curve, area under the curve (AUC) is estimated. Models associated with higher AUC values are said to yield better and accurate predictions. It should be close to 1 to indicate superior classification performance.

Apart from advancing an effective and accurate framework to predict the directional changes of financial cycle in Indian context, it is equally important to ascertain the contribution of the underlying leading, coincident, and lagging indicators in explaining the upswing and downswing movements. To delve into deeper understanding of the prediction process, the current endeavour utilizes Explainable Artificial Intelligence (XAI) to uncover the feature contribution structure.

4.4. *Explainable artificial intelligence (XAI)*

To interpret the predictive structure for uncovering the financial cycle dynamics, we have resorted to Explainable Artificial Intelligence frameworks. The underlying work relies upon the Shapley additive explanation (SHAP) values (Lundberg and Lee, 2017) to explain the prediction model globally. The entire simulation has been carried out utilizing the highly acknowledged 'Shapash' library of Python.

The SHAP measure provides new directions to estimate the contribution of individual features in explaining the target construct (Lundberg and Lee, 2017). Mathematically, it is computed using Eq. (18).

$$\varnothing_i = \sum\nolimits_{S \subseteq N\{i\}} \frac{|S|!(n - |S| - 1)!}{n!} [v(S \cup \{i\}) - v(S)] \tag{18}$$

Where, $\varnothing_i$ denotes the contribution of i^{th} feature, N is the set of all features with cardinality n, S is the subset of N with feature i, and $v(N)$ is the predicted outcome considering the i^{th} feature.

The explanation is specified by applying Eq. 19 as:

$$g(z') = \varnothing_0 + \sum\nolimits_{j=1}^{M} \varnothing_j z'_j \tag{19}$$

Where, $z' \in \{0, 1\}^M$, and M denotes the number of features under consideration.

Features are ranked on the basis of their respective relative contribution. SHAP offers a different model explainer (Jabeur et al., 2024) for accomplishing the task. Successful utilization of SHAP in explaining time series modeling problems has been reported in the literature (e.g., Shajalal et al., 2024).

5. Results and discussions

5.1. *Outcome of predictive modeling*

To carry out the predictive modeling across the select time regimes, data samples corresponding to individual regimes are partitioned into training (80 %) and test (20 %) segments. The common issue of data imbalance has also been observed in financial cycle classification, too. The SMOTE algorithm has been executed on the respective training segments to resolve the problem. The details of the same are outlined in Table 2.

After balancing the training segment, we proceed to deploy the six DES models, KNORAE, KNORAU, METDES, DESP, DESKNN, and DESRRC, on RF, BG, GB, XGB, and the pooling classifiers for building the respective models. The select DES algorithms are implemented using the *'DESLib'* package in Python, while the *'scikit-learn'* package is used to simulate the base classifiers. The hyperparameters of the different classifiers, viz., number of estimators, maximum depth, learning rate, choice of kernels, batch size, etc. are tuned using 'GridSearchCV' utility in Python programming environment using 10-fold cross validations on the training segment. On the other hand, the chosen DES algorithms are reliant upon the nearest neighbor values (k), which are optimized during the cross-validation stage, considering the BCA metric as the objective performance. The outcome of predictive exercises in terms of the

Table 2
Sample Distribution across Classes.

Regime	Original Dataset	After Applying SMOTE (Training Segment)
CYCLE	Upswing Samples: 928 Downswing Samples: 542	Upswing Samples: 732 Downswing Samples: 732
UPWARD TREND	Upswing Samples: 494 Downswing Samples: 120	Upswing Samples: 398 Downswing Samples: 398
DOWNWARD TREND	Upswing Samples: 416 Downswing Samples: 203	Upswing Samples: 333 Downswing Samples: 333
CYCLE 2	Upswing Samples: 627 Downswing Samples: 105	Upswing Samples: 586 Downswing Samples: 586

classification performance indicators described in Section 3.2, on test data segments of respective time regimes, are enunciated in Tables 3–7.

The performance of the underlying DES models on RF, BG, GB, XGB, and Pooling has emerged to be supremely precise, as manifested by the figures of BCA, MCC, F1, AUC, Sensitivity, and Specificity. The values of BCA are above 0.9 for all different combinations. KNORAU, DESP, and DESRRC attain the highest BCA value (0.9413) on the RF model. Nevertheless, no significant change in the performance of other DES frameworks on the respective set of classifiers could be observed. The outcome of the classification performance of XGB-driven DES frameworks across the six tools has appeared to be uniform. The other performance indicators also strongly substantiate the claim. Therefore, any DES methodology can be leveraged with five different classifier options for decoding the movement of the financial cycle. Overall, inference can be drawn that the propounded methodological framework can be utilized to predict financial cycles during the chosen time regime with a supreme degree of precision.

The performance indicators clearly suggest that the classification performance during the UNPWARD TREND phase has seen a marginal deterioration, compared to the CYCLE phase. Nonetheless, the values of the performance indicators are well above the threshold range to label the financial cycle prediction during the select regime as highly satisfactory. The values of the Sensitivity metric have emerged to be greater than 0.9 for all six DES models on RF, BG, GB, and XGB, barring Pooling. The values of the BCA and AUC metrics are above 0.8, while the figures for F1 are substantially greater than 0.9. The performance accuracy of the DES models on BG can be seen to be relatively low compared to the other models. In a nutshell, despite the marginal decay in accuracy, it can be concluded that the said approach is effective in uncovering the predictive dynamics of the financial cycle.

The predictive exercise to predict the financial cycle in the DOWNWARD TREND phase has transpired to be highly accurate. The accuracy of the DES models on the GB model is relatively high, followed by RF. The performance of pooling-based classifiers emerged relatively inferior. However, the figures of the utilized indicators have assumed values greater than 0.9 for respective DES models on RF, BG, and XGB. No discrimination in the classification performance among the DES techniques for GB as manifested by the respective indicators. The magnitude of the performance metrics indicates that the classification accuracy in DOWNWARD TREND has surpassed the other two regimes. Likewise, in the previous scenario, DES models on XGB resulted in uniform predictive outcomes like GB. Thus, the presented approach has been efficient in modeling the directional changes in the financial cycle during the chosen regime. The DOWNWARD TREND regime overlaps with initial phases of COVID-19 pandemic, and thus the predictive accuracy of framework was seen to be efficient even in turbulent times.

Table 3
Comparison of DES Performance during CYCLE regime.

Series	Metric	RF	BG	GB	XGB	Pooling
KNORAE	BCA	0.9362	0.9337	0.9311	0.9209	0.9337
	MCC	0.8703	0.8570	0.8501	0.8337	0.8465
	F1	0.9565	0.9509	0.9482	0.9433	0.9449
	AUC	0.9362	0.9337	0.9311	0.9209	0.9337
	Sensitivity	0.9541	0.9388	0.9337	0.9337	0.9184
	Specificity	0.9184	0.9286	0.9286	0.9082	0.9490
KNORAU	BCA	0.9413	0.9235	0.9311	0.9209	0.9286
	MCC	0.8783	0.8350	0.8501	0.8337	0.8293
	F1	0.9590	0.9430	0.9482	0.9433	0.9362
	AUC	0.9413	0.9235	0.9311	0.9209	0.9286
	Sensitivity	0.9540	0.9286	0.9337	0.9337	0.8980
	Specificity	0.9286	0.9184	0.9286	0.9082	0.9591
METADES	BCA	0.9362	0.9286	0.9311	0.9209	0.9082
	MCC	0.8703	0.8489	0.8501	0.8337	0.7952
	F1	0.9565	0.9485	0.9482	0.9433	0.9263
	AUC	0.9362	0.9286	0.9311	0.9209	0.9082
	Sensitivity	0.9541	0.9388	0.9337	0.9337	0.8980
	Specificity	0.9183	0.9184	0.9286	0.9082	0.9184
DESP	BCA	0.9413	0.9260	0.9311	0.9209	0.9311
	MCC	0.8783	0.8419	0.8501	0.8337	0.8356
	F1	0.9590	0.9457	0.9482	0.9433	0.9390
	AUC	0.9413	0.9260	0.9311	0.9209	0.9311
	Sensitivity	0.9541	0.9337	0.9337	0.9337	0.9031
	Specificity	0.9286	0.9184	0.9286	0.9082	0.9592
DESKNN	BCA	0.9362	0.9209	0.9311	0.9209	0.9362
	MCC	0.8703	0.8337	0.8501	0.8337	0.8583
	F1	0.9565	0.9433	0.9482	0.9433	0.9506
	AUC	0.9362	0.9209	0.9311	0.9209	0.9362
	Sensitivity	0.9541	0.9336	0.9337	0.9337	0.9337
	Specificity	0.9184	0.9082	0.9286	0.9082	0.9388
DESRRC	BCA	0.9413	0.9260	0.9311	0.9209	0.9311
	MCC	0.8783	0.8419	0.8501	0.8337	0.8356
	F1	0.9590	0.9457	0.9482	0.9433	0.9390
	AUC	0.9413	0.9260	0.9311	0.9209	0.9311
	Sensitivity	0.9541	0.9337	0.9337	0.9337	0.9031
	Specificity	0.9286	0.9184	0.9286	0.9082	0.9591

Table 4
Comparison of DES Performance during UPWARD TREND regime.

Series	Metric	RF	BG	GB	XGB	Pooling
KNORAE	BCA	0.8947	0.8472	0.8947	0.9051	0.9236
	MCC	0.7697	0.6772	0.7697	0.8102	0.8363
	F1	0.9474	0.9263	0.9474	0.9583	0.9634
	AUC	0.8947	0.8472	0.8947	0.9051	0.9236
	Sensitivity	0.9375	0.9167	0.9375	0.9583	0.9583
	Specificity	0.8519	0.7778	0.8519	0.8519	0.8889
KNORAU	BCA	0.8843	0.8472	0.8947	0.9051	0.8947
	MCC	0.7327	0.6772	0.7697	0.8102	0.7697
	F1	0.9362	0.9263	0.9474	0.9583	0.9474
	AUC	0.8843	0.8472	0.8947	0.9051	0.8947
	Sensitivity	0.9167	0.9167	0.9375	0.9583	0.9375
	Specificity	0.8519	0.7778	0.8519	0.8519	0.8519
METADES	BCA	0.8843	0.8472	0.8947	0.9051	0.8999
	MCC	0.7327	0.6772	0.7697	0.8102	0.7895
	F1	0.9362	0.9263	0.9474	0.9583	0.9529
	AUC	0.8843	0.8472	0.8947	0.9051	0.8999
	Sensitivity	0.9167	0.9167	0.9375	0.9583	0.9479
	Specificity	0.8519	0.7778	0.8519	0.8518	0.8519
DESP	BCA	0.8843	0.8472	0.8947	0.9184	0.9294
	MCC	0.7327	0.6772	0.7697	0.8160	0.7813
	F1	0.9362	0.9263	0.9474	0.9579	0.9399
	AUC	0.8843	0.8472	0.8947	0.9184	0.9294
	Sensitivity	0.9167	0.9167	0.9375	0.9479	0.8958
	Specificity	0.8519	0.7778	0.8519	0.8889	0.9630
DESKNN	BCA	0.8895	0.8472	0.8947	0.9184	0.9080
	MCC	0.7508	0.6772	0.7697	0.8160	0.7779
	F1	0.9418	0.9263	0.9474	0.9579	0.9468
	AUC	0.8895	0.8472	0.8947	0.9184	0.9080
	Sensitivity	0.9271	0.9167	0.9375	0.9479	0.9271
	Specificity	0.8519	0.7778	0.8519	0.8889	0.8889
DESRRC	BCA	0.8843	0.8472	0.8947	0.9288	0.9294
	MCC	0.7327	0.6772	0.7697	0.8576	0.7813
	F1	0.9362	0.9263	0.9474	0.9688	0.9399
	AUC	0.8843	0.8472	0.8947	0.9288	0.9294
	Sensitivity	0.9167	0.9167	0.9375	0.9688	0.8958
	Specificity	0.8519	0.7778	0.8519	0.8889	0.9630

The outcome of predictive exercises in the CYCLE 2 phase indicates a marginal dip in classification accuracy, as compared to the CYCLE phase. The highest value of BCA is 0.9295, corresponding to KNORAE, KNORAU, METADES, and DESKNN on XGB, as compared to 0.9413 during the CYCLE phase. However, the performance is better than the UPWARD TREND period. The accuracy of pooling classifier-based DES tools was relatively low. The respective DES models trained on XGB have a marginal edge over other configurations in terms of classification accuracy. The CYCLE-2 timeline coincides with worldwide geo-political turmoil events like Russia-Ukraine and Israel-Palestine conflicts. The findings of the classification exercises in this phase suggest robustness of the integrated framework in accurately estimating upswing and downswing movements in a volatile environment.

Overall classification performance clearly signifies the effectiveness of leading, coincident, and lagging indicators-driven DES modelling in obtaining predictions of supreme accuracy in CYCLE, DOWNWARD TREND, and CYCLE 2 phases. The classification accuracy suffers a marginal dip in UPWARD TREND regime. Amongst the models, RF and XGB transpire to be highly reliable in building the KNORAE, KNORAU, METADES, DESP, DESKNN, and DESRRC techniques.

In addition to the conventional DES modelling, we have also executed dynamic Frienemy pruning (DFP) to the six dynamic selection methodologies to gauge whether the same can improve the predictive accuracy further. Basically, the DFP procedure is an online pruning framework that critically explores the competence region to identify the proportion of samples from different classes (Cruz et al., 2020). Subsequently, it eliminates the base classifiers, which fail to correctly classify at least a pair of samples from different classes. Traditionally, DES models coupled with DFP methodology are referred to as Frienemy Indecision Region Dynamic Ensemble Selection (FIRE-DES) frameworks. Thus, the six DES methodologies used in this work, when integrated with DFP, are denoted as: FIRE-KNORAE, FIRE-KNORAU, FIRE-METADES, FIRE-DESP, FIRE-DESKNN, and FIRE-DESRRC. In the simulations, the overall accuracy of the DFP-induced DES models were found to be similar to the unpruned models as indicated by the BCA metric. No significant change could be observed. Fig. 2 depicts the predictive performance manifested by BCA values on the test segment of the chosen models applying RF as base classifiers. The detailed results are available on request.

We extended the simulations in other phases, too, which yielded similar findings, i.e. no significant change in the performance. Those results are also available from the authors on request. Since, no significant performance improvement was recorded, we proceeded with unpruned configurations.

Table 5
Comparison of DES Performance during DOWNWARD TREND regime.

Series	Metric	RF	BG	GB	XGB	Pooling
KNORAE	BCA	0.9550	0.9100	0.9637	0.9475	0.9211
	MCC	0.9181	0.8350	0.9195	0.8873	0.7931
	F1	0.9813	0.9627	0.9811	0.9736	0.9457
	AUC	0.9550	0.9100	0.9637	0.9475	0.9211
	Sensitivity	0.9850	0.9700	0.9774	0.9699	0.9173
	Specificity	0.9250	0.8500	0.9500	0.9250	0.9250
KNORAU	BCA	0.9512	0.9062	0.9637	0.9475	0.9336
	MCC	0.9024	0.8197	0.9195	0.8873	0.8115
	F1	0.9774	0.9588	0.9811	0.9736	0.9494
	AUC	0.9512	0.9062	0.9637	0.9475	0.9336
	Sensitivity	0.9774	0.9624	0.9774	0.9699	0.9173
	Specificity	0.9250	0.8500	0.9500	0.9250	0.9500
METADES	BCA	0.9512	0.9187	0.9637	0.9475	0.8699
	MCC	0.9024	0.8374	0.9195	0.8873	0.7398
	F1	0.9774	0.9624	0.9811	0.9736	0.9398
	AUC	0.9512	0.9187	0.9637	0.9475	0.8699
	Sensitivity	0.9774	0.9624	0.9774	0.9699	0.9398
	Specificity	0.9250	0.8750	0.9500	0.9250	0.8000
DESP	BCA	0.9512	0.9062	0.9637	0.9475	0.9336
	MCC	0.9024	0.8197	0.9195	0.8873	0.8115
	F1	0.9774	0.9588	0.9811	0.9736	0.9494
	AUC	0.9512	0.9062	0.9637	0.9475	0.9336
	Sensitivity	0.9774	0.9624	0.9774	0.9699	0.9173
	Specificity	0.9250	0.8500	0.9500	0.9250	0.9500
DESKNN	BCA	0.9550	0.9225	0.9637	0.9475	0.9475
	MCC	0.9181	0.8525	0.9195	0.8873	0.8873
	F1	0.9813	0.9663	0.9811	0.9736	0.9736
	AUC	0.9550	0.9225	0.9637	0.9475	0.9475
	Sensitivity	0.9850	0.9699	0.9774	0.9699	0.9699
	Specificity	0.9250	0.8750	0.9500	0.9250	0.9250
DESRRC	BCA	0.9512	0.9062	0.9637	0.9475	0.9336
	MCC	0.9024	0.8197	0.9195	0.8873	0.8115
	F1	0.9774	0.9588	0.9811	0.9736	0.9494
	AUC	0.9512	0.9062	0.9637	0.9475	0.9336
	Sensitivity	0.9774	0.9624	0.9774	0.9699	0.9173
	Specificity	0.9250	0.8500	0.9500	0.9250	0.9500

5.2. Robustness check and validation

Though DES-driven frameworks utilizing the leading, coincident, and lagging indicators emerge to be highly accurate in classifying upswing and downswing movements, it is crucial to gauge the robustness and validity of the predictive findings systematically. To accomplish this, we initially evaluate the relative efficiency of the proposed framework by testing its predictive accuracy on a surrogate dataset. The robustness check reconstructs the NIFTY time series by inducing perturbations utilizing the 'tseriesEntropy' package of 'R'. The platform resorts to sieve bootstrap (Bühlmann, 1997) to simulate the surrogate series. The autoregressive (AR) model is used to resample the residuals with replacement to enable simulation. On the surrogate NIFTY series, financial cycles are defined by applying Eqs. 1 and 2. As the KNORAE model appeared to be relatively superior in terms of classification accuracy across the phases, the capacity of the same is subjected to a robustness check on surrogate data. Similar results were found for other DES models. The detailed reports are available upon request from the authors. Table 7 reports the findings on test data segments.

The classification metrics suggest a marginal drop in the predictive accuracy in comparison to the classification outcome on original observations. Nevertheless, the figures of all six indicators are well above the threshold to mark the attempt to predict financial cycle successful. Thus, the propounded methodological framework transpires robust for precise modelling in noisy setup. Next, we explore the sensitivity of the classification performance on different lagged values. The present approach considers five-day and ten-day lagged values for constituting the lagged indicators. We check the predictive performance of the KNORAE models on three-day and seven-day based lagged indicators. Table 8 reports the findings of the exercise on test data segment.

An introspection of predictive performance on the different lagged figures reveals no significant change in predictive accuracy compared to that of the original ones across the phases, as reported in Tables 4–6. Thus, the usage of five-day and ten-day lagged values to account for weekly and biweekly effects is justified as altering lagged components does not result in any noticeable impact on the classification performance. Finally, we delve into the validation rationale by ascertaining the utility of selecting three distinct sets of explanatory variables, i.e., leading, coincident, and lagging indicators. The said inspection is necessary to validate the contributions of the chosen groups of predictors. We compare the predictive accuracy in terms of the ROC metric to ascertain comparative evaluation. Figs. 3–6 exhibit the visual comparison of the outcome on the test data segment.

The findings clearly indicate the overall effectiveness and superiority of utilizing leading, coincident, and lagging indicators together. Prediction accuracy decays significantly when used separately. Hence, the present contribution of the selection and

Table 6
Comparison of DES Performance during CYCLE 2 regime.

Series	Metric	RF	BG	GB	XGB	Pooling
KNORAE	BCA	0.8995	0.8425	0.8928	0.9295	0.8522
	MCC	0.8252	0.7075	0.7978	0.8353	0.6612
	F1	0.9600	0.9333	0.9530	0.9589	0.9091
	AUC	0.8995	0.8425	0.8928	0.9295	0.8522
	Sensitivity	0.9730	0.9459	0.9595	0.9459	0.8783
	Specificity	0.8261	0.7391	0.8260	0.9130	0.8261
KNORAU	BCA	0.9213	0.8643	0.8928	0.9295	0.8522
	MCC	0.8557	0.7399	0.7978	0.8353	0.6612
	F1	0.9664	0.9396	0.9530	0.9589	0.9091
	AUC	0.9213	0.8643	0.8928	0.9295	0.8522
	Sensitivity	0.9730	0.9459	0.9595	0.9459	0.8783
	Specificity	0.8696	0.7826	0.8260	0.9130	0.8261
METADES	BCA	0.8995	0.8425	0.8928	0.9295	0.8305
	MCC	0.8252	0.7075	0.7978	0.8353	0.6273
	F1	0.9600	0.9333	0.9530	0.9589	0.9028
	AUC	0.8995	0.8425	0.8928	0.9295	0.8305
	Sensitivity	0.9730	0.9459	0.9595	0.9459	0.8784
	Specificity	0.8261	0.7391	0.8260	0.9130	0.7826
DESP	BCA	0.9145	0.8643	0.8928	0.9227	0.9175
	MCC	0.8290	0.7399	0.7978	0.8118	0.7615
	F1	0.9595	0.9396	0.9530	0.9517	0.9286
	AUC	0.9145	0.8643	0.8928	0.9227	0.9175
	Sensitivity	0.9595	0.9459	0.9595	0.9324	0.8784
	Specificity	0.8696	0.7826	0.8260	0.9130	0.9565
DESKNN	BCA	0.8995	0.8425	0.8928	0.9295	0.8710
	MCC	0.8252	0.7075	0.7978	0.8353	0.7663
	F1	0.9600	0.9333	0.9530	0.9589	0.9467
	AUC	0.8995	0.8425	0.8928	0.9295	0.8710
	Sensitivity	0.9730	0.9459	0.9595	0.9459	0.9594
	Specificity	0.8261	0.7391	0.8260	0.9130	0.7826
DESRRC	BCA	0.9145	0.8643	0.8928	0.9227	0.8942
	MCC	0.8290	0.7399	0.7978	0.8118	0.7571
	F1	0.9595	0.9396	0.9530	0.9517	0.9379
	AUC	0.9145	0.8643	0.8928	0.9227	0.8942
	Sensitivity	0.9595	0.9459	0.9595	0.9324	0.9189
	Specificity	0.8696	0.7826	0.8260	0.9130	0.8696

deployment of explanatory variables is justified. Additionally, we have performed the pairwise McNemar's test to facilitate statistical comparisons. The utility of McNemar's test in statistical comparison of classification models has been widely reported in the literature (Azedou et al., 2025; Günen, 2025). Table 9 outlines the results.

Significant differences in classification accuracy are apparent from the comparative evaluation, which validates the initial findings from visualizing the ROC figures on respective setups. Hence, the combined usage of different categories of explanatory features underscores the contributions of the present work, which survives the robustness and validation checks. In addition to the said checks, comparative classification analyses have also been performed to illustrate the relative efficiency of the DES framework when rated against conventional ensemble modeling and deep learning algorithms. In the current work, we choose RF with 500 decision trees as base learners, a deep neural network (DNN) comprising two hidden layers with 100 neurons each with sigmoid activation function, and Google's transformer-driven Interpretable Tabular Learning (TabNet) framework (Arik and Pfister, 2021), available in Google Cloud, to facilitate the same. Table 10 enlists the outcome pairwise McNemar's test statistic values.

The findings clearly demonstrate the superiority of the KNORAE, DNN, and TabNet frameworks over RF. No significant difference in classification accuracy between the DES and deep learning methodologies can be observed. Thus, the relative efficiency of the DES methodology is duly established as it outshines the conventional ensemble learning model and emerges equally effective when compared with advanced deep learning architectures.

The DES methodologies emerge as highly successful and robust in predicting the evolving patterns of financial cycles in the Indian context. Nevertheless, the major novelty of the methodological contribution of the present work lies in the systematic selection and utilization of leading, coincident, and lagging indicators, which ensures the proper training of the chosen classification frameworks. Usage of all these features in tandem transpired to be statistically superior, as well. Therefore, it is essential to emphasize the identification of key explanatory variables for deploying DES models to perform predictive analytics of financial markets.

5.3. Outcome of XAI-based analysis

We now proceed to the SHAP principle-based XAI framework to unveil the feature contribution structure in predicting financial cycles in CYCLE, UPWARD TREND, DOWNWARD TREND, and CYCLE 2 phases. For interpretation, we have chosen the XGB-based DES model in this paper. As the underlying financial cycle estimation is a typical binary classification task, feature contributions for both

Table 7
Classification Performance on Surrogate Setup.

Series	Metric	RF	BG	GB	XGB	Pooling
CYCLE						
KNORAE	BCA	0.9337	0.9337	0.9337	0.9186	0.9337
	MCC	0.8570	0.8570	0.8570	0.8337	0.8465
	F1	0.9509	0.9509	0.9509	0.9218	0.9449
	AUC	0.9337	0.9337	0.9337	0.9209	0.9237
	Sensitivity	0.9388	0.9388	0.9388	0.9337	0.9184
	Specificity	0.9286	0.9286	0.9286	0.8785	0.9490
UPWARD TREND						
KNORAE	BCA	0.8843	0.8270	0.8843	0.8843	0.9294
	MCC	0.7327	0.6544	0.7327	0.7327	0.7813
	F1	0.9362	0.9148	0.9362	0.9362	0.9399
	AUC	0.8843	0.8270	0.8843	0.8843	0.9294
	Sensitivity	0.9167	0.9088	0.9167	0.9167	0.8958
	Specificity	0.8519	0.7632	0.8519	0.8519	0.9630
DOWNWARD TREND						
KNORAE	BCA	0.9062	0.9062	0.9336	0.9062	0.9062
	MCC	0.8197	0.8197	0.8115	0.8197	0.8197
	F1	0.9588	0.9588	0.9494	0.9588	0.9588
	AUC	0.9062	0.9062	0.9336	0.9062	0.9062
	Sensitivity	0.9624	0.9624	0.9173	0.9624	0.9624
	Specificity	0.8500	0.8500	0.9500	0.8500	0.8500
CYCLE 2						
KNORAE	BCA	0.8995	0.8425	0.8305	0.9295	0.8305
	MCC	0.8252	0.7075	0.6273	0.8353	0.6273
	F1	0.9600	0.9333	0.9028	0.9589	0.9028
	AUC	0.8995	0.8425	0.8305	0.9295	0.8305
	Sensitivity	0.9459	0.8784	0.8784	0.9459	0.8784
	Specificity	0.7391	0.7826	0.7826	0.7391	0.7826

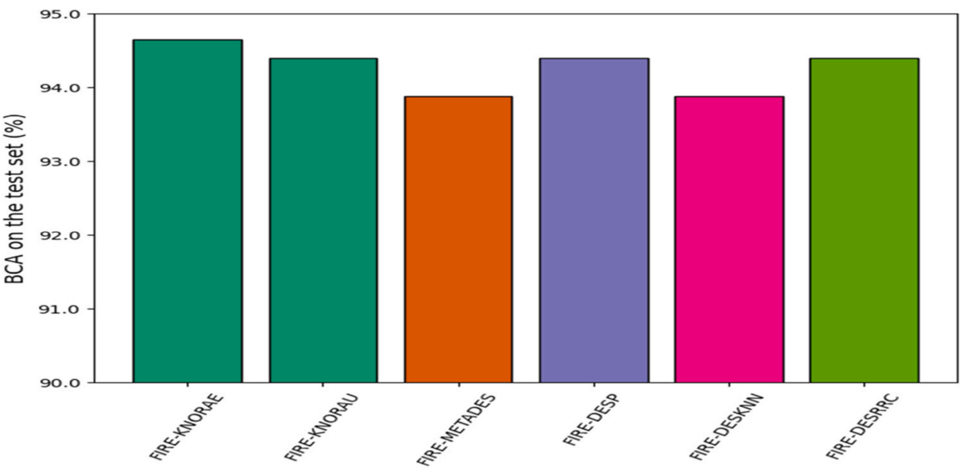

Fig. 2. Performance of the DES-RF Models after Applying DFP during CYCLE Phase.

classes, i.e., Upswing and Downswing movements are interpreted separately. Findings on other models are available from authors on request. Figs. 7–10 depict the feature rankings across the regimes of Upswing movement classification.

The steep influence of foreign exchange rates on the financial cycles is amply evident as four exchange rate-linked coincident and lagged indicators appear in the top five significant features for predicting upswing movement. The roles of coincident and lagging indicators of INFRA and OIL have emerged to be significant. The predictive impact of leading indicators, BANKDMA, DELREALTY, and NIFTYDMA, is relatively weak in comparison to the other categories of indicators. VIX and PE do not appear in the top 20 critical feature list in this phase.

As is evident from Fig. 1, the Cycle Period does not demonstrate any trend, but indicates volatility. The emergence of the exchange rate as both coincident and lagged indicator reflects this economic uncertainty. The proposed framework thus suggests exchange rate management as a policy tool for cooling the markets. As India is a large importer of crude oil, crude oil prices emerge as a significant variable during volatile times. Thus, oil price management also becomes crucial during the Cycle Period.

In the upswing classification in the UPWARD TREND phase, three leading indicators namely, BANKDMA, DELCG, and NIFTYDMA,

Table 8
Predictive Performance on Different Lagged-based Indicators.

Series	Metric	RF	BG	GB	XGB	Pooling
CYCLE						
KNORAE	BCA	0.9362	0.9337	0.9311	0.9209	0.9337
	MCC	0.8703	0.8570	0.8501	0.8337	0.8465
	F1	0.9565	0.9509	0.9482	0.9433	0.9449
	AUC	0.9362	0.9337	0.9311	0.9209	0.9209
	Sensitivity	0.9541	0.9388	0.9337	0.9337	0.9184
	Specificity	0.9082	0.9286	0.9082	0.9082	0.9490
UPWARD TREND						
KNORAE	BCA	0.8947	0.8472	0.8947	0.9051	0.9236
	MCC	0.7697	0.6772	0.7697	0.7697	0.8363
	F1	0.9474	0.9263	0.9474	0.9583	0.9634
	AUC	0.8947	0.8472	0.8947	0.8947	0.9236
	Sensitivity	0.9375	0.9167	0.9375	0.9375	0.9583
	Specificity	0.8519	0.7778	0.8519	0.8519	0.8889
DOWNWARD TREND						
KNORAE	BCA	0.9550	0.9100	0.9637	0.9475	0.9211
	MCC	0.9181	0.8350	0.9195	0.8873	0.7931
	F1	0.9813	0.9627	0.9811	0.9736	0.9457
	AUC	0.9550	0.9100	0.9637	0.9475	0.9100
	Sensitivity	0.9850	0.9700	0.9774	0.9699	0.9173
	Specificity	0.9250	0.8500	0.9500	0.9250	0.8500
CYCLE 2						
KNORAE	BCA	0.8995	0.8425	0.8928	0.9295	0.8522
	MCC	0.8252	0.6612	0.7978	0.8353	0.6612
	F1	0.9600	0.9333	0.9530	0.9589	0.9091
	AUC	0.8995	0.8425	0.8928	0.9295	0.8522
	Sensitivity	0.9730	0.9459	0.9595	0.9459	0.8783
	Specificity	0.8261	0.7391	0.8260	0.9130	0.8260

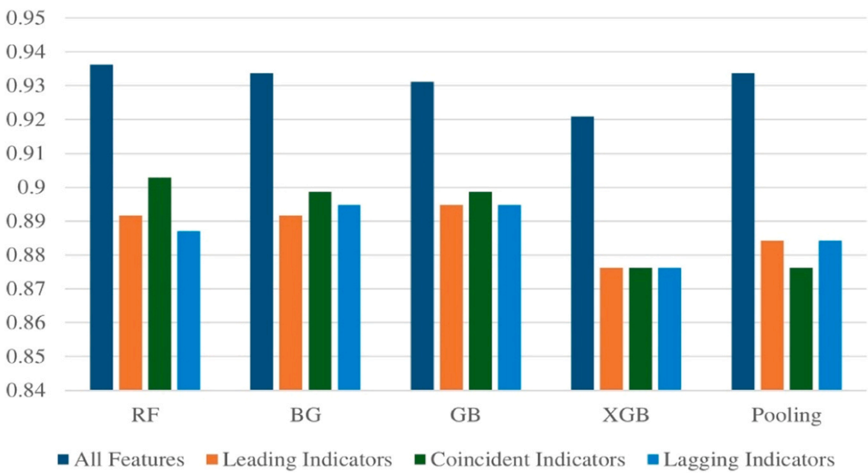

Fig. 3. Comparative Evaluation in CYCLE Regime.

occupy the top 3 significant feature spots. The effect of DELREALTY has intensified. The impact of the foreign exchange rate has seen a decline. Coincident and lagging indicators of INFRA have transpired to exert strong predictive prowess. Akin to the CYCLE phase, VIX and PE do not appear in the top 20 feature list. Thus, it can be asserted that leading indicators play pivotal roles in conjunction with the other indicators in accurately predicting upswing movements in the UPWARD TREND period.

During UPWARD TREND Period for Upswing Class, the economy is observing positive growth and a buoyant environment as indicated by significance of NIFTY DMA. This is accompanied by expansion in bank credit, capital formation, and expansion in the realty sector. The proposed framework correctly identifies the factors behind economic growth, and suggests policy makers to lower interest rates, monitor the rate of inflation, and also monitor the tax and duty structures.

The top 5 important features for classifying the upswing patterns in DOWNWARD TREND are OILLAG10, DELCOM, OILLAG5, and PE. Hence, both leading and lagging indicators are crucial for drawing robust predictions. Interestingly, PE, which deemed to be not so prudent in predicting the upswing movements in CYLE 2 and UPWARD TREND phases, has transpired to exert strong predictive influence. Similarly, VIX too has featured in top 20 variable list. BANKDMA, which was identified as the most influential feature in

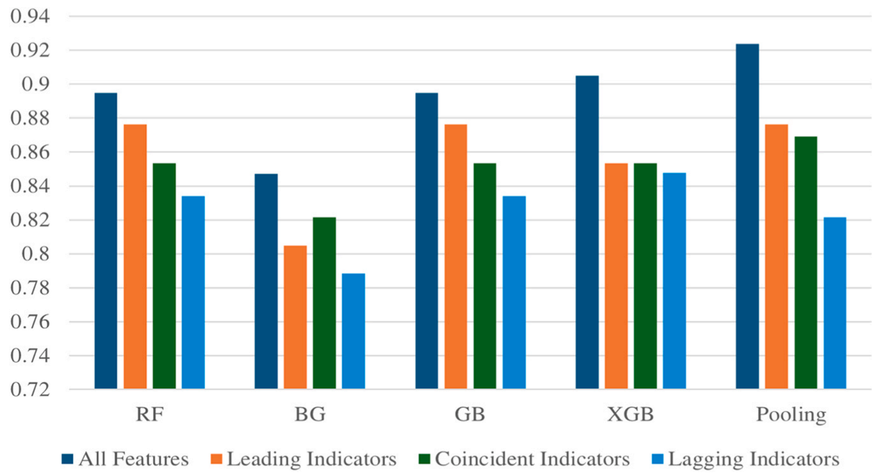

Fig. 4. Comparative Evaluation in UPWARD TREND Regime.

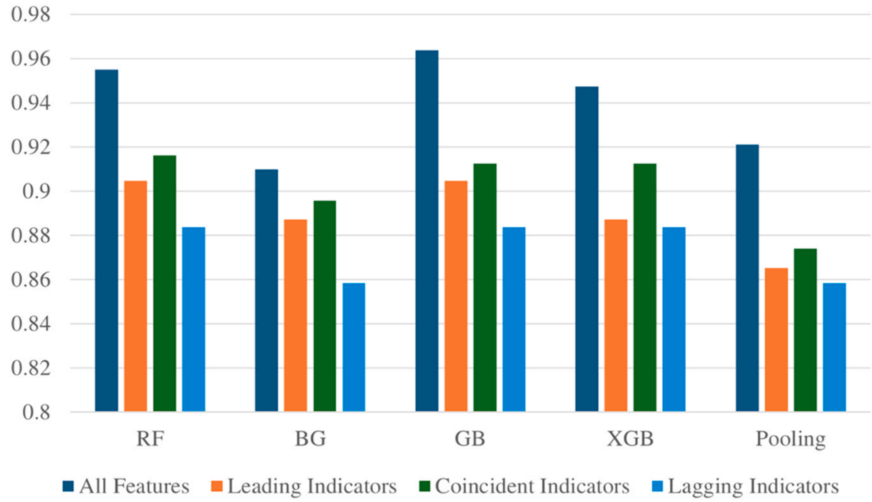

Fig. 5. Comparative Evaluation in DOWNWARD TREND Regime.

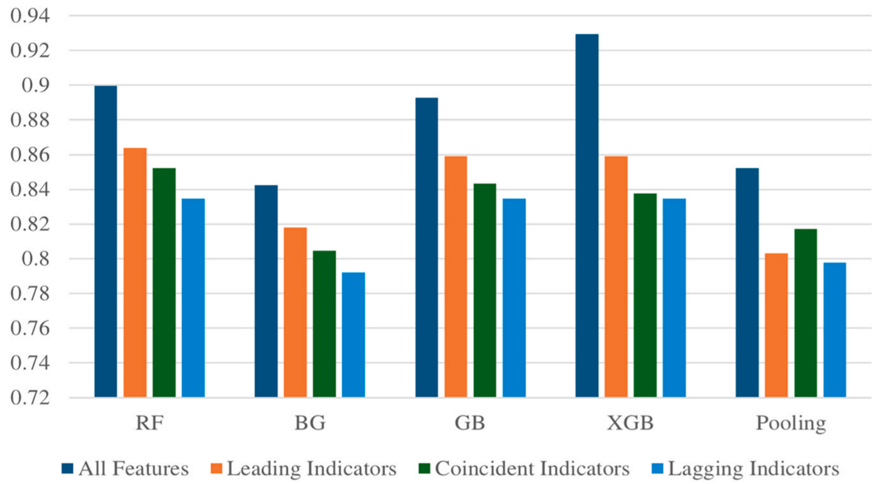

Fig. 6. Comparative Evaluation in CYCLE 2 TREND Regime.

Table 9
Outcome of McNamer's Test-based Evaluation.

	All Features	Leading Indicators	Coincident Indicators	Lagging Indicators
CYCLE				
All Features	-	-	-	-
Leading Indicators	32.458***	-	-	
Coincident Indicators	17.981***	9.824***	-	-
Lagging Indicators	18.435***	2.71#	7.545**	-
UPWARD TREND				
All Features	-	-	-	-
Leading Indicators	37.416***	-	-	
Coincident Indicators	23.212***	13.116***	-	-
Lagging Indicators	25.168***	1.92#	9.814***	-
DOWNWARD TREND				
All Features	-	-	-	-
Leading Indicators	47.550***	-	-	
Coincident Indicators	27.882***	11.365***	-	-
Lagging Indicators	29.317***	2.014#	8.8725**	-
CYCLE 2				
All Features	-	-	-	-
Leading Indicators	31.656***	-	-	
Coincident Indicators	19.217***	10.235***	-	-
Lagging Indicators	20.926***	2.56#	9.718***	-

Table 10
Outcome of Comparative Statistical Assessment.

	KNORAE	RF	DNN	TabNet
CYCLE				
KNORAE	-	-	-	-
RF	15.046***	-	-	
DNN	1.850#	13.984***	-	-
TabNet	1.592#	14.515***	1.685#	-
UPWARD TREND				
KNORAE	-	-	-	-
RF	17.611***	-	-	
DNN	2.349#	14.782***	-	-
TabNet	2.105#	15.431***	1.424#	-
DOWNWARD TREND				
KNORAE	-	-	-	-
RF	19.825***	-	-	
DNN	1.882#	18.917***	-	-
TabNet	2.170#	21.072#	1.890#	-
CYCLE 2				
KNORAE	-	-	-	-
RF	16.143***	-	-	
DNN	1.785#	15.886***	-	-
TabNet	1.989#	17.158***	1.623#	-

during UPWARD TREND, does not feature in the said list during the DOWNWARD TREND.

During this phase, the significance of VIX indicates an overall bearish trend. Crude oil prices exert further pressure on the negative mood of the economy. As daily requirements cannot be drastically cut down, DELCOM remains significant. This period experienced the Covid 19 pandemic accompanied by lockdowns and economic standstill. Thus, BANK DMA, DELCAP, or DELREALTY do not feature as significant. The policy prescription during such periods of economic uncertainty would include government support for demand expansion and healthcare needs.

In the CYCLE 2 regime, the coincident indicator foreign exchange has emerged to be the most dominant attribute, similar to CYCLE duration. The influence of PE is also paramount, as the same assumes the 2nd spot of feature ranking. FMCGLAG5 and FMCGLAG1 feature in the top 5 attribute list, signifying the contribution of the FMCG sector in classifying the upswing traits. CONS also appears as a strong feature in the predicting financial cycles. BANKDMA, DELCG, and VIX, too, reside in the top 20 significant feature list.

Fig. 1 shows, that the CYCLE 2 Period was marked by economic recovery, and subsequent slowdown. Thus, FMCG, BANKDMA, and DELCOM, along with the exchange rate, emerge significant. The significance of VIX indicates presence of economic uncertainty. Such periods require policy measures conducive for economic expansion, along with exchange rate stability and stability of financial markets.

In Figs. 11–14, we depict the outcome of SHAP-based feature contribution assessment, during Downswing state of financial cycle, in each phase. It may be observed, that for all the phases, the feature rankings remain the same, irrespective of whether we consider upswings or downswings. This implies that, the influence of the respective explanatory variables remains the same, during the entire

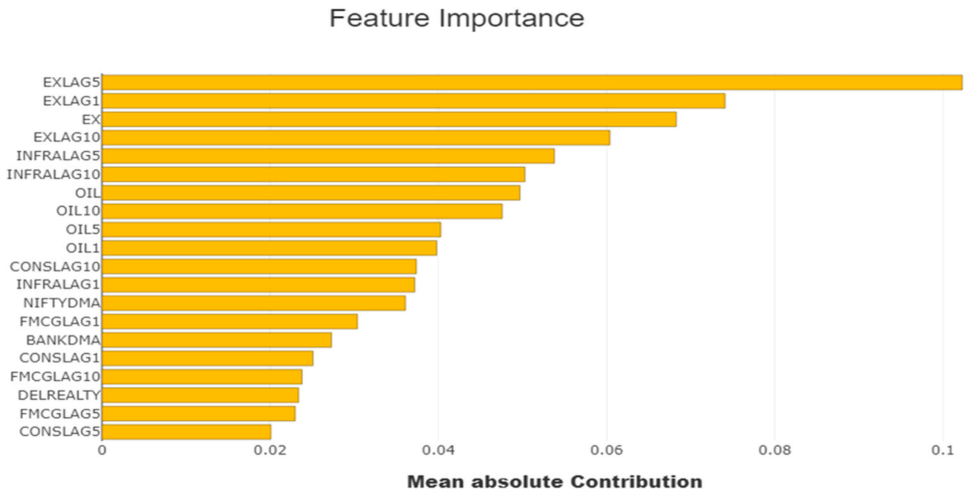

Fig. 7. Feature Contribution in CYCLE Period for Upswing Class.

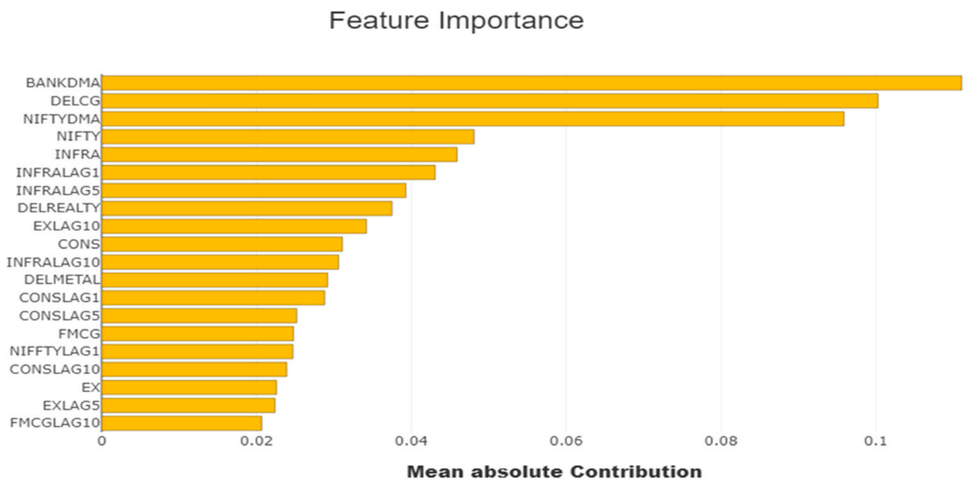

Fig. 8. Feature Contribution in UPWARD TREND Period for Upswing Class.

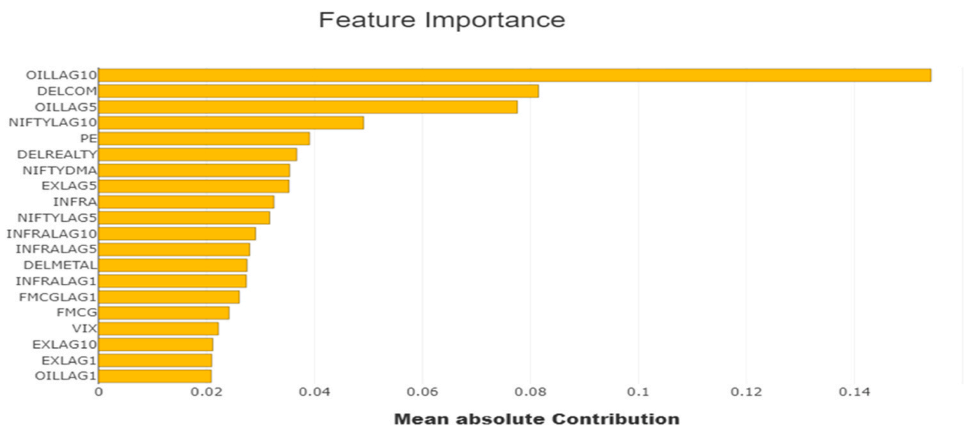

Fig. 9. Feature Contribution in DOWNWARD TREND Period for Upswing Class.

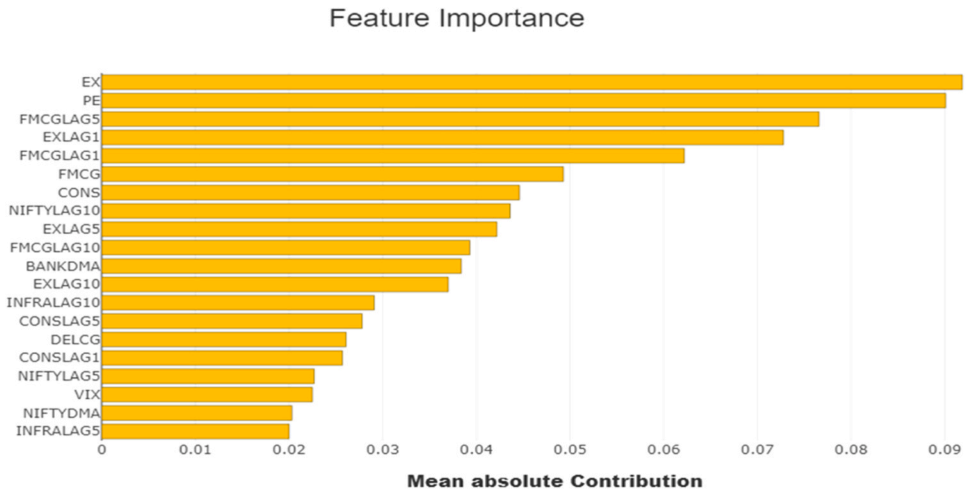

Fig. 10. Feature Contribution in CYCLE 2 Period for Upswing Class.

period of a phase. This may make the job of policy makers relatively easier to monitor and intervene.

6. Discussion

The paper proposes a DES based framework for predicting financial cycles. It utilizes 6 distinct DES models, namely, *K*-Nearest Oracle Elimination (KNORAE), *K*-Nearest Oracle Union (KNORAU), Meta-Learning for Dynamic Ensemble Selection (METADES), Dynamic Ensemble Selection Performance (DESP), Dynamic Ensemble Selection-K Nearest Neighbor (DESKNN), and Dynamic Ensemble Selection Randomized Reference Classifier (DESRRC). For implementing the DES models, the homogeneous pool of classifiers considered for modelling are Random Forest (RF), Bagging (BG), Gradient Boosting (GB), and Extreme Gradient Boosting (XGB). The heterogeneous pools are simulated through pooling framework combing Support Vector Machine (SVM), K Nearest Neighbor (KNN), Decision Tree (DT), and Logistic Regression (LR). Given the binary nature of the dependent variable, Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the data set.

For the purpose, the paper resorts to stock market indicators like sectoral indices, the P/E multiple and VIX. The sectoral indices are chosen to represent specific aspects of the macroeconomic environment, and these explanatory variables also feature in the literature. In addition, crude oil prices and the exchange rate are included in the exercise to factor in the effects of external shocks, as the study is over time periods where the external environment was quite turbulent. The explanatory variables have been classified under leading, coincident, and lagging indicators.

The results of the study indicate that the forecasting framework is overall efficient, irrespective of the time phase of the analysis. The efficiency metrics have significant values indicating appropriateness of choice of explanatory variables. However, feature importance differs from phase to phase and supports the choice of the explanatory variables. It was observed that the relative

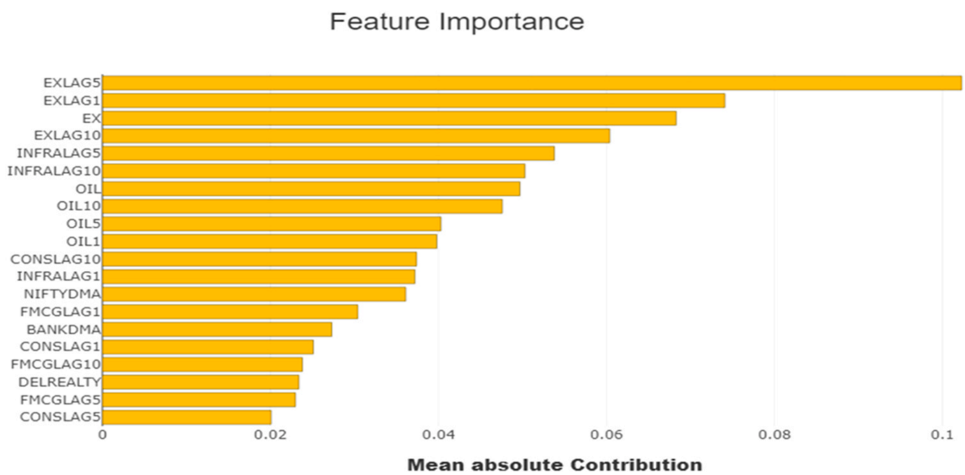

Fig. 11. Feature Importance in CYCLE Period for Downswing Class.

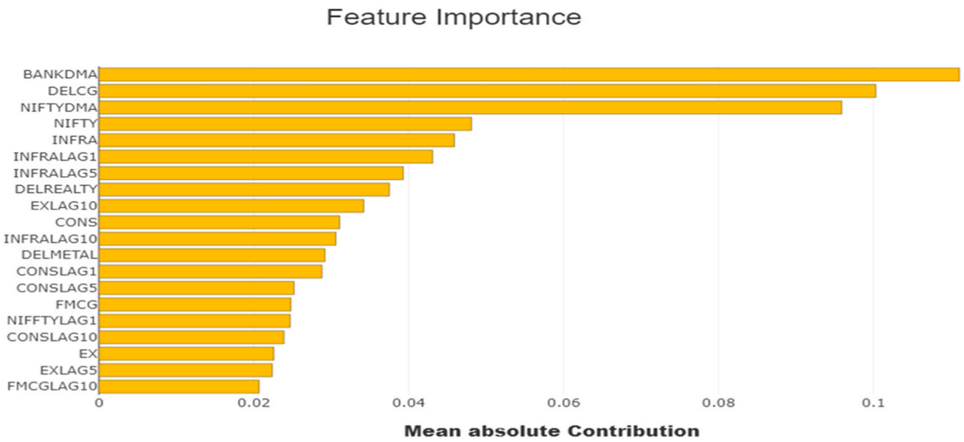

Fig. 12. Feature Contribution in UPWARD TREND Period for Downswing Class.

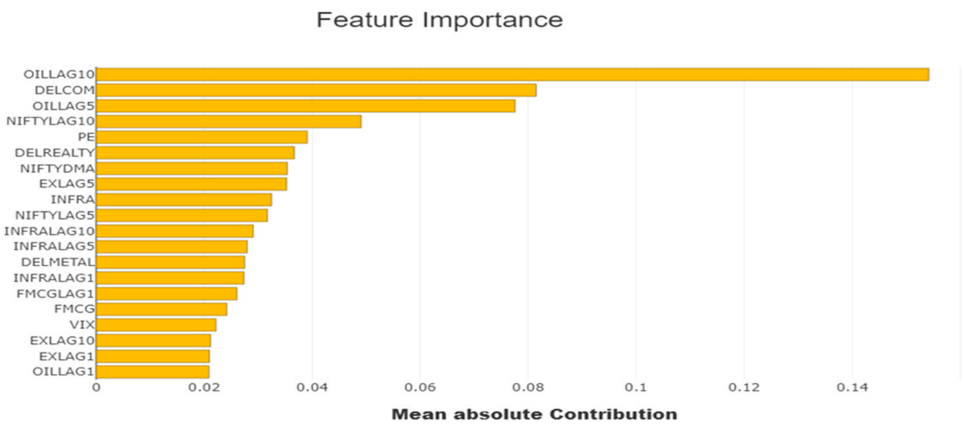

Fig. 13. Feature Contribution in DOWNWARD TREND Period for Downswing Class.

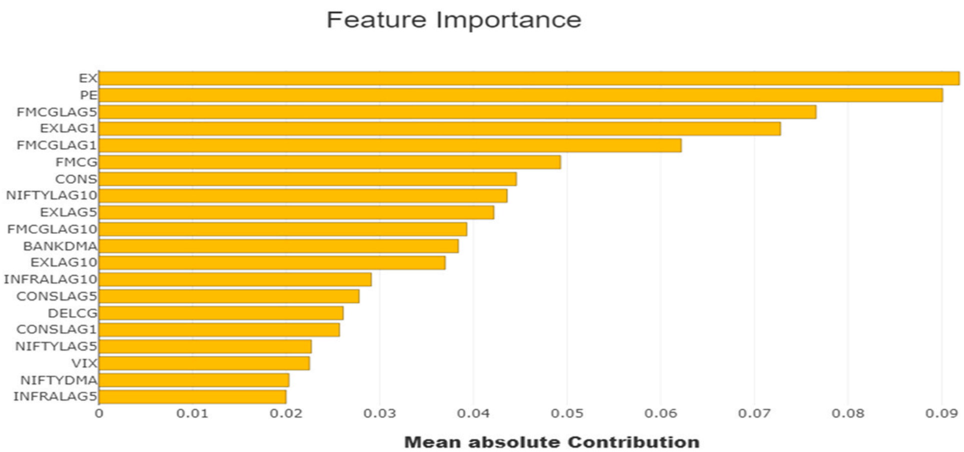

Fig. 14. Feature Importance in CYCLE 2 Period for Downswing Class.

importance of the exchange rate and crude oil was the highest in both the cyclical phases of NIFTY. These are both coincident indicators, and the latter cycle coincided with the on-going international conflicts. The impact of coincident and lagged indicators was more than leading indicators. In these phases, changes in the external environment put pressure on the economy, and the corresponding policy responses were demand expansion, exchange rate management, and oil price determination.

For the upward phase, leading indicators like credit expansion, capital goods capacity expansion, metal sector capacity expansion, growth in consumer goods market size, infrastructure growth, and overall market sentiment, emerged as the leading explanatory variables. This resonates with the literature where credit growth and realty sector expansion, accompany economic growth phases. In such a period, internal market structures play a significant role in driving growth. This is reflected in the significance of variables like BANKDMA, DELCAP, DELMETAL, and DELINFRA. This pattern changes in the downward trend phase where oil prices, realty indices, and VIX emerge to be important.

The second cyclical phase, CYCLE 2, is different from CYCLE, as the former has an upward trend, and comes on the back of a rising trend. Given the international conflict environment, the exchange rate emerges to be most significant in explaining financial cycle. However, given the overall upward trend, leading indicators like the P/E multiple, VIX, Bank Index, and Infrastructure Index also emerge as important features. The findings of this phase suggest a combination of expansionary and stabilization measures for sustaining economic growth in the face of external shocks.

Overall, the significant features vary from phase to phase in the forecasting framework, and they truly represent the characteristics of the phases. The analysis also throws up possible policy measures appropriate for each phase. The choice of leading, coincident, and lagged indicators has been quite appropriate, along with the forecasting methodology.

The findings of the underlying research contribute to the existing strand of financial cycle estimation literature wherein the usage of financial market-linked variables has been reported (Farrell and Kemp, 2020; Setshegetso and Mado, 2024; Tian et al., 2024). Nevertheless, the novelty of the proposed classification framework in anticipating the movements of different states of the financial cycle across the select regimes truly underscores the effectiveness of the research contributions. The steep dependence of the financial cycle on the exchange rate and VIX conforms with the findings of Menden and Proaño (2017) and Raheem and Vo (2020). Overall, the proposed methodological approach emerges as effective and serves actionable insights for policy implications conforming with the findings of the work of Melo-Velandia et al. (2025).

7. Concluding remarks

Studying financial cycles is important, as it has a relation with business cycles, and also reflects the robustness of the financial sector and the regulatory system. Overheating of financial markets can have disruptive effects on individual wealth and demand, which in turn can affect output and employment. Thus, the policy makers should have metrics in place that can provide early warning signals. For this purpose, identifying appropriate variables are important for monitoring, and this paper provides examples of such variables. The paper also advances an efficient forecasting framework. The novel findings of the paper are that some indicators are more important than others in different market states, with different macroeconomic characteristics. It was observed that importance of the exchange rate and crude oil was the highest in both the cyclical phases of NIFTY calling for policy measures aimed at exchange rate management and oil price determination. In an upward phase, expansion in bank credit, capital formation, and expansion in the realty sector emerged to be significant. The policy prescription during such periods would be government incentives for capital expansion like lowering interest rates, and modifying tax and duty structures. In the downward phase, VIX and oil prices emerge to be significant. This calls for growth measures, and government support for demand expansion.

The seamless integration of SMOTE, different DES methodologies and the XAI framework has proved to be highly effective in classifying and interpreting the movements of financial cycles. In our future work, we intend to apply different methods for identifying cycles. Specifically, the utility of deep learning-based classification frameworks can be leveraged to anticipate financial cycles, and a comparative study with the presented DES methodologies can be accomplished. Scope of the current research is strictly restricted to Indian context. Applying this predictive framework to other economies is also part of future research agenda.

Macroeconomic events and financial sector developments had given some indications prior to financial sector crises in the past. Growth in volume of derivative instruments and real estate booms are some of the events that preceded such crises. These events did lead to development of policy measures as a check for such events not repeating themselves. However, continuous monitoring of the environment is necessary, and the present paper provides a framework for the same. Incorporating stock market indices, reflecting both real sector and financial sector variables, in a forecasting framework can help management of financial institutions and policy makers to anticipate financial crises and take early mitigating measures. However, instead of purely depending on historical stock market data, future research would incorporate macroeconomic variables like employment, output, rate of interest, and foreign trade in the study. Future research would also focus on application of the DES framework in other economies and asset markets.

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CRediT authorship contribution statement

Mohammad Zoynul Abedin: Writing – review & editing, Validation, Supervision, Project administration, Data curation, Conceptualization. **Layal Isskandarani:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Tamal Datta**

Chaudhuri: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Indranil Ghosh:** Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization.

Consent for publication

All authors are very positive to publish this manuscript on this journal.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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