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ORIGINAL RESEARCH

Prediction and decoding of metaverse coin dynamics: a granular quest using MODWT-Facebook's prophet-TBATS and XAI methodology

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Abstract
The growing media buzz and industry focus on the emergence and rapid development of Metaverse technology have paved the way for the escalation of multifaceted research. Specific Metaverse coins have come into existence, but they have barely seen any traction among practitioners despite their tremendous potential. The current work endeavors to deeply analyze the temporal characteristics of 6 Metaverse coins through the lens of predictive analytics and explain the forecasting process. The dearth of research imposes serious challenges in building the forecasting model. We resort to a granular prediction setup incorporating the Maximal Overlap Discrete Wavelet Transformation (MODWT) technique to disentangle the original series into subseries. Facebook's Prophet and TBATS algorithms are utilized to individually draw predictions on granular components. Aggregating components-wise forecasted figures achieve the final forecast. Facebook's Prophet is deployed in a multivariate setting, applying a set of explanatory features covering macroeconomic, technical, and social media indicators. Rigorous performance checks justify the efficiency of the integrated forecasting framework. Additionally, to interpret the black box typed prediction framework, two explainable artificial intelligence (XAI) frameworks, SHAP and LIME, are used to gauge the nature of the influence of the predictor variables, which serve several practical insights.

Keywords Metaverse coin · Maximal overlap discrete wavelet transformation (MODWT) · Facebook's prophet · TBATS · Explainable artificial intelligence (XAI)

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1 Introduction

The term *"metaverse"* was initially coined by Neal Stephenson in 1992 in his novel "Snow Crash" centered around the struggle for social status controlling digital avatars in a virtual realm (Zhao et al., 2022). Since then, the concept of Metaverse has been confined to several novels and movies (Spielberg et al., 2018). The technological disruption of Metaverse in revolutionizing the human–computer interface has seen a continuous surge in adoption and media traction. It embodies Web 3.0, Blockchain technology, and augmented and virtual reality to advance the next-generation computing platform, enabling users to experience extended reality in 3D virtual cyberspace (Lee et al., 2021). The phenomenal rise of Metaverse technology has unearthed infinite possibilities for innovation in the wide industrial arena. Growing adoption of the Metaverse platform in entertainment, art, exhibition, tourism, etc. sectors is being anticipated (Akour et al., 2022; Dincelli and Yayla, 2022). Mark Zuckerberg's announcement to rename 'Facebook' with 'Meta' to align the company's focus on developing the end-to-end Metaverse ecosystem has further catalyzed the prospect.

Financial markets have undergone spillover effects as a consequent imperative of rapid technological enhancement. Specific Metaverse coins have come into existence late, and market capitalization is expected to grow steadily in the near future. The inception of Metaverse coins has been accompanied by the recent surge in non-fungible token (NFT) and decentralized finance (DeFi) instruments, linked to a market capitalization of over 1 trillion US dollars (Howcroft, 2021; Dowling, 2022) as an evolution of Ethereum ecosystem. Like Metaverse coins, NFTs and DeFis are also niche assets (Aharon and Demir, 2021). Nevertheless, NFTs and DeFis have already initiated garnering researchers' attention. The literature has reported behavioral dynamics and spillover contagion of these assets (Aharon and Demir, 2021; Corbet et al., 2023; Yousaf et al., 2022). On the contrary, the Metaverse financial marketplace, a hub of several tokens introduced as early as the first quarter of 2022, is almost unexplored to date. To the best of our knowledge, barring Vidal-Tomás's (2022) work on analyzing the empirical aspects of Metaverse coins, dedicated literature on deeper assessment of Metaverse coins and the interplay with other financial assets is extremely scanty. As a result, the scarcity of scalable frameworks to predict the future movements of the major Metaverse tokens is imminent. It, nevertheless, is of paramount importance to thoroughly examine the inherent evolutionary pattern for various practical purposes. Research on the potential utilization of Metaverse for the betterment of operations in education (Hwang and Chen, 2022), media platforms (Prieto et al., 2022), healthcare (Skalidis, 2022), transportation (Pamucar et al., 2022), etc. have been undertaken. Thus, the daily transactions of Metaverse coins will facilitate the adoption and smooth operations. Therefore, the development of a predictive framework to forecast daily Metaverse coins is vital for effective planning and financial decision-making. The emergence of machine learning and explainable artificial intelligence (XAI) techniques in successfully decoding complex phenomena (Nyawa et al., 2023; Puram et al., 2022) has generated growing traction in the adoption of the said methodologies for financial variables (Ghosh et al., 2023; Yang et al., 2023). Despite the scarcity of data-based analytical models for predicting future values of Metaverse coins and understanding their reliance on suitable indicators, there remains ample opportunity for contributions in methodology.

The dearth of previous research to uncover the temporal behavioral patterns of the niche Metaverse financial market is amply apparent. Nevertheless, due to its growing adoption in different industrial verticals, it is of paramount practical relevance to demystify this emerging digital currency market. The literature on fathoming the dependence structure of Metaverse financial assets on financial and economic variables is also scanty. To the best of our knowledge, after a thorough scrutiny of the cognate literature, no research has strived to forecast future figures of explicit Metaverse tokens throughout the prevailing pandemic time horizon. A lack of understanding of the influence of explanatory variables poses an arduous task to decode the temporal dynamics of Metaverse coins holistically.

To bridge the research gaps, firstly, the underlying work strives to critically analyze the daily closing prices of six Metaverse Coins, namely, Axie Infinity (AXS), Gala (GALA), Decentraland (MANA), The Sandbox (SAND), SushiSwap (SUSHI), and WAXP considering the COVID-19 pandemic timeline. Secondly, due to the absence of standard predictive frameworks and considering the highly turbulent external environment, the study propounds a novel hybrid forecasting structure combining the maximal overlap discrete wavelet transformation (MODWT), Facebook's Prophet, and the integrated structure of the trigonometric seasonality, Box-Cox transformation, auto regressive moving average errors, trend, and seasonal components (TBATS) technique seamlessly for predictive analysis of chosen Metaverse tokens. Thirdly, the research aims to understand the interplay structure between the explanatory variables and the chosen tokens using the explainable artificial intelligence (XAI) methodologies. The efficacy and reliability of the integrated methodology are established by subjecting the same to a stringent series of quantitative and statistical performance checks to truly rationalize it as a data science framework. The novelty of the same lies in end-to-end data-driven insight generation for drawing final inferences.

The current research work contributes to the methodological front end as well by propounding a granular forecasting structure comprised in a neoteric manner. MODWT is used to decompose the original time series observations of chosen Metaverse coins into a set of linear and nonlinear subseries to drive the prediction process effectively. The granular decomposition is extremely useful for modeling the abrupt changes, extreme nonlinearity, and speculative components of financial time series (Jana and Ghosh, 2022; Ren et al., 2022). The MODWT procedure results in a major approximation and a set of highly oscillating components (Jana and Ghosh, 2023). We rely upon Facebook's Prophet algorithm, an emerging time series forecasting technique (Jana et al., 2022; Ning et al., 2022), in a multivariate framework incorporating a set of explanatory features to perform predictive modeling in approximation components that accounts for the maximum variation of the original series of respective coins. On the other hand, the univariate TBATS model, a univariate forecasting tool (Munim, 2022, Tavakoli et al., 2022), is used to fetch forecasts on the detailed components. Component-wise forecasts are aggregated to compute the final forecasts. The aforesaid combination of MODWT, Facebook's Prophet, and TBATS forms a novel methodological framework for identifying the governing pattern of unexplored Metaverse Coins. It should be noted that the underlying three components of the integrated structure alongside their close variants have been successfully utilized for time series modeling separately (Ghosh and Datta Chaudhuri, 2017; Kim and Kim, 2021; Ghosh et al., 2022; Jana et al., 2022; Nasirtafreshi, 2022). The seamless integration of these three techniques is exclusively used to successfully predict a class of niche digital assets. As financial time series forecasting is an extensively well-known field (Akhtar et al., 2022; Akyildirim et al., 2022; Bui et al., 2018; Chen et al., 2022; Eachempati, 2021; Ghosh et al., 2023; Jiang et al., 2022; Li et al., 2021; Liu et al., 2021; Liang et al., 2022; Park et al., 2022; Scholz et al., 2022; Tao et al., 2022, Yao and Kan, 2024), statistical efficacy of the propounded structure is established through comparative performance evaluation against benchmarking models to solidify its positioning. The predictive structure leverages a set of explanatory features covering macroeconomic, technical, and social media indicators while yielding forecasts on the approximation component using Facebook's Prophet model. As discussed before, no previous studies examined the interrelationship of Metaverse tokens with other financial and economic variables. We have incorporated the variables on the basis of the technological microstructure of the Metaverse dependence structure of NFTs and DeFis, resembling Metaverse tokens on Blockchain ground, on allied variables, and manifests reflecting media and economic uncertainty in Twitter. Daily closing prices of Bitcoin and Ethereum were chosen based on the contribution of Blockchain technology to Metaverse development. Considering the uncertainty of the time horizon caused by the COVID-19 pandemic, economic and political uncertainty of the US (EPU) and the implied volatility index of the Chicago Board of Options Exchange (CBOEVIX) representing market fear in the US are incorporated as well. The daily closing prices of crude oil and gold are chosen as they have been reported to affect the NFTs and DeFis. Several technical indicators are selected to explain the dependence of the Metaverse coins on their historical states. Finally, a set of Twitter media and uncertainty indices are utilized as well to expound on the random fluctuation and speculative behavior by gauging the floating sentiment in social media. To accomplish the endeavor, XAI methodologies are invoked to serve model interpretation and gauge feature influence structure. Two XAI frameworks, SHAP and LIME, are employed to deduce explanations at global and local levels, respectively. In a nutshell, the contributions of the underlying work are enunciated below:

- The present research strives to delve into the granular dynamics of emerging Metaverse coins for forecasting temporal patterns through a robust framework.
- The underlying work aims to comprehensively perform forecasting of 6 Metaverse coins from their inception till October 7, 2024, which covers several black swan events timelines, the COVID-19 pandemic, the Russia-Ukraine conflict, and the ongoing Israel-Palestine war.
- As a paucity of past literature on Metaverse coins is imminent, the current endeavor carefully selects a series of explanatory variables covering orthodox technical indicators, macroeconomic variables, and social media sentiment constructs to predict the dynamics of the target variables.
- The methodological framework seamlessly combines MODWT, Facebook Prophet, and TBATS procedures to develop a robust and granular forecasting structure, which is subjected to a battery of numerical and statistical checks to justify the utility and validity of the framework.
- As the proposed framework is difficult to interpret owing to the complex operational steps of the respective procedures, XAI tools are invoked separately on the forecasting outcome to deduce the contributions of the utilized explanatory variables for drawing deeper insights.

The critical findings of the temporal introspection of 6 Metaverse coins suggest that the underlying assets strongly exhibit a nonlinear and persistent pattern. The presence of steep nonlinearity is expected, considering the timeline of the investigation. The persistent pattern also rationalizes the utilization of technical indicators as explanatory variables. The integrated hybrid predictive structure has appeared to be profoundly effective in accurately estimating the future figures of the select Metaverse coins, which, in the same way, survive a battery of numerical performance checks. The granular hybrid structure also emerges to be statistically superior to several benchmark forecasting models. The XAI-driven modeling on top of the hybrid predictive structure reveals that conventional cryptocurrencies and the technical indicators largely explain the variation of the evolutionary pattern of the target variables globally, whereas the Twitter media and economy uncertainty indicators are important to monitor at the local level to anticipate the short run fluctuations. Market fear and global economic uncertainty in the physical realm have appeared to exert relatively low predictive power on the chosen coins. Finally, the integrated data-driven research methodology emerges to be a significant addition to the decision support system discipline by seamlessly yielding accurate predictions and unveiling granular insights on feature contribution. The combined approach of Facebook Prophet and XAI tools as a robust decision support system can easily be extended to resolve complex data science problems.

Apart from contributing toward the methodological front, the findings of the research can be translated into practical relevance. The discovered predictable nature of all Metaverse coins during a period of distress is of paramount significance for traders and investors. The presence of deep-seated inefficiencies in the Metaverse financial market, as highlighted by ongoing trends, is prompting cryptocurrency enthusiasts to act strategically in digital currency markets when bubbles appear in other assets. Different market players can exploit the inefficient behavioral dynamics of the Metaverse to reap portfolio realignment and hedging benefits.

The strong dependence on BTC and ETH, whilst comparatively more immunity towards conventional market fear and uncertainty owing to geopolitical events, caters to strategic insights for monitoring and regulating the said assets. The industrial verticals, viz. tourism, healthcare, etc., have seen a rapid change in the course of the pandemic, embracing the usage of Metaverse-driven technologies to innovate the offerings. Thus, controlling the circulation of Metaverse coins is going to be a critical task in the near future, which will occasionally require government interventions. Comprehending the short and long-run interrelation with the key macroeconomic variables, therefore, could be immensely beneficial.

The remaining segment of the article is constructed as follows. A brief review of cognate literature to identify the research gaps and position the current work is enunciated in Sect. 2. Detailed methodological frameworks describing the data sources, definitions of the variables, components of the hybrid predictive architecture, and the XAI procedures have been elucidated in Sect. 3. A thorough discussion of the detailed results and critical implications is presented in Sect. 4. Finally, the article draws the closure in Sect. 5, highlighting the key findings, scope, and future research agendas.

2 Literature review

In this section, we briefly highlight the previous cognate literature on digital crypto assets, methodological trends, and XAI-driven frameworks to properly comprehend the existing research gaps, trends, and positioning of the current work.

2.1 Digital niche crypto assets

Owing to the emergence and penetration of blockchain technologies in different technological spheres, several digital crypto-assets, NFT, DeFis, etc., barring the conventional cryptocurrencies, have started garnering growing traction in literature (Qian et al., 2022; Teplova et al., 2023; Zalan and Toufaily, 2024). They are fundamentally different from the conventional financial variables yet reported to offer diversification and hedging benefits (Karim et al., 2022). Both NFTs and DeFis have been observed to be dependent on BTC and ETH in the long run (Corbet et al., 2022; Yousaf and Yarovaya, 2022). Occasional nexus with macroeconomic indicators has been documented, too (Umar et al., 2022; Yousaf et al., 2022). Unlike the NFT and DeFi counterparts, research on spillover contagion or dynamic association of Metaverse-specific tokens with key financial assets is extremely scanty. Nevertheless, some fundamental and economic orientations of some Metaverse coins have been examined from a macro perspective (Thomason, 2022; Vidal-Tomás, 2022). The research of Ghosh et al. (2024) echoes the dependence of emerging Metaverse coins on media chatter about the Russia-Ukraine war. However, the dearth of studies explaining the temporal behavioral pattern of the said digital financial assets, let alone the development of robust predictive structures, is amply apparent. Considering the growth of the Metaverse technologies and the search for an alternative reliable financial asset for trading, risk mitigation, etc., it is of paramount importance to thoroughly analyze the Metaverse assets.

2.2 Predictive frameworks

Literature is replete with predictive modeling of financial variables using sophisticated computational intelligence and machine learning-based models (Gao et al., 2022; Ghosh and Datta Chaudhuri, 2022; Hao et al., 2023; Hafiz et al., 2024; Niu et al., 2023; Tao et al., 2022; Yolcu et al., 2022). We highlight the literature summary focusing on predictive modeling of different cryptocurrencies. Estimating trends and absolute figures of future movements of orthodox cryptocurrencies, too, has seen the adoption of hybrid models. Ideally, the existing literature can be categorized into two broad strands. One category of research has extensively used these methodologies on aggregate data of respective variables. Alonso-Monsalve et al. (2020) designed a hybrid structure of convoluted long and short-term memory network (LSTM) for accurate trend estimation of five distinct cryptocurrencies using a set of technical indicators. Ghosh et al. (2022) presented two hybrid frameworks, namely, auto encoder (AE)-driven deep neural network and kernel principal component analysis (KPCA)-driven regularized greedy forest (RGF) methods for precisely predicting the Indian futures markets. Caliciotti et al. (2024) systematically modeled the bitcoin price through support vector regression-based machine learning framework. The propounded modeling outshined conventional classical regression methodologies. On the other hand, granular forecasting structures using time series decomposition methodologies have been proven to be pretty effective as well in discovering the governing pattern of complex financial time series data. Empirical mode decomposition (EMD), MODWT, etc., are highly used decomposition methodologies that are well-known for disentangling linear and nonlinear time components. Jana et al. (2021) propounded a granular hybrid framework comprising MODWT, polynomial regression with interaction, support vector regression, and differential evolution to successfully predict bitcoin prices. Lin et al. (2022) incorporated complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), a time series decomposition tool, and an LSTM network for accurate predictive analysis of Chinese, European, and US stock markets. Parameswaran et al. (2024) leveraged wavelet transformation for automatic feature extraction and bidirectional LSTM model for accurate trend prediction of several emerging crypto coins. The utilization of Facebook Prophet for successfully carrying out the financial market modeling-driven first category of forecasting has been reported in the literature (Cheng et al., 2024; Ghosh and Jana, 2024). One advantage of the second category of models over the first one lies in the operational procedures of segregating the linear and nonlinear parts, enabling efficient training of the pattern learning model. Our framework aims to ripe the aforementioned advantage as the market under consideration is completely unexplored previously, and the timeline of the study during which market crashes and bubbles have been anticipated.

2.3 Explainable artificial intelligence

Of late, XAI modeling on top of the black box type predictive modeling structure has garnered attention amongst researchers in a wider foray of applications (Holzinger et al., 2022;

Karthikeyan et al., 2022). The utility of the XAI methodologies lies in the process of capturing the unearthed interaction between the target and predictor variables, which is vital for strategic decision-making. The XAI methodologies predominantly use SHAP, LIME, TreeExplainer, partial dependence plots, etc., for interpreting complex predictive models (Ghosh and Sanyal, 2021; Wang et al., 2022). Amini et al. (2022) utilized the leave-one-covariate-out and TreeExplainer-driven XAI frameworks to identify the severe risk factors of automobile crashes. Chew and Zhang (2022) recorded that contact tracing, public gathering rules, and government stringency largely contributed to the growth of COVID-19 infection by applying dedicated XAI frameworks. Ghosh et al. (2022), in their work of predicting the Indian futures market through the lens of hybrid machine learning models, leverage dedicated XAI methodologies to comprehend the impact of different macroeconomic variables on futures prices. Mohanty et al. (2022) provided scrupulous explanations for the risk of readmission in healthcare setup using a cohort of independent variables using XAI methodologies. The XAI frameworks can, therefore, be helpful in gauging the interrelationship between the chosen explanatory features and the respective Metaverse coins at a deeper level.

The summary of the past research elucidates the paucity of studies to ascertain the daily dynamics of closing prices of Metaverse coins explicitly. The lack of work to measure the influence of external variables complicates the identification of explanatory features and, therefore, the analysis of the completely unexplored pattern. The present work aims to bridge the gap by propounding a hybrid granular forecasting framework capable of yielding predictions of supreme accuracy during the timeline characterized by steep turmoil. The current research also leverages XAI frameworks to infer the dependence structure of select Metaverse coins on the key explanatory features. The combined approach strives to augment the capacity of orthodox optimization models in implementing an end-to-end decision support-based ecosystem for accomplishing research endeavors.

3 Research methodology

In this section, we elucidate the data sources, variable definitions, and component-wise methodological details used for accomplishing the research endeavors.

3.1 Data description

3.1.1 Metaverse coins

The present work considers the daily prices of six Metaverse coins, AXS, GALA, MANA, SAND, SUSHI, and WAXP, and compiles the same from www.investing.com data repository. The samples of respective tokens span across different time horizons owing to the varying timeline of market entry and computational requirements of the technical indicators. Table 1 displays the range of the samples.

In general, the time horizon of the investigation overlaps with the ongoing pandemic regime. Figure 1 depicts the evolutionary pattern of the 6 Metaverse coins.

The existence of random fluctuation and nonlinearity entrenched in the temporal dynamics of the said assets is evident from the exhibit. The explanatory variables utilized to forecast the underlying Metaverse coins are discussed next.

Table 1 Sample timeline of respective Metaverse Coins

Series	AXS	GALA	MANA	SAND	SUSHI	WAXP
Period	December 4, 2020–October 7, 2024	January 12, 2022–October 7, 2024	July 16, 2019–October 7, 2024	January 4, 2022–October 7, 2024	January 12, 2020–October 7, 2024	May 30, 2018–October 7, 2024

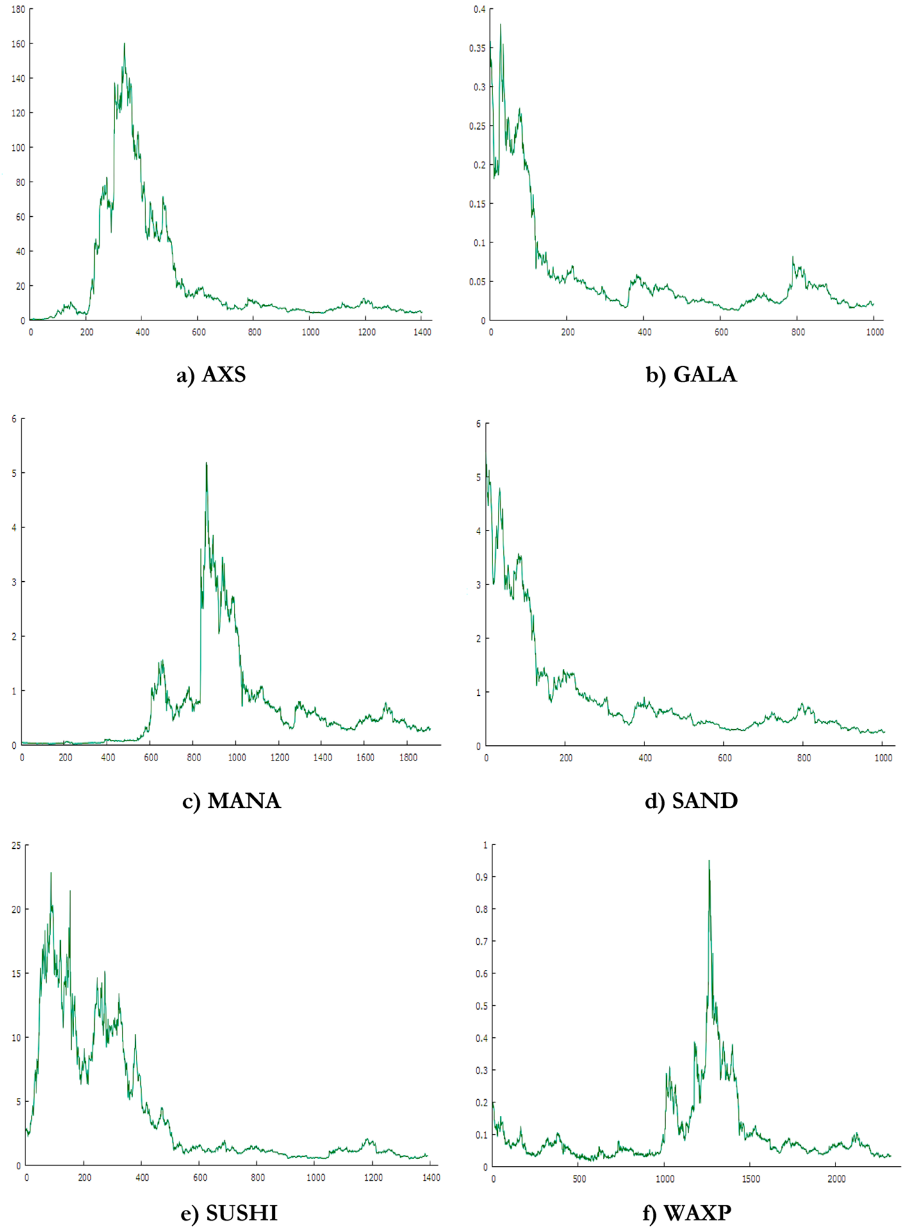

Fig. 1 Evolutionary Pattern of the Metaverse Coins

3.1.2 Explanatory variables

As stated earlier, daily closing prices of BTC, ETH, OIL, and GOLD have been used as explanatory features considering the dependence of Metaverse on Blockchain technology and cognate literature of NFTs and DeFis. CBOEVIX is utilized to compensate for the overall market fear in the US in the context of the pandemic. The data is collated from the same repository. EPU is used to account for the economic and political situations in the US. The daily observations of EPU are collected from the www.policyuncertainty.com portal. Data points are collated in accordance with the quantum of samples of respective target constructs. The Twitter-derived measures of uncertainty proposed by Baker et al. (2021) hosted in www.policyincertainty.com portal are used to measure social media sentiment's impact on the target constructs. The indicators are derived based on daily joint occurrences of uncertainty and economic activity-related terms in tweets from people in the US. A total of 8 indices reflecting media and economic uncertainty are used in this work. As the US is the major technological breeding hub of the Metaverse platform, the majority of the explanatory variables are US-centric. The said indices are Twitter Economic Uncertainty for United States (TEU-USA), TEU Index-based on English words (TEU-ENG), scaled TEU index (TEU-SCA), weighted TEU-index (TEU-WGT), Twitter-based market uncertainty (TMU) for United States (TMU-USA), TMU Index-based on English words (TMU-ENG), scaled TMU index (TMU-SCA), weighted TMU-index (TMU-WGT). In addition to these variables, eight technical indicators, defined in Table 2, are extracted from respective response variables and applied as independent features.

Table 2 Definitions of the Technical Indicators

Sl. No	Features	Formulae
1	5-day moving average (MA5)	$MA5 = \frac{\sum_{i=j-4}^{j} P_i}{5}$ where P_i denotes the closing price of ith day
2	10-day moving average (MA10)	$MA10 = \frac{\sum_{i=j-9}^{j} P_i}{10}$
3	5-day momentum (MTM5)	$MTM5 = P_i - P_{i-5}$
4	10-day momentum (MTM10)	$MTM10 = P_i - P_{i-10}$
5	5-day exponential moving average (EMA5)	$EMA5 = \frac{2}{5+1} \times P_5 + \frac{5-1}{5+1} \times EMA4$, where $EMA1 = P_1$
6	10-day exponential moving average (EMA10)	$EMA10 = \frac{2}{10+1} \times P_9 + \frac{10-1}{10+1} \times EMA9$
7	Upper Bollinger band (UB)	$UB = MA20 + (20 \times \sigma_{20})$ where σ_{20} denotes the standard deviation of closing prices of the previous 20 days
8	Lower Bollinger band (LB)	$LB = MA20 - (20 \times \sigma_{20})$

The formulae in the third column are utilized explicitly to estimate the figures of the technical indicators of respective series

3.2 Methodology

Here, we thoroughly elaborate on the methodological components used for predictive modeling and subsequent model interpretation, respectively. The methodology endeavors to imitate a robust end-to-end decision support system by ensuring precise predictive modeling and enabling lucid interpretation to comprehend the contributions of explanatory variables in estimating future figures. The integrated hybrid framework comprises MODWT, Facebook's Prophet, and the TBATS algorithm. The novel granular structure is referred to as MOD-Pro-T hereafter throughout the remainder of the manuscript. First, we describe the operation procedure of the MODWT models.

3.2.1 Maximal overlap discrete wavelet transformation (MODWT)

It is a wavelet analysis-driven time series decomposition process capable of disentangling time series observations into granular level subseries accounting for different time–frequency horizons (Gençay et al., 2002). In the decomposition process, MODWT preserves the inherent time series features, viz., non-stationarity, nonlinearity, heteroscedasticity, volatility clustering, etc. (Ghosh et al., 2021; Jana et al., 2021). MODWT is often preferred over conventional discrete wavelet transformation (DWT) owing to the capacity of the former to be invariant to circular shift and modeling non-dyadic data sets (Das et al., 2018). It performs translating and dilating operations on the raw signal to produce father and mother wavelets at scales defined beforehand. The resultant transformation is exceptionally robust and non-orthogonal.

Mathematically, an underlying time series signal $f(t)$ into subcomponents as:

$$f(t) = \sum_k v_{j,k}\varphi_{j,k}(t) + \sum_k w_{j,k}\psi_{j,k}(t) + \sum_k w_{j-1,k}\psi_{j-1,k}(t) + \cdots + \sum_k w_{1,k}\psi_{1,k}(t) \tag{1}$$

where father (φ) and mother (ψ) wavelets denote low and high-frequency parts of the original signal; $v_{j,k}$, $w_{j,k}$, …, $w_{1,k}$ denote the respective coefficients created through the wavelet transformation process. The signal,$y(t)$ can be represented as a J-level multi-resolution decomposition process using the following equation:

$$f(t) = v_j(t) + w_j(t) + w_{j-1}(t) + \cdots + w_1(t) \tag{2}$$

where frequency components w_j (detailed scales) account for short, medium, or long-lived variations at 2^j time scale and v_j (approximation level) is the determined residual after removing the detailed components from the original signal. Decomposed parts of lower frequency bandwidth prevail for longer periods, whilst the components associated with higher bandwidth prevail for shorter periods. Facebook's Prophet is used in multivariate mode, utilizing the chosen predictor variables to yield future figures of the approximation component. TBATS, on the other hand, is used to obtain forecasts for the remaining four detailed components in univariate mode. The final forecast is estimated by performing arithmetic addition on component-wise predictions. The granular forecasting setup as a complete data science framework is ideal for capturing the inherent pattern of large observations of variables, which have hardly seen any prior examination in the existing literature.

3.2.2 Facebook prophet

Prophet, developed by Facebook's core data scientists (Taylor and Latham, 2018), is an applied predictive modeling algorithm that has recently received increased traction in carrying out time series forecasting exercises. It is capable of yielding superior forecasts for complex daily, weekly, monthly, and yearly time series observations through precise segregation of trends, sharp regime shifts, seasonality, holiday effects, etc.

The prophet model specification can be expressed as:

$$y(t) = g(t) + s(t) + h(t) + x(t) + \epsilon_t \tag{3}$$

where $y(t)$ refers to the target construct or time series, $g(t)$ reflects for the trend component accounting for linear or nonlinear effects, $s(t)$ refers to periodic components, $h(t)$ measures the holiday effects owing to irregular schedules, the influence of exogenous features is assessed through $x(t)$, and finally, ϵ_t denotes the error term.

For predictive modeling of chosen variables, only the holiday component has not been considered. On the other hand, the macroeconomic, technical, and social media indicators have been treated as exogenous features for predicting the underlying coins. The growth part has been modeled using a piecewise constant function, which offers high accuracy. Mathematically, it can be expressed as:

$$g(t) = \left(k + a(t)^T \delta\right)t + \left(m + a(t)^T \gamma\right) \tag{4}$$

Here, k denotes the growth rate, $\delta\left(\in \mathbb{R}^S\right)$ is the rate adjustment parameter that allows S change points to be incorporated in the model, m represents the offset parameter, and γ controls the magnitude of the rate of change. For daily samples, Prophet automatically estimates weekly and yearly seasonality segments. Seasonality is modeled using a Fourier series as:

$$s(t) = \sum\nolimits_{n=1}^{N} \left(a_n cos\left(\frac{2\pi nt}{P}\right) + b_n sin\left(\frac{2\pi nt}{P}\right)\right) \tag{5}$$

where P denotes the period of the time series (Yearly, Weekly, Daily, etc.). Therefore modeling seasonality demands computations of $2N$ parameters, $\beta = [a_1 b_1 \ldots a_N b_N]^T$.

The fitting process of the Prophet algorithm applies a maximum posterior probability (MAP) process or full Bayesian statistical inference with Markov Chain Monte Carlo (MCMC) sampling. Once the learning is completed, Prophet can be used to forecast the test segment, where the average frequency and magnitude of trend change are assumed to be constant. Prophet has emerged to be robust to outliers, missing data, nonlinearity, regime shifts, etc. The *'fbprophet'* library has been used in the Python programming environment to implement Facebook's Prophet algorithm.

3.2.3 Trigonometric seasonality, box-cox transformation, auto regressive moving average errors, trend and seasonal components (TBATS)

Originally proposed by De Livera et al. (2011), TBATS combines the well-known Box-Cox transformation and exponential smoothing procedure to capture nonlinearity while yielding forecasts. It also carefully accounts for the trend and seasonality counterparts. As mentioned before, the present work leverages TBATS to fetch predictions in detailed high-frequency components. It is also invariant to autocorrelation properties of time series. The mathematical framework of TBATS is enunciated with the following equations

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{(\omega)} - 1}{\omega}, & \omega \neq 0 \\ log y_t, \ \omega = 0 \end{cases} \tag{6}$$

$$y_t = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} S_{t-m_i}^{(i)} + d_t \tag{7}$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t \tag{8}$$

$$b_t = (1-\phi)b + \phi b_{t-1} + \beta d_t \tag{9}$$

$$s_t^{(i)} = s_{t-m_i}^{(i)} + \gamma_i d_t \tag{10}$$

$$d_t = \sum\nolimits_{i=1}^{p} \varphi_i d_{t-i} + \sum\nolimits_{i=1}^{p} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{11}$$

$$s_t^{(i)} = \sum\nolimits_{j=1}^{k_i} s_{j,t}^{(i)} \tag{12}$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} cos\lambda_j^{(i)} + s_{j,t-1}^{*(i)} sin\lambda_j^{(i)} + \gamma_1^{(i)} d_t \tag{13}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1}^{(i)} sin\lambda_j^{(i)} + s_{j,t-1}^{*(i)} cos\lambda_j^{(i)} + \gamma_2^{(i)} d_t \tag{14}$$

$$\lambda_j^{(i)} = 2\pi / m_i \tag{15}$$

Here, $y_t^{(\omega)}$ denotes the Box-Cox transformed values of the time series under consideration at time t with parameter ω, l_t reflects the local level at timestamp t, b_t is the corresponding trend component, $s_t^{(i)}$ stands for the ith seasonal component, d_t represents an autoregressive moving average model encompassing a Gaussian white noise process, ε_t, ϕ denotes the damping constant of the trend counterpart, α, β, and γ_i represent the smoothing parameters for $i = 1,2, \ldots, T$, and λ is the Box-Cox transformation. The model parameters are estimated on the basis of the Akaike Information Criterion (AIC). The *'tbats'* package of Python has been used to implement the model and fetch forecasts on detailed components of respective Metaverse coins.

The process parameters of the respective modules of the hybrid MOD-Pro-T framework are outlined in Table 3.

The algorithmic pseudo-code of the MOD-Pro-T framework is outlined below. The entire predictive exercises have been simulated on 2 data setups. The first setup proportions the In-Sample and Out-of-Sample into 85% and 15% segments, while the other segments distribute the in 70% and 30% ratios. The segmentation is carried out in a forward-looking orientation for the respective series, which has been documented as a standard time series predictive analysis procedure (Ghosh et al., 2019; Jana et al., 2021). Using two different setups is

Table 3 Process Parameters of constituent components

Sl. No	Component	Parameters
1	MODWT	{Wavelet filter: 'haar'; levels of decomposition: 4; boundary: 'periodic'}
2	Facebook's Prophet	{Model: 'additive'; seasonality: 'monthly'; Fourier order: 5; change point detection: 'automatic'; additional regressors: the chosen explanatory features}
3	TBATS	{Seasonal Periods: 12; trend selection criteria: AIC; inclusion of ARMA residuals: 'true'}

helpful in ascertaining the capacity of the predictive framework to produce quality forecasts in the presence of adequate and fewer training samples.

Step 1: Decompose the original series of respective Metaverse coins into 4 subseries using MODWT.

Step 1.1: For the approximation component, perform:

Step 1.1.1: Fit Facebook's Prophet on the approximation component using the explanatory features.

Step 1.1.2: Fetch forecasted figures.

Step 1.2: For the individual details components, perform:

Step 1.2.1: Fit TBATS model in univariate setup

Step 1.2.2: Fetch forecasted figures.

Step 2: To draw final forecasts, perform arithmetic summation on estimated forecasted values on respective granular series.

Step 3: Repeat steps 1 and 2 on In-Sample and Out-of-Sample segments of respective series of Metaverse coins to derive forecasted figures.

3.2.4 Measurement of Predictive Performance

Four performance indicators, namely, Nash–Sutcliffe Efficiency (NSE), Theil Index (TI), Index of Agreement (IA), and Directional Predictive Accuracy (DA), have been estimated to quantitatively ascertain the quality of the predictions. They are computed using Eqs. 16–19:

$$NSE = 1 - \frac{\sum_{t=1}^{N}\left\{\widehat{Y}_t - Y_t\right\}^2}{\sum_{i=1}^{N}\left\{Y_t - \overline{Y_t}\right\}^2}, \tag{16}$$

$$TI = \frac{\left[\frac{1}{N}\sum_{t=1}^{N}\left(\widehat{Y}_t - Y_t\right)^2\right]^{1/2}}{\left[\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{Y}_t\right)^2\right]^{1/2} + \left[\frac{1}{N}\sum_{i=1}^{N}\left(Y_t\right)^2\right]^{1/2}} \tag{17}$$

$$IA = 1 - \frac{\sum_{t=1}^{N}\left(\widehat{Y}_t - Y_t\right)^2}{\sum_{i=1}^{N}\left\{\left|\widehat{Y}_t - \overline{Y_t}\right| + \left|Y_t - \overline{Y_t}\right|\right\}^2} \tag{18}$$

$$DA = \frac{1}{N}\sum_{t=1}^{N} D_t,\ D_t = \begin{cases} 1,\ (Y_{t+1} - Y_t)\left(\widehat{Y}_{t+1} - Y_t\right) \geq 0 \\ 0,\ Otherwise \end{cases} \tag{19}$$

The parameters Y_t and $\widehat{Y}_t$ represent actual and predicted figures, respectively, and $\overline{Y_t}$ denotes the average of actual values. For efficient predictions, NSE, IA, and DA values close to 1 signify high accuracy of directional predictions. Higher DA values indicate precise estimation of directional change in the movements of the chosen assets. Hence, a model characterized by high DA values is capable of yielding trading rules to suggest trading decisions in terms of buying or selling assets. Predictive models with high DA figures are extremely lucrative for traders as they imply accurate trend prediction. On the other hand, TI values for superior predictions must be as low as possible. To carry out a statistical comparative predictive assessment, a pairwise Diebold-Mariano (DM) test for equal predictive ability is used, which is essential to rationalize the propounded multivariate predictive structures.

3.2.5 Explainable artificial intelligence (XAI)

Though the primary objective of the current work is to gauge the degree of predictability of the unorthodox and emerging Metaverse tokens, it is equally important to critically evaluate the nature of the influence of the respective explanatory features to draw insights for practical purposes. Identifying the key contributors and comprehending the interplay can be paramount to short and long-term planning. As mentioned, the dearth of previous literature makes the selection of predictor variables arduous. Therefore, interpreting the chosen variables' role would also be challenging. The propounded MODWT-Facebook's Prophet-TBATS framework is tailormade to recognize the inherently complex pattern of volatile time series during the prevailing COVID-19 pandemic. Nevertheless, the integrated structure barely offers any interpretation, unlike the orthodox regression-based approaches. Therefore, it becomes difficult to comprehend the contribution of the respective explanatory variables used in the forecasting exercises. To resolve this, the present research resorts to the emerging XAI methodological frameworks. Recently, the field has garnered growing traction in decoding high-end black box-type AI frameworks and resulted in different tools to accomplish the objectives (Gradojevic and Kukolj, 2022; Yang et al., 2023). The XAI methodologies can be used to interpret the models globally and locally. In this work, we resort to the SHAP-based framework to interpret the feature contribution globally and the LIME-based framework for ascertaining the predictive influence at the local scale. The model outcome for individual data points is determined by aggregating SHAP (SHapley Additive exPlanations) values. The measure SHAP was originally introduced by Shapley (1953) to estimate the contribution of individual entities in the collaborative game. Of late, development and work on XAI have opened up new avenues to leverage the SHAP metric for feature evaluation (Lundberg and Lee, 2017). Mathematically, it is computed using Eq. 20:

$$\varnothing_i = \sum_{S \subseteq N\{i\}} \frac{|S|!\,(n - |S| - 1)!}{n!}[v(S \cup \{i\}) - v(S)] \tag{20}$$

where $\varnothing_i$ denotes the contribution of the i$^{\text{th}}$ 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$^{\text{th}}$ feature.

The explanation is specified by applying Eq. 21:

$$g(z') = \varnothing_0 + \sum_{j=1}^{M} \varnothing_j z'_j \tag{21}$$

where $z' \in \{0, 1\}^M$, 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 (Molnar, 2020) for accomplishing the task. The present research has utilized the TreeSHAP utility to draw insights into features that are of relative importance. Additionally, local interpretable model-agnostic explanations (LIME) (Ribeiro et al., 2016) have been used to examine the variation of the influence pattern of the said features at the local level. Combining the outcome of SHAP and LIME is useful for long-term and short-term planning.

Figure 2 depicts the flowchart of the integrated framework, meant to seamlessly integrate data forecasting and revealing model interpretation.

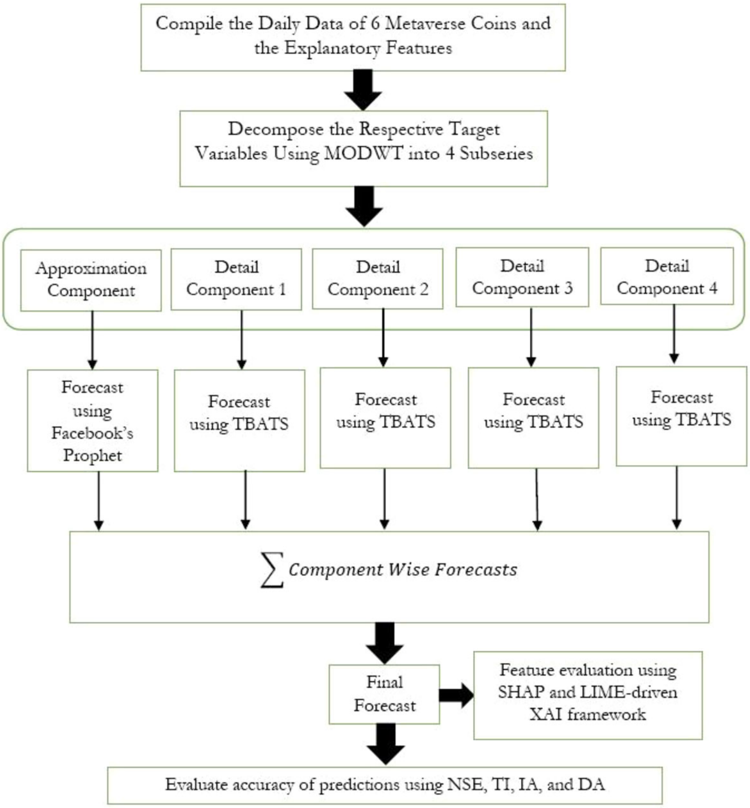

Fig. 2 Flowchart of the Forecasting Framework

4 Results & discussions

The underlying section highlights and critically analyzes the empirical properties, results of predictive analysis, comparative performance assessment, and model interpretation sequentially.

4.1 Empirical Properties

The fundamental properties of respective time series are outlined in Table 4, which provides important empirical insights.

It can be noticed that amongst the selected assets, the daily prices of AXS are relatively on the higher side and linked to higher variability as well. The JB and AD tests suggest that all coins exhibit nonparametric traits. Nonetheless, as 4 out of 6 series violate parametric properties, deploying frameworks capable of modeling such behavior is necessary. ADF test statistics indicate that AXS, GALA, MANA, and WAXP are strictly nonstationary, whereas SAND and SUSHIS exhibit stationary behavior. The presence of nonlinear movements entrenched in the evolutionary pattern of all 6 Metaverse coins is apparent from Terasvirta's test statistics. Therefore, designing a nonparametric predictive framework that

Table 4 Key Statistical Properties of the Underlying Coins

Series	AXS	GALA	MANA	SAND	SUSHI	WAXP
Minimum	0.43	0.01	0.02	0.23	0.50	0.02
Maximum	160.38	0.38	5.19	5.46	22.87	0.95
Mean	22.50	0.06	0.66	0.94	4.03	0.10
Median	7.93	0.04	0.43	0.56	1.31	0.06
Std. Dev	32.78	0.07	0.83	1.00	4.84	0.12
Skewness	2.24	2.50	2.42	2.33	1.51	3.11
Kurtosis	4.30	5.50	6.10	4.78	1.13	12.29
JB Test	2265.1***	2313.9***	4833.2***	1881.5***	601.99**	18,420***
AD Test	219.83***	158.3***	185.76***	140.34***	169.38***	295.73***
ADF Test	−1.2132#	−1.1435#	−1.3102#	−4.4572***	−2.9194***	−1.3170#
Terasvirta’s NN Test	7.443**	24.03***	22.602***	21.353***	81.87***	43.10***
Hurst Exponent	0.8567***	0.8313***	0.8486***	0.8411***	0.8740***	0.8480***

The table summarizes the values of measures of central tendency, dispersion, and some time series features. JB Test: Jarque–Bera Test, 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 is apt for handling nonlinear and nonstationary patterns is of utmost relevance, considering the temporal characteristics of the majority of the variables. On the other hand, the values of the Hurst exponent of the respective series have transpired to be substantially greater than 0.5, close to 1, and significant, implying the underlying series strongly exhibits a persistent pattern (Jana et al., 2022). Persistent behavioral pattern is linked to long memory dependence, which justifies the incorporation of technical indicators to track futuristic movements.

4.2 Outcome of predictive modeling

The first step of predictive analytics is to decompose the original time series of respective Metaverse coins into granular components using MODWT. Figure 3 depicts the granular decomposition process. The forecasting is performed on subseries separately to draw the final forecasts.

As mentioned, Facebook's Prophet is invoked on the approximation component in multivariate setup using the explanatory features, whilst TBATS is used for drawing forecasts on the details components. The dataset of the respective variable is segregated into In-Sample and Out-of-Sample segments in a forward-looking manner for training and testing the integrated granular forecasting structure. The forward-looking data partition is well suited for time series predictive modeling and enables evaluating the efficacy of forecasting structures in fetching multi-step ahead predictions (Ghosh et al., 2019; Jana and Ghosh, 2022). Two distinct sets of setups have been used. Figures 4 and 5 betray the actual and predicted figures for AXS and MANA on 85%-15% and 70%-30% setups as samples.

Simultaneously, the forecasting exercises are carried out on the remaining granular components using the TBATS procedure. The final forecast is estimated by aggregating the predictions made by Facebook's Prophet and TBATS. The quality of the final predictions is assessed using the four performance indicators. Results are summarized in Tables 5 and 6.

It can be observed that the values of NSE and IA have emerged to be above 0.99 in the In-Sample and above 0.96 in the Out-Of-Sample segments for all series. The values of TI are substantially low in both segments as well. The range of all three indicators indicates the generation of highly accurate forecasts by the integrated predictive framework. The predictive performance has marginally deteriorated in Out-Of-Sample segments, as expected. However, considering the timeline of the exercise, i.e., the COVID-19 pandemic and the non-availability of any prior study on Metaverse financial markets, the outcome of the forecasting exercise can be regarded as highly successful. Additionally, the values of DA have appeared to be highly encouraging, too. Amongst the assets, AXS and WAXP are found to be relatively better predictable in both segments. Nevertheless, the investors can rely upon the remaining 4 Metaverse tokens too. Therefore, an inference can be drawn that the MOD-Pro-T-based predictive structure can be leveraged to estimate directional change, which can be used for trading purposes. We now inspect the predictability in the 70%-30% setup.

Similar to the earlier setting, predictive performance in the 70%-30% setting has emerged to be exceptionally praiseworthy, too, indicating the capability of the propounded granular structure to fetch precise forecasts in the absence of a high quantum of training data points. Values of NSE and IA have resembled to be above 0.99 in the In-Sample and above 0.96 in the Out-Of-Sample segments. Reasonably low TI values in both segments further solidify the claim. High DA values rationalize the efficacy of the MOD-Pro-T framework in trading applications. Likewise, in the 85%-15% setting, AXS is relatively more predictable. The predictability of MANA and SAND has also been improved in the Out-Of-Sample section, suggesting excess training samples might cause overfitting. Overall, the thorough scrutiny

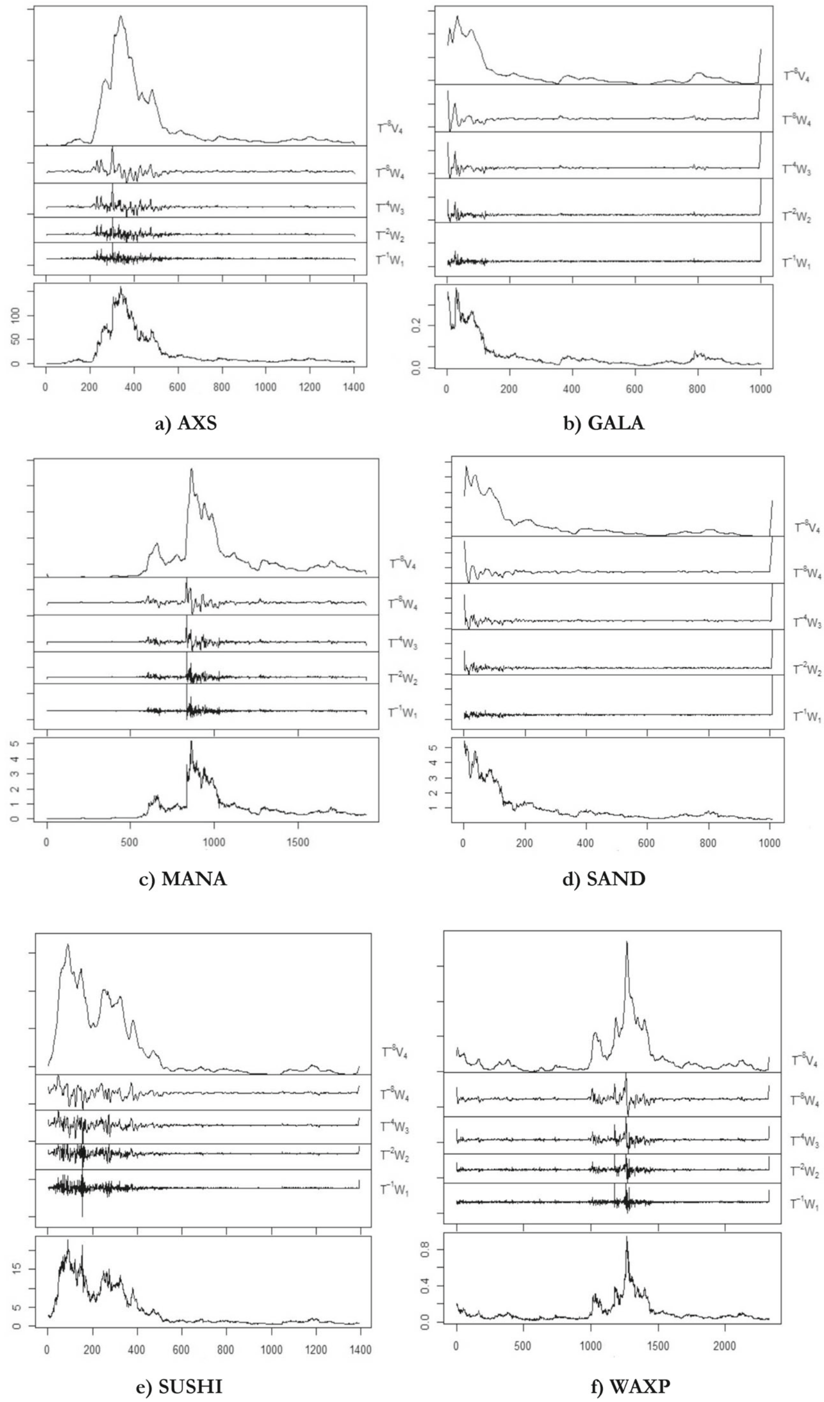

Fig. 3 Granular Decomposition of the Underlying Metaverse Coins

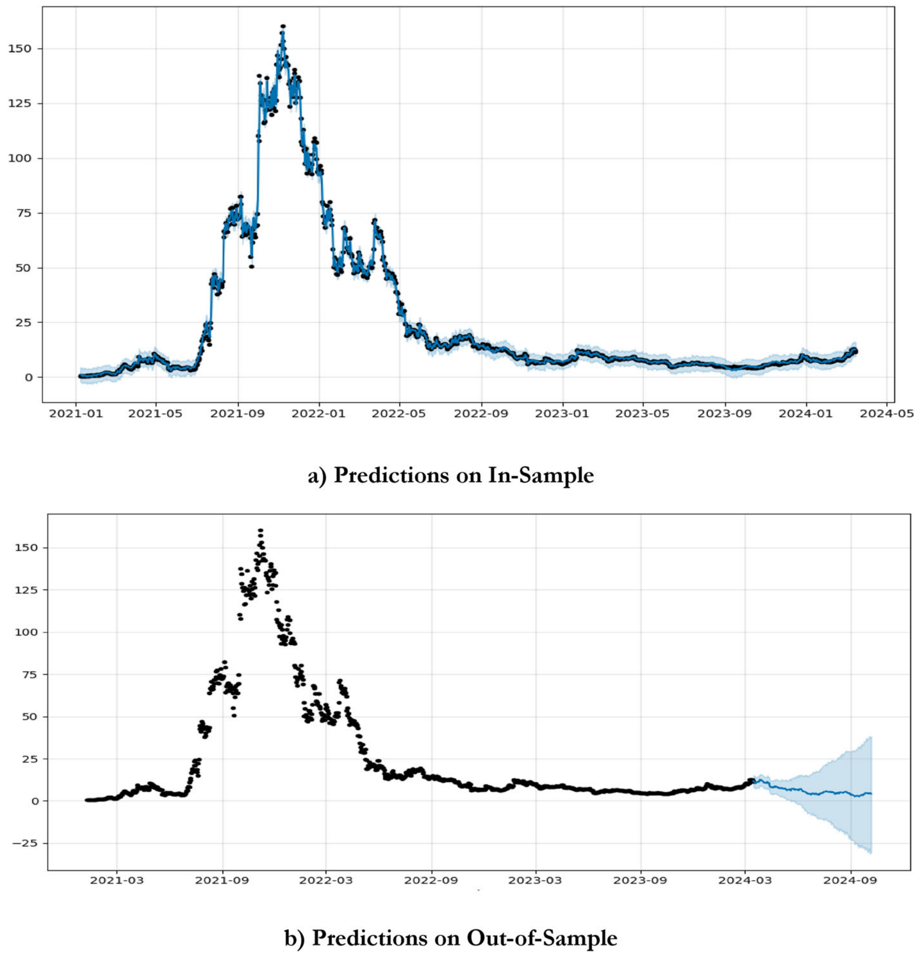

Fig. 4 Predictions on Approximation Component by Facebook Prophet for AXS on 85–15% Setting

of the predictive performance in two different setups duly justifies the deployment of the integrated MOD-Pro-T framework to forecast future figures of Metaverse coins. The selection of explanatory variables and the granular prediction process can effectively be utilized to leverage unorthodox assets to a great extent.

4.3 Comparative performance evaluation

The efficacy of the integrated framework of MODWT-Facebook's Prophet-TBATS in accurately predicting the absolute figures and directional changes of the considered Metaverse tokens has been established. Traders and investors can effectively utilize the framework to penetrate the niche digital financial market for practical purposes. Next, we ascertain the statistical ascendency of the propounded structure against benchmark forecasting approaches to justify the positioning of the work using the DM test. We compare the propounded

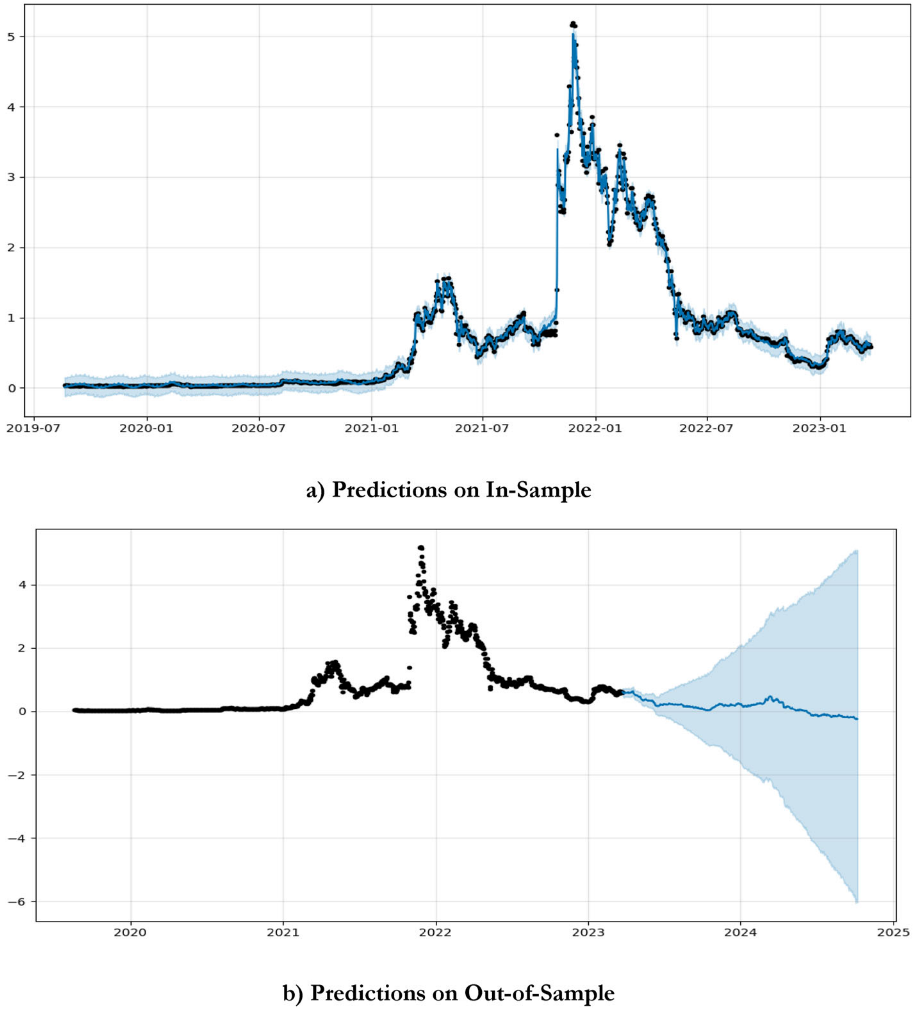

Fig. 5 Predictions on Approximation Component by Facebook Prophet for MANA on 70–30% Setting

model with three well-known forecasting techniques: Auto-Regressive Integrated Moving Average (ARIMA), Seasonal Auto-Regressive Integrated Moving Average (SARIMA), and Auto-Regressive Fractionally Integrated Moving Average (ARFIMA). Additionally, Facebook's Prophet and TBATS in standalone univariate mode are used as well for comparison to justify the effectiveness of the chosen explanatory variables and granular decomposition through MODWT. The DM test is a statistical test capable of critically evaluating comparative differences of multiple prediction models measured through mean-squared error. Since its operations are based on paired comparisons, it is essential to set the order of the constituents in the pair to report the outcome. The respective models in the said comparison process have been marked with an index number inside parenthesis to refer to the order. Suppose the test statistic is found to be positively significant. In that case, the model, indicated by the number 2 in the parenthesis, is implied to be statistically better predictable than the model

Table 5 Predictive Performance on 85–15% Setup

	NSE	TI	IA	DA
In-Sample				
AXS	0.99954	0.00387	0.99975	0.99165
GALA	0.99811	0.00833	0.99879	0.98689
MANA	0.99971	0.00425	0.99988	0.99228
SAND	0.99167	0.00906	0.99280	0.97433
SUSHIS	0.99923	0.00461	0.99956	0.98685
WAXP	0.99862	0.00792	0.99903	0.99082
Out-Of-Sample				
AXS	0.97874	0.00521	0.98536	0.98217
GALA	0.97602	0.01149	0.98119	0.97540
MANA	0.98115	0.00616	0.98731	0.98325
SAND	0.96635	0.01185	0.97678	0.96476
SUSHI	0.97831	0.00730	0.98475	0.97730
WAXP	0.97527	0.00963	0.98394	0.98357

The values of 4 performance indicators are computed on In-Sample and Out-of-Sample segments separately to judge the quality of the forecasts

Table 6 Predictive Performance on 70%-30% Setup

	NSE	TI	IA	DA
In-Sample				
AXS	0.99922	0.00409	0.99941	0.98893
GALA	0.99785	0.00862	0.99813	0.98144
MANA	0.99936	0.00455	0.99962	0.98773
SAND	0.99129	0.00944	0.99157	0.97054
SUSHIS	0.99847	0.00492	0.99868	0.98241
WAXP	0.99511	0.00817	0.99846	0.98586
Out-Of-Sample				
AXS	0.97822	0.00559	0.98234	0.97795
GALA	0.97569	0.01182	0.98051	0.97163
MANA	0.98082	0.00667	0.98638	0.97959
SAND	0.96594	0.01213	0.97572	0.96138
SUSHI	0.97784	0.00782	0.98412	0.97402
WAXP	0.97678	0.00995	0.98337	0.97671

The values of 4 performance indicators are computed on In-Sample and Out-of-Sample segments separately to judge the quality of the forecasts marked number 1. The emergence of negative significant test statistics suggests the opposite scenario, i.e., the model marked number 1 in parenthesis is statistically more predictable than the second. Finally, if the test statistic turns out to be insignificant, it is assumed that there exists no significant difference between the models in terms of predictability. The results of the comparative performance assessment are displayed in Tables 7 and 8.

The outcome of the pairwise DM test suggests the statistical superiority of the integrated MODWT-Facebook's Prophet-TBATS framework over the competing models. The rationale of accomplishing the forecasting task by combining a set of explanatory features and granular decomposition is justified as standalone TBATS and Facebook's Prophet models fail to statistically outperform the accuracy of the propounded framework. Facebook's Prophet, nonetheless, surpasses the remaining competing models.

The statistical ascendency of the developed predictive structure is realized in the 70%-30% setting as well. The supremacy of the propounded forecasting structure over the benchmark models is apparent. Likewise, in the previous setup, the standalone Facebook Prophet was superior to the other four models but could not surpass the designed MOD-Pro-T model.

As the propounded framework outclassed all competing models in both setups, the effectiveness and methodological contributions of the framework are proven. The statistical

Table 7 Outcome of DM Test for 85%-15% Setting

Regimes	ARIMA (1)	SARIMA (1)	ARFIMA (1)	TBATS (1)	Facebook Prophet (1)	MOD-Pro-T (1)
ARIMA (2)	–					
SARIMA (2)	0.227#	–				
ARFIMA (2)	0.246#	0.215#	–			
TBATS (2)	0.217#	0.223#	0.234#	–		
Facebook Prophet (2)	4.7248***	4.7482***	4.6878***	4.4227***	–	
MOD-Pro-T (2)	6.9163***	6.9257***	6.9105***	6.8159***	6.7386***	–

[Note: # Not Significant, *** Significant at 1% Level of Significance]

Table 8 Outcome of DM Test for 70%-30% Setting

Regimes	ARIMA (1)	SARIMA (1)	ARFIMA (1)	TBATS (1)	Facebook Prophet (1)	MOD-Pro-T (1)
ARIMA (2)	–					
SARIMA (2)	0.229#	–				
ARFIMA (2)	0.235#	0.207#	–			
TBATS (2)	0.211#	0.235#	0.226#	–		
Facebook Prophet (2)	4.6671***	4.7048***	4.6325***	4.5317***	–	
MOD-Pro-T (2)	7.4106***	7.3892***	7.3458***	7.2267***	7.1052***	–

Not Significant, *** Significant at 1% Level of Significance

superiority of the data-driven granular prediction system underscores its potential for the precise discovery of hidden patterns of high-frequency datasets. The forecasting architecture can easily be extended to predicting complex time series data.

4.4 Model Explanation

As discussed, the forecasting framework successfully conducts the predictive analytics task at the expense of almost negligible insights into the influence pattern of the predictors. XAI framework is used to overcome the shortcomings. The SHAP measure-based XAI framework is used to evaluate the relative feature contribution of three distinct categories in explaining the prediction process at a global level for respective Metaverse coins. Higher SHAP values reflect higher contributions of the respective explanatory features. The features are ranked on the basis of average SHAP values estimated using Eq. 20 in descending order. Figures 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16 and 17 display the ranking of the top twenty predictors alongside their contribution pattern based on the estimated SHAP figures.

Feature contribution assessment of AXS daily price forecasting signifies the dominance of technical indicators. The impact of conventional cryptocurrencies, BTC and ETH, in the overall prediction process appears to be negligible as they are not included in the top 20 feature list. Uncertainty manifested in Twitter and news articles exerts less predictive influence. Thus, the technological development of Metaverse appears to be immune to social media sentiment and geopolitical distress in the US. The predictive contribution of EPU emerges to be significant. The local level analysis through LIME shall serve deeper insights on the same. The said finding is of paramount practical implications in the context of long-term planning.

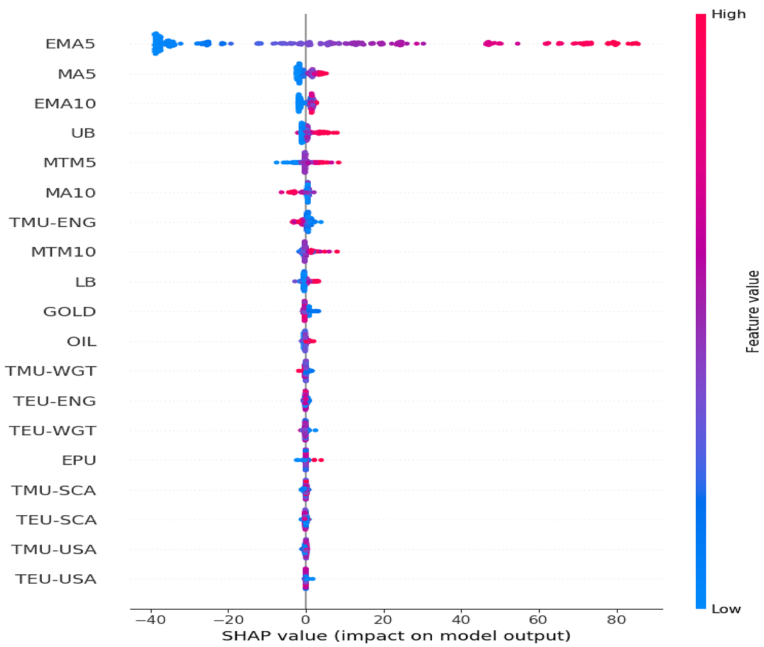

Fig. 6 Feature Importance Explanation for AXS Prediction

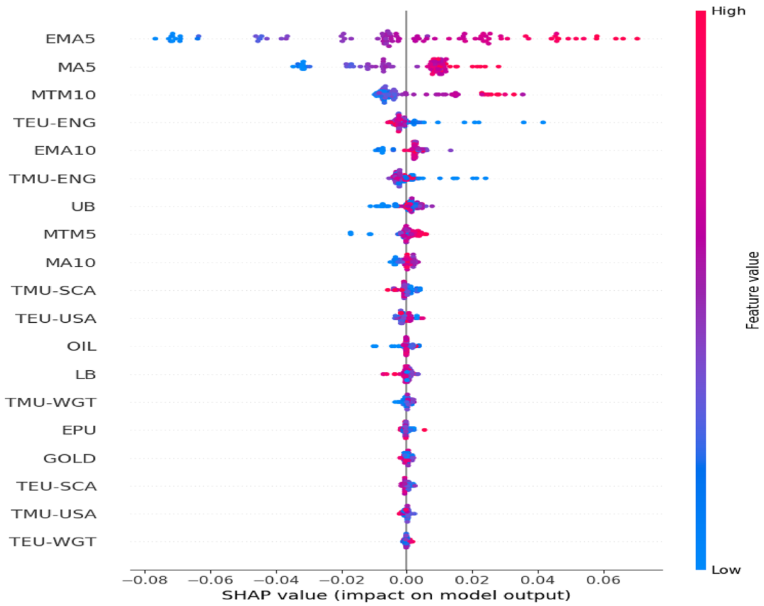

Fig. 7 Feature Importance Explanation for GALA Prediction

Similar to the AXS daily price explanation results, the significance of the chosen technical indicators in driving GALA is evident. The influence of Twitter-based uncertainty indices has seen steady growth in predicting the price movement of GALA, as manifested by the ranking. Additionally, OIL, GOLD, and EPU have been placed in the top 20 influential feature list. The influence of EPU has also been marginally intensified. Interestingly, the implied volatility of the US, CBOEVIX, has not featured in the dominant variable list.

Interpretation of the prediction of the MANA prices through SHAP reveals exciting findings. Firstly, akin to the previous two Metaverse tokens, MANA also exhibits no significant dependence on BTC and ETH. Both conventional cryptocurrencies are not even featured in the top 20 feature lists. CBOEVIX also lacks significant contribution. Barring the technical indicators, GOLD and OIL significantly explain the variation of the MANA. Dependence on economic and political rhetoric reflected in different media platforms is low. Thus, MANA tokens, which emerged as the best predictable assets, are more susceptible to traditional macroeconomic commodity and their past information.

SAND coin prediction interpretation implies a strong influence on the technical indicators. No influence of conventional cryptocurrencies, BTC and ETH, can be observed. OIL plays a critical part as well. SAND coins display weaker dependence on EPU and other social media-linked variables, indicating low speculative behavior.

Interpretation of SUSHI prediction demonstrates the profound influence of macroeconomic indicators in conjunction with technical ones. GOLD resembled the 2nd most important feature spot. The dominance of technical indicators in explaining the dynamics is amply apparent, as well. Twitter media uncertainty indicators exert significant predictive influence, too. SUSHI demonstrates dependence on OIL and EPU.

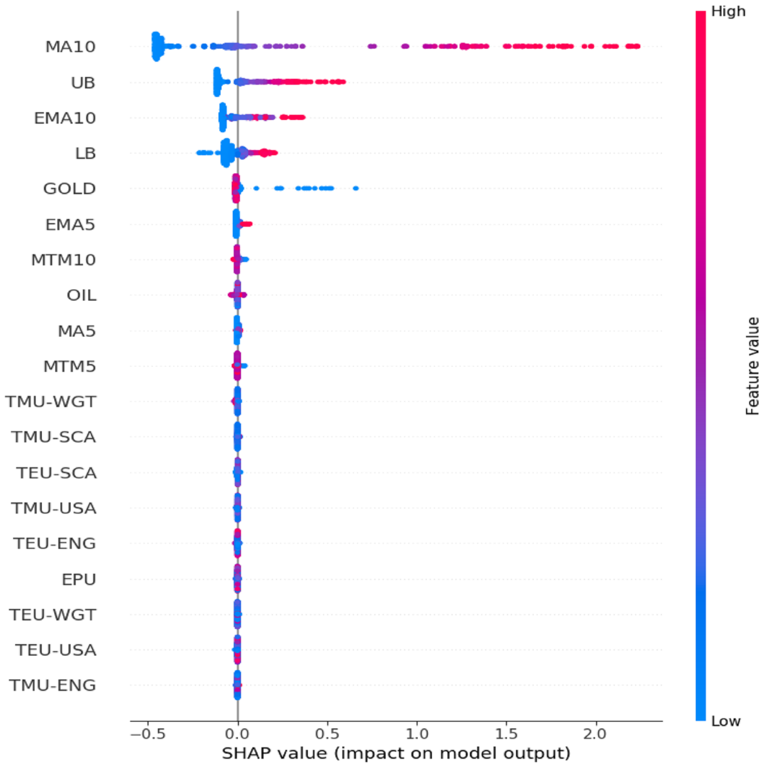

Fig. 8 Feature Importance Explanation for MANA Prediction

Decoding the WAXP forecasting through the lens of SHAP reveals the domination of technical indicators in broadly explaining the variation. GOLD and OIL appear to be significant among the macroeconomic reflectors.

It can be observed that technical indicators, viz. MA5, MA10, EMA5, EMA10, UB, LB, etc., have been found to largely explain the temporal movements of the select Metaverse coins globally. The strong dependence on technical indicators clearly indicates the long-memory dependence behavior of the chosen coins. The future trend of the same can be accurately predicted on the basis of well-defined technical indicators, which in turn can be used for facilitating trading. Thus, inference can be drawn that the emerging Metaverse coins exhibit similarity with conventional financial assets owing to dependence on immediate past information even during the turmoil regimes. Higher values of the highly ranked features induce higher contribution, as manifested by the respective SHAP figures representing the horizontal axis.

Overall, the model explanation using SHAP draws several interesting reflections. In general, all 6 Metaverse coins display sharp dependence on technical indicators, which simply conforms to the persistent property of the underlying variables as manifested in Table 1. Although the scanty literature (Aharon and Demir, 2021; Corbet et al., 2022) reports a strong nexus of conventional cryptocurrencies, BTC and ETH, and NFT/DeFi, the current work indicates not all Metaverse coins are highly dependent on the same. Market fear in terms of anticipated volatility in the options market possesses a subdued impact on the majority of

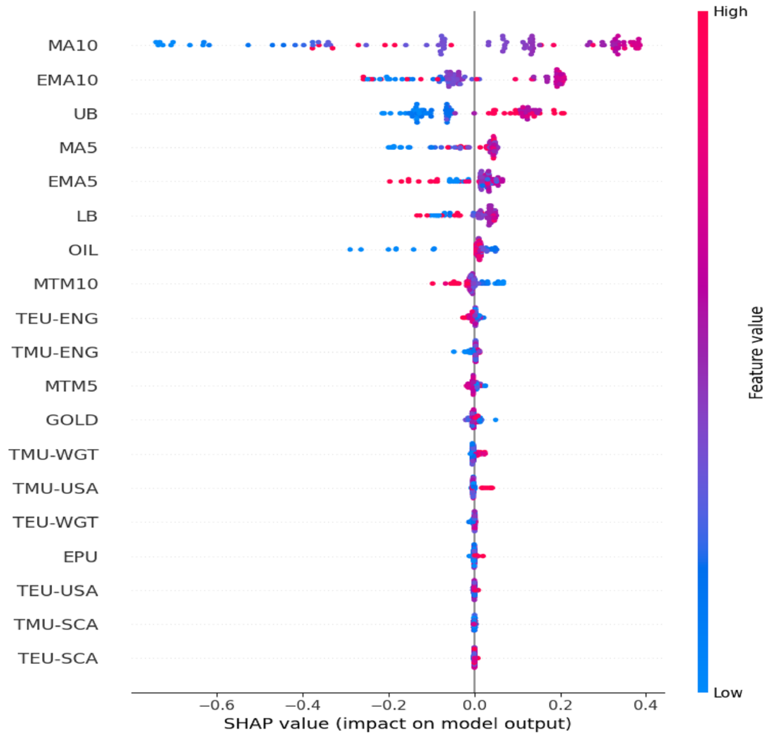

Fig. 9 Feature Importance Explanation for SAND Prediction

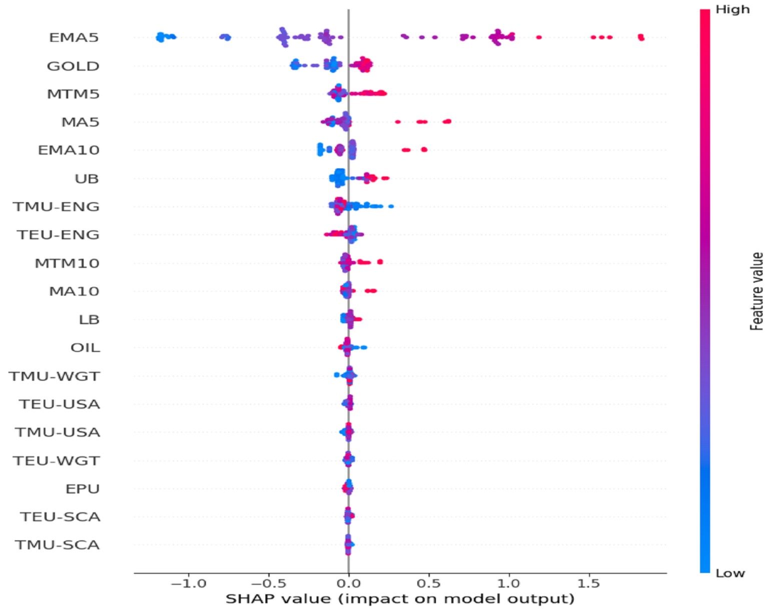

Fig. 10 Feature Importance Explanation for SUSHI Prediction

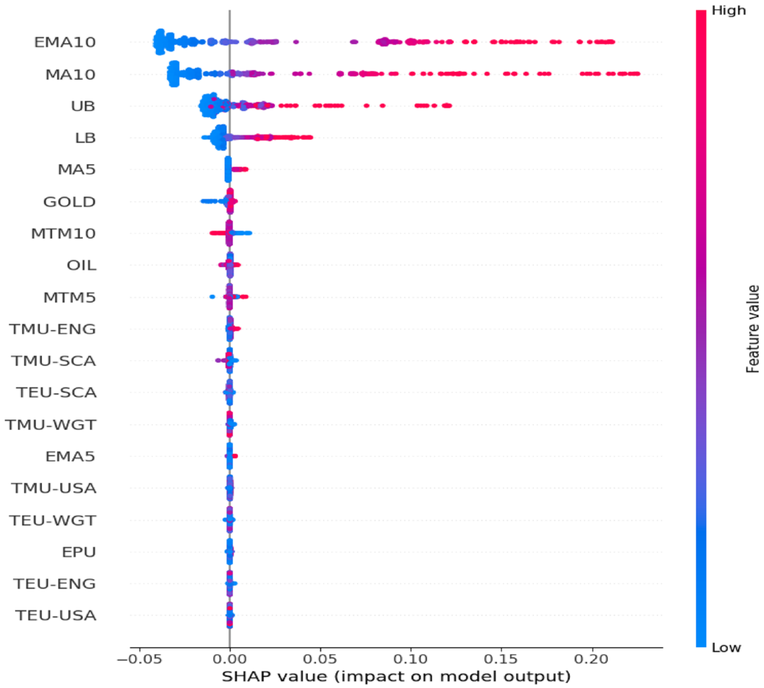

Fig. 11 Feature Importance Explanation for WAXP Prediction

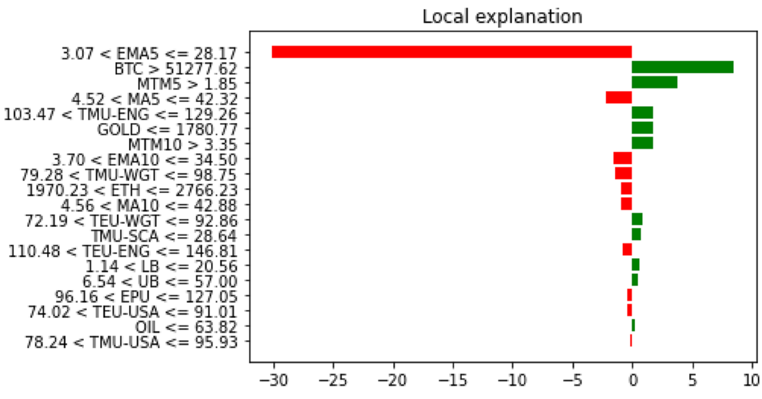

Fig. 12 Local Level Feature Contribution Explanation for AXS Prediction

Metaverse coins. The influence of EPU is moderate, too. Thus, an inference can be drawn that the technological developments of Blockchain and allied cryptocurrencies do not entirely mimic the orthodox financial variables and can be utilized heavily for diversification benefits. Investors can strategically leverage emerging financial assets in the long run, owing to the relatively weak penetration of floating chaotic news and sentiment on social media.

We now evaluate the feature importance at a local level, i.e., decoding the prediction process on a random data instance using the LIME methodology. The LIME procedure

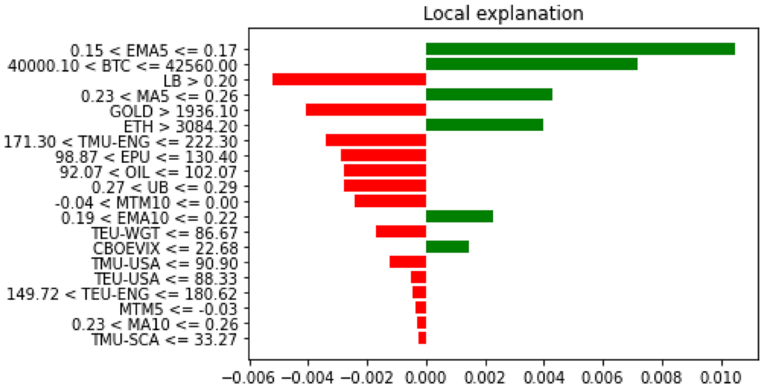

Fig. 13 Local Level Feature Contribution Explanation for GALA Prediction

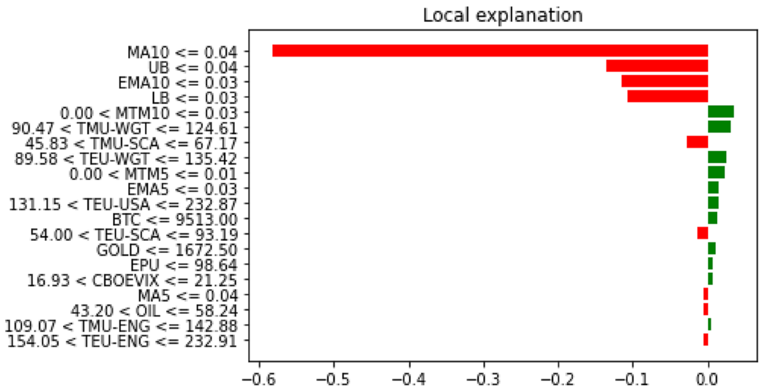

Fig. 14 Local Level Feature Contribution Explanation for MANA Prediction

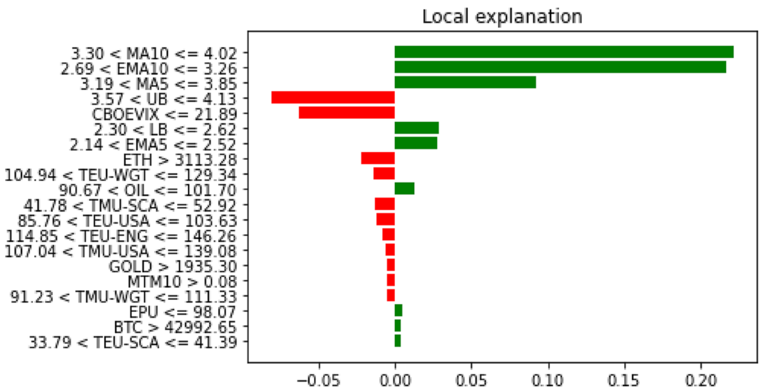

Fig. 15 Local Level Feature Contribution Explanation for SAND Prediction

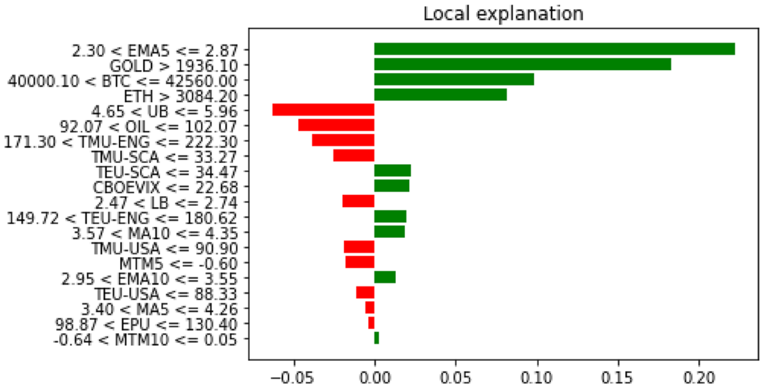

Fig. 16 Local Level Feature Contribution Explanation for SUSHI Prediction

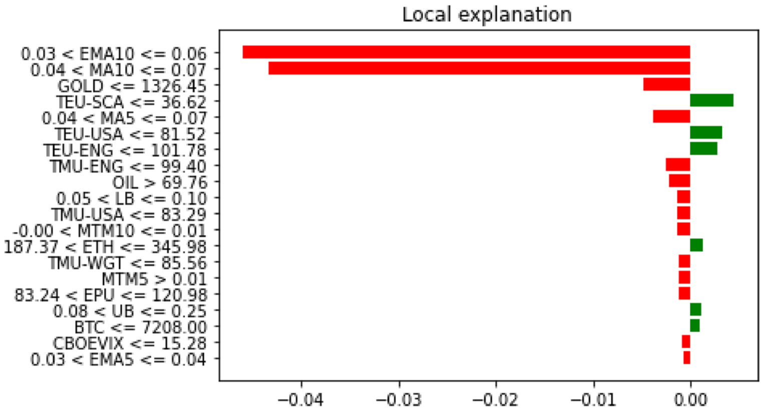

Fig. 17 Local Level Feature Contribution Explanation for WAXP Prediction

records the predictive contribution of the explanatory features in predicting the target on a random data point. Figures 13, 14, 15, 16 and 17 exhibit the outcome of the inspection.

The findings of local-level feature analysis using the LIME framework are not identical to those of global-level assessment. The role of the media uncertainty index has seen a profound intensification as two features lie in the top 10 contributor list. Therefore, it is critical to monitor the social media uncertainty and economic uncertainty reflected in social media to estimate the short-run movement precisely. The AXS coins may not appear highly speculative from a global outlook, but resorting to media indices is necessary to demystify the local level volatility truly. The extent and direction of the influence of the respective explanatory variables vary abruptly from negative to positive scale.

Likewise, the AXS prediction and the local-level inspection of GALA forecasting serve more profound reflections. EPU, which appeared to possess low dependence power, has seen an upliftment in predictive ability at the local level. The impact of conventional crypto coins, i.e., BTC and ETH, for the chosen sample is highly significant. GOLD lies in the top 5 feature list as compared to the top 10 list at the global level in the form of substantial negative form. CBOEVIX resumes explanatory prowess at the local scale. On the other hand, the impact of a few technical indicators, MTM5 and MA10, weakened, signifying the relevance of macroeconomic and social media variables in the precise estimation of future closing prices of GALA.

MANA demonstrated strong immunity to conventional cryptocurrencies and media and economic uncertainty globally. However, social media indicators have emerged as being linked to steep predictive power, while BTC exerts explanatory influence at the local level. As many as three media-linked series resemble three spots in the top 10 contributing feature list. Interestingly, the predictive strength of GOLD slightly weakens, while CBOEVIX makes its presence felt when explaining the local variation of the MANA token. The speculative property at the local level is imminent, as manifested by the strong negative influence of the technical indicators and the dominance of Twitter-linked variables.

Local analysis of feature contribution for SAND forecasting yields findings similar to those of global explanation. The dominance of technical indicators is apparent. The implied volatility counterpart, CBOEVIX, reappears in exerting a strong negative influence locally and inhibits the short-term growth of the SAND coin. ETH, too, exerts an adverse predictive influence. The impact of EPU and BTC is on the lower end. The strong positive effects of technical indicators and the relatively milder role of social media indicators suggest that SAND has low volatile and speculative properties at the local scale.

Likewise, the SAND, a local-level inspection of the SUSHI prediction process, conforms to the outcome of the global-level explanation with minor changes. GOLD and BTC emerge to be highly significant and induce strong positive predictive dependence in driving SUSHI prices locally. Additionally, the role of ETH in the explanation process positively intensifies. SUSHI exhibited sensitivity towards the social media and economic uncertainty indices holistically. The said indices also play a critical role locally, with a mixture of positive and negative influences. The major change at the local level is the placement of a couple of technical indicators at the lower end of the top 20 contributor list.

Local feature contribution assessment reveals drastically different results for the WAXP prediction process. Firstly, GOLD solidifies its position in the top 5 significant feature rankings by exerting profound negative predictive power. Second, a steep rise in the ranking for the Twitter-linked series can be observed, indicating the substantial role of social media in monitoring local fluctuations of the asset. Both BTC and ETH are linked to marginal impact, whereas their influence was completely diminished on the global scale. Similar to GALA and SUSHI, two technical indicators are confined to the lower end of feature contribution ranking.

It should be noted that unlike the SHAP procedure, which aggregates the feature contribution throughout the entire sample, LIME extracts the relative contribution of features for a specific data point. Thus, the difference in ranking in LIME-based interpretation prevails. Nonetheless, it is equally important to critically analyze the LIME-based findings too. Dedicated introspection using LIME on top of SHAP-driven model interpretation serves holistic comprehension of the granular dynamics of Metaverse coins. The local feature contribution suggests the utility of all explanatory variables in the precise prediction of future figures. It has been observed that several features have appeared to be not highly significant in exerting predictive influence globally. Nevertheless, their capacity to explain random fluctuation of the underlying coins in the short run has been justified as per the findings of LIME-based modeling. Contributions of BTC, ETH, CBOEVIX, etc., have been detected despite showing negligible impact when all samples are considered. Hence, to accurately forecast the chosen Metaverse coins irrespective of the time regimes, it is crucial to precisely track all explanatory variables. Close monitoring of the sentiment reflecting media and economic uncertainty on Twitter is important to decode the daily dynamics as they account for the speculative part.

GALA, SUSHI, and WAXP are similar in terms of speculative aspects. In a nutshell, both XAI frameworks duly justify the effectiveness of the selection of explanatory features in the absence of previous research. Overall, the conjunction of XAI methodologies with the granular forecasting procedure properly accomplishes the research endeavor by implementing a robust decision support system capable of uncovering practical insights. Although classical optimization-based prediction systems have been reported to produce accurate results for forecasting tasks (Sun et al., 2022; Xu et al., 2022), they primarily suffer from a lack of interpretability, which confines the application spectrums. The methodological contributions of the underlying research significantly enrich the data-driven decision-making and operations research literature by appropriately resolving the limitations of the classical models.

5 Concluding remarks

The lack of proper understanding of the temporal dynamics of the Metaverse coins in the backdrop of the amazing technological growth motivates us to undertake the present research. The quality of the predictions and the deeper insights into the nature interplay substantiate the work's endeavor to contribute to the literature gap. As no previous study strives to scrupulously introspect the dynamics of the emerging and niche assets, the overall implications of the present research set the tone for subsequent exploration. The research firmly establishes the predictable structure of high-end digital financial assets. On the methodological front, the research advances an integrated forecasting structure capable of producing superior absolute figures and accurate estimation of directional changes in a granular setup. The framework is scalable and survives a battery of numerical and statistical checks to be regarded as a reliable and effective forecasting tool for Metaverse financial markets. Usage of XAI results in meaningful and actionable insights in terms of the dependence structure of the considered assets on conventional ones on short and long-run scales. The practitioners and different market players can leverage the major findings and methodological approach for investing, reaping diversification benefits, hedging, etc. The key findings of the present research are highlighted below:

- All 6 Metaverse Coins are found to not abide by the efficient market hypothesis as manifested by the presence of long memory dependence.
- The degree of speculative behavior cannot be completely ruled out for the Metaverse financial market. Close tracking of several explanatory features can assist in averting the same.
- The integration of MODWT, Facebook's Prophet, and TBATS is extremely powerful in recognizing the granular dynamics of underlying coins. Statistically, the framework has appeared to be sublime in forecasting future movements.
- The supremacy of the standalone Facebook's Prophet in handling complex time series is proven as it appears to outclass the other competing models.
- Moving average and exponential moving average-based technical indicators should be tracked precisely for accurate estimation of future figures of the Metaverse assets.
- Despite being fundamentally dependent on the Blockchain platform, heavy predictive reliance on conventional cryptocurrencies is not omnipresent.
- On the contrary, daily closing prices of gold as a commodity have proven to share a strong bond with the niche market. Its influence is relatively stronger than the crude oil price.

- The floating uncertainty on Twitter has emerged as a vital factor in explaining short-run fluctuations. Daily and short-term trading can be facilitated by keeping a close watch on the media and economic uncertainty in allied platforms.
- The timeline of investigation covers several extremely volatile regimes, i.e., the COVID-19 pandemic, the Russia-Ukraine conflict, and the Israel-Palestine war. Thus, the sound, predictable behavior of the underlying assets during the turmoil periods truly rationalizes the effectiveness of the presented methodological framework.

The scope of the present research is limited to chosen Metaverse coins in the context of predictability and model explanations. As the said market is highly dynamic and flooded by the frequent inception of new coins, it would be imperative to extend the investigation to a broad spectrum of assets over time. To explicitly analyze the random leftover component in the market, whether herding is instigated or not should be introspected. The said investigation can cluster similar Metaverse tokens and provide useful information for risk mitigation. The current research does not examine the nexus of the other niche digital assets, NFTs, DeFis, etc., with Metaverse-linked assets. In the future, the interrelationship can be explored to reveal further exciting inferences.

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Declarations

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Ethics approval and consent to participate This article does not contain any studies with human participants or animals performed by any of the authors.

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