Decoding Market Prices of Sustainable Cryptocurrencies: Fresh Insights from Ensemble Machine Learning and Explainable AI

Abstract

This research develops an integrated framework that combines ensemble machine learning and explainable artificial intelligence to predict the performance of sustainable cryptocurrencies, including Avalanche, BNB Chain, Polkadot, and Solana, and to reveal the dependencies between these assets and key explanatory features. The framework employs a comprehensive predictive structure that integrates supervised and unsupervised feature processing with a metaheuristic-tuned ensemble learning model. BorutaShap identifies significant explanatory variables, while Isometric Mapping obtains an optimized feature representation. Predictions are generated using the Extreme Gradient Boosting algorithm, with hyperparameters optimized through Particle Swarm Optimization. To ensure interpretability, the predictive methodology undergoes rigorous analysis using multiple explainable artificial intelligence techniques that decode dependency patterns at both global and local levels, facilitating a comprehensive understanding of market dynamics for the selected assets. Results reveal that market sentiment, technological outlook, and US options market fear are the primary determinants of sustainable crypto asset performance.

Keywords: Feature Processing; Extreme Gradient Boosting; Cryptocurrency, Sustainability, Explainable Artificial Intelligence.

1. Introduction

The emergence and adoption of cryptocurrencies in financial transactions, development of decentralized applications (dApps), and transitions into smart contracts have seen a rapid boom in recent times (Corbet et al., 2023). The first digital cryptocurrency, Bitcoin, enables peer-to-peer financial transactions on top of the blockchain network (Nair and Kayal, 2022). The Bitcoin ecosystem is referred to as blockchain 1.0. On the other hand, Ethereum extends the utility of the same by providing customized solutions to asset transfers, monitoring the supply chain, and enhancing governance under the umbrella of blockchain 2.0 (Groesen and Pauwels, 2022). The pre-eminence of technological revolution of the non-fungible token (NFT), decentralized finance (DeFi), and metaverse has increased reliance on the said platform exceedingly.

The conventional crypto-ecosystems are extremely energy intensive owing to the proof-of-work (PoW) mining protocol (de Vries, 2018; Gallersdörfer et al., 2020). The hazardous impact of energy-intensive cryptocurrencies has been manifested by the accumulation of excess electronic waste, which induces severe disruption to environmental sustainability (Jana et al., 2022). Proof-of-stake (PoS) mining protocol-driven blockchain platforms are used to resolve the excessive energy appetite for preserving sustainability (Dou et al., 2022; Milunovich, 2022). Recent technological developments have introduced several equivalent platforms running on PoS or its variant protocols to host dApps for various industrial purposes. Thus, sustainable crypto assets will likely attract investment, and the financial markets will prosper. In the stated context, delving into emerging niche digital asset market prices is highly important.

Despite a steady criticism and thorough research on the trade of different aspects of blockchain technology (Farnoush et al., 2022; Tsai, 2023), the paucity of attempts to analyse the dynamics of sustainable cryptocurrencies is amply apparent. Research in the cryptocurrency spectrum has largely been confined to modelling for performing predictive analysis and discovering potential benefits in the form of hedging, diversification, etc. (Fakhfekh et al., 2023; Yadav et al., 2022). Majority of the existing study primary focuses upon the conventional financial markets (Sun et al., 2024). Ren and Lucey (2022) propounded a scheme to classify cryptocurrencies into clean and dirty categories based on spillover connectedness with clean energy assets. The notion of disentangling cryptocurrencies into distinct categories has largely been inspired by the nature of interconnectedness with different financial and macroeconomic variables (Manavi et al., 2020). However, the looming crisis of energy discharge has intensified the search for alternative assets for investments from market players at different hierarchies. In anticipation of the market crash in the new normal, adversarial traits have resulted in bubbles in conventional crypto assets. The dearth of scalable frameworks to comprehend the market perception of sustainable counterparts is a major obstacle to leveraging trading benefits.

The primary objectives of this research are positioned to fill the apparent research gap regarding the market dynamics of sustainable cryptocurrencies. Specifically, this work seeks to:

- **Predict Market Prices:** To precisely predict the future market figures of four major Proof-of-Stake (PoS) based sustainable cryptocurrencies.
- **Propose an Integrated Framework to Contribute on Methodological Front:** To introduce a novel, integrated predictive framework that combines supervised feature selection (using BorutaShap) and unsupervised feature transformation (using Isometric Mapping) with a metaheuristic-tuned ensemble machine learning model (PSO-tuned XGBoost).
- **Uncover Dependence Structures:** To uncover the dependence relationship between the market prices of these assets and a series of key macroeconomic, financial, and technical indicators, with a focus on US-centric health indicators.
- **Identify Key Determinants:** To identify the crucial determinants of growth for these sustainable crypto assets, which are found to be market sentiment, technological outlook, and options market fear in the US.

This comprehensive approach simultaneously forecasts future figures and explains the dependence structure on predictor variables, marking it as a first-of-its-kind study.

Market prices of four sustainable cryptocurrency ecosystems - Polkadot, BNB Chain, Solana, and Avalanche in the new normal time regime have been examined to accomplish the endeavour. We include several important macroeconomic and market volatility-related indicators to assess the dynamic nexus for predicting future prices and uncovering the dependence pattern. As the considered digital assets are mostly United States-centric, the present work embodies a series of indicators reflecting the state of the region's macroeconomic, geopolitical, and financial health, in addition to orthodox technical indicators to demystify the highly volatile patterns of the sustainable cryptocurrencies in the turmoil period. The interlinkage with market prices of Bitcoin and Ethereum has been delved into as well. The research contributes to methodological fronts for modelling financial time series. Firstly, the forecasting framework seamlessly integrates the supervised and unsupervised feature selection, nature-inspired optimization algorithm tuned ensemble machine learning (ML) model for drawing precise predictions. The integration of supervised feature screening and unsupervised feature transformation to build the forecasting framework is a significant contribution to the methodological front, which survives scrupulous scrutiny of numerical and statistical checks. The significance lies in the fact that this two-step process, transitioning from rigorous statistical selection to intrinsic geometric optimization, ensures that the forecasting model is built upon the most relevant and optimally represented set of drivers, making a significant contribution to financial time series modeling. Secondly, we resort to dedicated explainable artificial intelligence (XAI) frameworks to interpret the apparently black box-type integrated predictive methodology globally and locally to extract the nature of the interplay between the respective target and explanatory features. The current work leverages XAI at different hierarchies to reflect the contribution of key explanatory variables globally and locally.

The methodological framework for forecasting uses the BorutaShap algorithm to implement the supervised feature selection process. In contrast, the isometric mapping (ISOMAP) technique acts as the final feature engineering step. On the engineered features, a Particle Swarm Optimization (PSO)-driven Extreme Gradient Boosting (XGBoost) ensemble model is trained to predict the future figures of Polkadot, BNB Chain, Solana, and Avalanche separately. We deploy the XAI tools to interpret the prediction process globally using SHAP figures and accumulated local effects and locally by local explainable model-agnostic justifications to expound on the contribution of the potential drivers. The deployment of the XAI framework transforms the complex ML algorithm into an interpretable one.

The article is structured as follows: A Survey of past research is briefly enunciated subsequently in section 2. Next, we outline the descriptions and critical statistical properties of utilized variables for accomplishing research endeavours in section 3. Then, the detailed descriptions of the research methodology are expounded in section 4. Results and discussions are offered in section 5. The overall implications of the research in terms of theoretical contribution, managerial contribution, and future research directives are documented in section 6. Finally, we conclude the paper in section 7.

2. Previous Research

This section briefly summarizes relevant research agendas and trends on the sustainability angle of blockchain technology, cryptocurrencies, and future roadmaps.

A plenteous of research has been made for conventional cryptocurrencies wherein hybrid frameworks embodying granular methodologies, feature selection, and applied predictive tools were highly successful (Ghosh et al., 2025; Jana et al., 2021). Nevertheless, the need to extend the exercises to decipher patterns of the emerging cryptocurrencies ensuring lower energy and resource intake, has unfortunately seen very little attention. Unlike the well-explored interconnectedness of Bitcoin, Ethereum, etc. with key market variables, the absence of studies on the dependence structure of chosen assets with potential predictors is the first hurdle for drawing accurate forecasts. Table 1 briefly enunciates the past research trends on the practical implications of blockchain platforms.

[INSERT TABLE 1 HERE]

The scrutiny of past research signifies that despite the tremendous potential of sustainable crypto assets, the paucity of research to explain the impact of market enablers and subsequent predictive analysis is amply apparent. A handful of research is inadequate to infer the market trend of the assets completely. Understanding the behavioural dynamics of these niche assets as alternative instruments to resource-intensive conventional cryptocurrencies is of enormous practical implications. The current research aims to bridge the gap by developing a robust framework to yield the future figures of the said assets, which will attract investors and ascertain the influence structure of key enablers for strategic decision-making.

3. Variable Summary and Empirical Properties

We shortly outlined the fundamental aspects of sustainable ecosystems and inspected them to meet the research goals.

3.1 Sustainable assets

3.1.1 Avalanche

The Avalanche blockchain is a premiere scaling solution for Web 3.0 and dApps by implementing secured and eco-friendly smart contracts. The asset has been argued to be faster than the Bitcoin, Ethereum, and Polkadot blockchains (Tanana, 2019). It assists in the transfer of assets to the Ethereum blockchain by utilizing the Avalanche virtual machines for deploying Solidity-compatible smart contracts. The Avalanche (AVL) cryptocurrency is the default token for operations.

3.1.2 Binance

The combination of the classical Binance chain and Binance smart chain gave rise to the modern-day Binance (BNB) blockchain to facilitate MetaFi offerings, hosting DeFi on Metaverse. The integrated ecosystem serves alternative financial solutions and embraces several large-scale applications to enable chai governance, decentralized autonomous organization (DAO), etc. (Ellinger et al., 2023; Vidal-Tomás et al., 2023). The Build and Build (BNB) is the de-facto token in the BNB blockchain.

3.1.3 Polkadot

The Polkadot ecosystem enables interoperability by allowing cross-blockchain transfers of data and assets seamlessly. The secured ecosystem is also referred to as parachains that form a basis for a true decentralized web 3.0. Its capability of interfacing multiple blockchains provides unprecedented economic scalability. It uses a nominated PoS (NPoS) scheme, which is claimed to be linked to the lowest carbon footprint (Gehrlein et al., 2023). The Polkadot (POL) cryptocurrency is used for transactions on the said platform.

3.1.4. Solana

The Solana blockchain is a decentralized platform tailor-made for enabling scalable, user-friendly applications (Pierro and Tonelli, 2022). It hosts several DeFi and Web 3.0 projects and is emerging as a key marketplace for NFT trading. The default token for the system is Solana (SOL) currency.

The daily closing prices of AVL, BNB, POL, and SOL are compiled from https://www.investing.com/. The data of AVL is collated for the timespan of January 20, 2021, to September 7, 2022. The daily closing prices of BNB are sampled from January 17, 2020, to September 7, 2022. The data for POL comprises a sample spanning from February 24, 2021, to September 7, 2022. Lastly, the data for SOL is collated from August 3, 2020, to September 7, 2022. The difference in starting date for respective samples is driven by the availability of the data and the space needed for computing several technical indicators. Nevertheless, the samples duly cover the COVID-19 pandemic regime, which is vital for ascertaining the reliability of the research model during the turmoil regime. The analysis focuses on the pandemic period because it represents an extraordinary stress regime for global financial markets, characterized by elevated volatility, structural disruptions in macroeconomic indicators, and amplified investor uncertainty. The cryptocurrency market, including sustainable PoS-based assets, witnessed pronounced fluctuations driven by shifts in risk appetite, liquidity constraints, and heightened speculative behavior during this time. Examining sustainable cryptocurrencies within such an extreme environment is particularly valuable for two reasons. Firstly, as these emerging assets are still in their early stages of adoption compared to their conventional counterparts, their behavior under crisis conditions remains underexplored in the literature. Secondly, the pandemicinduced turmoil provides a natural experiment to evaluate the resilience, predictability, and sensitivity of sustainable crypto assets to macroeconomic, financial, and sentiment-driven variables. Understanding their dynamics under stress offers meaningful insights for traders, policymakers, and investors assessing their viability as eco-friendly alternatives within volatile market ecosystems. The important statistical characteristics of the underlying assets are summarized in Table 2.

[INSERT TABLE 2 HERE]

Among the time series, BNB and SOL appear to be comparatively more volatile, as manifested by higher figures of measure of dispersion. To examine the normality of the variables, we employ the Anderson–Darling (AD) test, which provides a more sensitive evaluation of deviations from normality, particularly in the tails of the distribution. This characteristic makes it better suited for financial time-series data, which are well-documented to exhibit heavy-tailed and non-Gaussian behavior. Compared to other normality assessment tests, viz., the Kolmogorov–Smirnov test or the Shapiro–Wilk test, the AD test places greater emphasis on tail behavior, enabling a more accurate reflection of distributional irregularities inherent in volatile cryptocurrency datasets. The outcome of the AD test indicates that the underlying sustainable digital assets do not exhibit a normal distribution. Meanwhile, the augmented Dickey-Fuller (ADF) test statistics have turned out to be insignificant for all four variables implying a strong existence of a nonstationary pattern. The existence of profound nonlinearity is apparent, too, as Terasvirta's NN test statistics are highly significant. Therefore, the chosen niche assets over the chosen timespan demonstrate nonparametric, nonstationary, and nonlinear evolutionary trends. The Hurst exponent values are substantially larger than 0.5, suggesting the sign of long-memory structure driven by fractional Brownian motion (Ghosh et al., 2018). The said finding reciprocates the need to utilize the technical indicators for yielding precise future estimates of the closing prices.

3.2 Explanatory variables

As the past literature to track the dependence of niche digital assets is scanty, we include the critical variables reflecting the state of macroeconomic, financial, and investor sentiment in media to model the inherent patterns of the underlying variables. Table 3 outlines the said explanatory features for accomplishing the goal. Since the assets under consideration are the extension of classical blockchain-based cryptocurrencies to facilitate better offerings, it is expected that the select indicators in the form of market sentiment and fear, technology outlook, and energy commodities shall explain the temporal variability of four sustainable cryptocurrencies. One social media construct, TEU, and a newspaper-based volatility indicator, EMV, are used, which can compensate for the effects of speculative behavior.

[INSERT TABLE 3 HERE]

In addition to the above features, technical indicators, extremely effective for time series prediction, are used to exploit the inherent time series properties of the AVL, BNB, POL, and SOL. The current work utilizes ten rudimentary technical indicators, as shown in Table 4, for building the predictive structure. It may be noted that many more technical indicators exist for financial time series modelling that utilizes different properties of financial assets (Ghosh et al., 2024). The assets under investigation, nonetheless, are hardly explored to decipher the advanced time series features. Hence, the current work uses elementary technical indicators.

[INSERT TABLE 4 HERE]

4. Proposed Methodology

The current work endeavours to delve into the predictability of select sustainable cryptocurrencies using an integrated methodological framework, which is unique in producing accurate forecasts and deeper interpretations of the predictive process. It encompasses three core stages: First, establishing a precise predictive structure for the market prices of Avalanche, BNB Chain, Polkadot, and Solana using a PSO-tuned XGBoost ensemble model. Second, optimizing the features used for prediction by integrating BorutaShap for supervised selection and ISOMAP for unsupervised dimensionality reduction. Finally, deploying a dedicated XAI framework allows for meticulous interpretation of the model's output at both global and local scales, thereby deciphering the precise contributions of key drivers, such as market sentiment and options market fear, to the final price forecast. This methodology ensures the predictions are not only accurate but also fully transparent and actionable. Figure 1 exhibits the graphical replica of the proposed structure.

[INSERT FIGURE 1 HERE]

The novelty of the proposed framework in modelling complex financial time series lies in the seamless integration of supervised and unsupervised feature processing to facilitate the training of the PSO-tuned XGBoost predictive model. Most of the existing literature on predictive modelling of critical financial variables either resorts to supervised feature reduction or unsupervised feature transformation to develop hybrid predictive models. The forecasting framework integrates both supervised and unsupervised feature engineering to exploit the complementary strengths of each approach. Initially, the BorutaShap algorithm identifies statistically significant predictors by directly evaluating their contribution to the target variable in a supervised manner. It ensures that only prudent explanatory features with genuine predictive value are preserved for building the eventual predictive framework. Nevertheless, even after supervised feature selection, the retained predictors may still exhibit signs of multicollinearity, inability to mine complex non-linear patterns, or inefficient structural form to fetch predictions of supreme precision. To thwart these issues, unsupervised feature transformation using ISOMAP is subsequently invoked to capture the underlying non-linear manifold of the data and produce a compact, low-dimensional representation while preserving intrinsic geometric relationships. Combining supervised selection with unsupervised transformation ensures the removal of irrelevant variables while transforming the filtered feature set into an optimized representation. Embodying both approaches in a seamless manner is crucial for enhancing the stability and generalization of the PSO-tuned XGBoost model. A combination of supervised and unsupervised feature engineering to discover the inherent pattern of crypto assets is rare. The designed predictive structure is subjected to a battery of statistical and validation checks to establish its efficacy over the benchmark. Secondly, the proposed methodology emphasizes decoding the predictive process to infer the dependence structure of chosen sustainable crypto assets on selected explanatory variables locally and globally by interfacing the PSO-driven XGBoost model with dedicated XAI tools. To the best of our knowledge, striving to explain an advanced predictive model without compromising the quality of forecasts of future figures of niche crypto assets has not been explored before.

4.1 BorutaShap

BorutaShap mimics the wrapper feature selection principles by combining the Boruta and SHAP (Shapley Additive Explanations) algorithms to assess the relative feature ranking and significance. These two combinations can produce better feature selection than the traditional Boruta algorithm (Ghosh and Datta Chaudhuri, 2022). BorutaShap is used as a supervised feature selection instrument to filter out the features with significant predictive prowess for sustainable cryptocurrencies. The inclusion of the Shapley values helps in accurately determining features' contributions. The methodological structure of SHAP utilizes a collaborative game setup (Shapley, 1953). The advent and the recent development of the XAI frameworks have ushered in new avenues to completely utilize the potential of the SHAP. It is calculated as:

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

Where $\emptyset_i$ denotes the contribution of the i^{th} feature, N is the set of all features with cardinality n, S is the subset of N excluding feature i, and $v(S)$ is the predicted outcome using the feature set S. The explanation is specified by applying equation 2 as:

$$g(z') = \emptyset_0 + \sum_{j=1}^{M} \emptyset_j z'_j \tag{2}$$

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

BorutaShap uses the smallest sub-sample for ascertaining the relative importance of respective features to reduce the computational burden. We use the *'shap'* package in the Python for its implementation.

4.2 Isometric Mapping

The ISOMAP is an important feature engineering method. It was proposed by Tenenbaum et al. (2000). The method advances the fundamental multi-dimensional scaling (MDS) framework. MDS uses the conventional Euclidean norm for estimating the pairwise distance to carry out low-dimensional embedding. The steps of the method are mentioned next.

Step 1: Neighbourhood graph (G) construction: Set a linkage between points, i and j, with distance $\left(d_x(i,j)\right)$, if they are closer than ϵ, or $i \in K$ nearest neighbours of j. Let the length of the edge is $d_x(i,j)$.

Step 2: Shortest path determination: If i and j have a linkage, then set $d_G(i,j) = d_x(i,j)$, else $d_G(i,j) = \infty$. Replace all elements of $d_G(i,j)$ by minimum of $\{d_G(i,j), d_G(i,k) + d_G(k,j)\}$, $\forall\, k$ $(k = 1,2,\ldots,N)$. The final matrix $D_G = \{d_G(i,j)\}$ comprises the shortest paths.

Step 3: d-dimensional embedding creation: Let λ_p denotes the p^{th}-eigenvalue of $\tau(D_G)$ and v_p^i is the i^{th} component of the p^{th}-eigenvector, then the p^{th}-component can be written as $\sqrt{\lambda_p} v_p^i$.

The matrix $\tau(D_G)$ is estimated as:

$$\tau(D_G) = -\frac{1}{2} H {D_G}^2 H \tag{3}$$

where H represents the centering matrix $\left(H = I_n - \frac{1}{N} e_N e_N^T\right)$, with $e_N = [1, \ldots, 1]^T \in \mathbb{R}^N$

4.3 Particle Swarm Optimization (PSO)

PSO is a widely used metaheuristic algorithm (Eberhart and Kennedy, 1995). It enables candidate solutions to interact in the traversal process for fetching the near-optimal solutions at a reasonable expense of computational time and space. The present research uses PSO to speed up the search space as parameter tuning of the XGBoost involves a large-scale combinatorial setup. The algorithmic framework of the PSO constitutes a set of individual particles to move indiscriminately based on the adjoining location. The subsequent position of each particle is driven by accumulating self and assimilated know-how. Mathematically, the velocity and position are computed as:

$$V_i^{t+1} = \omega V_i^t + m_1 n_1 \left(p_{best,i}^t - Y_i^t\right) + m_2 n_2 \left(g_{best,i}^t - Y_i^t\right) \tag{4}$$

$$Y_i^{t+1} = Y_i^t + V_i^{t+1} \tag{5}$$

V_i^t denotes the velocities, and Y_i^t denotes the position of particle *i* at iteration *t*, Y_i^t denotes the position at iterations *t*; $p_{best,i}^t$ denotes the best position of the particle at step t; m_1, m_2 and ω are social effect, inertia, and cognitive parameter; $n_1, n_2 \in [0,1]$ are random parameters. We leverage the efficacy of the PSO algorithm for auto-tuning different process parameters of the XGBoost model to map the intrinsic relationship among the sustainable crypto assets and the engineered feature set comprising macroeconomic and technical indicators. We use the Python package *'pspso'* for the simulation.

4.4 Extreme Gradient Boosting (XGBoost)

The XGBoost is an ensemble predictive modelling algorithm (Friedman, 2001). It is a modified version of the conventional Boosting algorithm. In this algorithm, decision trees are used as base learners. It mimics the sequential and forward-looking ensemble operational procedures to resolve complex pattern recognition problems. For stepwise details, please see Friedman (2001). In this work, the classical regression tree is used as base learners, and the framework is implemented by employing the *'sklearn'* library in Python. The hyper-parameters are tuned using the PSO algorithm.

4.5 Performance evaluation

We employ the following measures for assessing the performance of the proposed XAI framework. Let (Y_t) denotes the observed series and $(\hat{Y}_t)$ denote the estimated series. Then the four measures, Index of Agreement (IA), Theil Index (TI), Nash-Sutcliffe Efficiency (NSE), and Directional Predictive Accuracy (DA) are defined as follows:

$$NSE = 1 - \frac{\sum_{t=1}^{N}\{Y_t - \hat{Y}_t\}^2}{\sum_{i=1}^{N}\{Y_t - \bar{Y}_t\}^2}. \tag{6}$$

$$IA = 1 - \frac{\sum_{t=1}^{N}(Y_t - \hat{Y}_t)^2}{\sum_{t=1}^{N}\{|\hat{Y}_t - \bar{Y}_t| + |Y_t - \bar{Y}_t|\}^2} \tag{7}$$

$$TI = \frac{\left[\frac{1}{N}\sum_{t=1}^{N}(Y_t - \hat{Y}_t)^2\right]^{1/2}}{\left[\frac{1}{N}\sum_{t=1}^{N}(\hat{Y}_t)^2\right]^{1/2} + \left[\frac{1}{N}\sum_{t=1}^{N}(Y_t)^2\right]^{1/2}} \tag{8}$$

$$DA = \frac{1}{T}\sum_{t=1}^{T} d_t \tag{9}$$

Where

$$d_t = \begin{cases} 1, & if\ (Y_{t+1} - Y_t)(\hat{Y}_{t+1} - Y_t) \geq 0 \\ 0, & Otherwise \end{cases} \tag{10}$$

A predictive modelling approach will be highly efficient if the *NSE*, *IA*, *and DA* values approach to one and the *TI* value approach to zero. We use the Diebold-Mariano (DM) test to ascertain the competing models' relative efficiency statistically. We also use the model confidence set (MCS) test to statistically assess the predictive capability.

4.6 Explainable AI

To interpret the contribution of identified significant predictor variables in explaining the daily closing prices of the sustainable crypto assets, AVL, BNB, POL, and SOL, the current work resorts to an emerging explainable AI framework for decoding the apparent block box type PSO-driven XGBoost predictive methodology. Model interpretation has seen traction in literature lately (Pramanik et al., 2024). The XAI techniques are increasingly employed to enhance the transparency of complex machine learning models, particularly in financial applications where interpretability is critical for trust and decision-making. Unlike traditional statistical models, ensemble learning algorithms such as XGBoost operate as black boxes, making it difficult to understand how individual predictors influence the model's output. To address this limitation, the present study employs three complementary XAI tools, SHAP, Accumulated Local Effects (ALE), and LIME, that together provide both global and local explanations of model behavior. SHAP quantifies each predictor's contribution to the model's predictions across the entire dataset, thereby providing an overall measure of each predictor's importance. ALE plots reveal how changes in a predictor influence the predicted outcome on average, even in the presence of correlated features. LIME, in contrast, focuses on explaining individual predictions by approximating the complex model locally with a simpler, interpretable structure. Figure 2 depicts the flow of explainable analytics.

[INSERT FIGURE 2 HERE]

4.6.1 Global feature evaluation

We utilize the SHAP-based feature evaluation to assess the contribution of each feature globally. The explanation is specified as:

$$g(z') = \emptyset_0 + \sum_{j=1}^{M} \emptyset_j z'_j \quad (11)$$

where $z' \in \{0, 1\}^M$, M is the features number. We use the TreeSHAP utility in BorutaShap to find the features importance utilized for developing the PSO-driven XGBoost model.

4.6.2 Accumulation local effect plot

Conceptualized by Apley and Zhu (2020), the accumulation local effect (ALE) plot aims to determine the average impact of the independent variable on the predictions by deciphering the black box operations of utilized ML models. It is computationally very fast and capable of extracting true interpretation of predictive contribution in the presence of correlated features. The local-dependence (LD) profile for a model $f(.)$ and predictor X^k are expressed as:

$$g_{LD}^{f,k}(z) = E_{\underline{X}^{-k}|X^k=z}\{f(\underline{X}^{k|=z})\} \quad (12)$$

It is the expected value of the model predictions on the conditional distribution of $\underline{X}^{-k}$ given $X^k = z$.

4.6.3 Local interpretable model agnostic explanations (LIME)

LIME is an explainable AI tool to interpret ML models locally (Ribeiro et al., 2016). It generates a new dataset applying a fitted black box model by perturbing the figures of the input variables and extracts the association between the input and target variables. LIME is primarily used to ascertain the local influence structure of the constituent explanatory features.

5. Results and Discussions

We discuss the outcomes of the applied predictive modelling and subsequent outcome of XAI frameworks sequentially in this section.

5.1 Outcome of feature engineering

At first, the supervised feature screening by BorutaShap is invoked to filter out the irrelevant explanatory variables for subsequent processing through the ISOMAP method. For AVL prediction, TEU, EMV, and MTM5 are insignificant, while EPU is considered tentative. Both insignificant and tentative typed features are discarded for subsequent analysis to eliminate the overfitting issue. BNB follows an exactly similar behavioural pattern to that of AVL, wherein TEU, EMV, and MTM5 are insignificant and EPU as tentative. These four features are discarded from subsequent unsupervised feature transformation steps. Feature selection for POL indicates a comparatively higher number of insignificant and tentative features. The features lacking significant predictive power, B5, B10, OIL, EMV, TEU, MTM10, MTM5, MA10, and EMA10, are eliminated from the final set of features for unsupervised feature transformation. The outcome of the BorutaShap feature selection procedure suggests TEU, EMV, and B5 are insignificant, while EPU and NG are tentative for predicting future figures of POL. These five features are not forwarded for subsequent processing for drawing forecasts.

Overall, it appears that the underlying crypto assets exhibit very little sensitivity toward TEU, EMV, and EPU. Next, the ISOMAP is applied to the filtered set of features to obtain an optimized format which is extremely useful for training the PSO-tuned XGBoost model. The ISOMAP acts as an unsupervised feature processing task as feature reduction is no longer required owing to the usage of BorutaShap. Figure 3 represents the sample outcome of ISOMAP feature transformation for AVL.

[INSERT FIGURE 3 HERE]

5.2 Outcome of predictive modelling

The dataset is partitioned into In-Sample (85%) and Out-Of-Sample (15%) subsets for conducting predictive analytics. The partition has been forward-looking, which has been reported as an ideal setup for predictive analytics financial time series (Ghosh et al., 2019; Jana et al., 2021; Jana and Ghosh, 2022). The In-Sample is used for building the auto-tuned XGboost model by the PSO algorithm, and the Out-Of-Sample is used for gauging the capability of the learned model on test samples. Table 5 reports the estimated figures of chosen performance indicators for both segments.

[INSERT TABLE 5 HERE]

The magnitude of NSE and IA figures have emerged to be profoundly high for all underlying assets. They are greater than 0.99 and 0.98 on In-Sample and Out-Of-Sample partitions, respectively. The TI values are substantially low in both segments. Therefore, the developed feature engineered PSO-based XGBoost has shown a high degree of proficiency in discovering the inherent pattern, producing superior forecasts of absolute closing prices of four sustainable cryptocurrencies. The difference in the accuracy of predictions between In-Sample and Out-Of-Sample is marginal, ruling out the possibility of overfitting. The said predictive outcome rationalizes the utility of the BorutaShap and ISOMAP methodologies for effective feature screening and transformation, which facilitates the sound training of the predictive model. The DA values are also close to 1 on both segments for all variables, which suggests the model's effectiveness in precisely predicting the trend movement. Hence, the predictive structure can help buy or sell decisions for trading purposes. As the test segment of individual setups covers a significant portion of the COVID-19 pandemic regime, the framework's capability to produce supreme estimations in turbulent circumstances is established. SOL is relatively more predictable among select crypto assets than its counterparts, as manifested by the respective performance indicators.

5.3 Performance validation and comparative evaluation

We evaluate the effectiveness of the forecasting architecture by subjecting the same to predict future figures of surrogate series constructed upon the respective sustainable assets. The same exercise will also validate the robustness of the framework properly. The current work invokes the *'tseriesEntropy'* package of 'R' for simulating the surrogate series using the Sieve Bootsrap (Buhlmann, 1997) procedure. The autoregressive (AR) model leverages bootstrapping approach to enable the simulation. Applying the inbuilt *'surrogate.AR'* function, we create six surrogate series for each sustainable crypto asset. Figure 4 displays the sample surrogate series for SOL.

[INSERT FIGURE 4 HERE]

The resultant surrogate series exhibit high volatility and random fluctuations. Thus, good predictions on the surrogate series would reflect the capacity of the predictive framework in extreme cases. Table 6 reports the corresponding results.

[INSERT TABLE 6 HERE]

Predictive exercises on the surrogate data series echo the efficiency of the proposed predictive structure. We observe that the quality of predictions has deteriorated to some extent in comparison to the original series. Nevertheless, it is also evident that NSE and IA values, reflecting the predictive accuracy of the test segment, are greater than at least 0.95 across the six surrogate series, while the TI values are not exceedingly high. The performance of the feature-engineered PSO-based XGBoost is highly lucrative due to the excessive volatile and chaotic patterns of the surrogate series. Therefore, the performance on the surrogate series validates the claim of the effectiveness of the predictive framework in forecasting turbulent time series in turmoil circumstances. We proceed to comparative performance analysis, wherein the proposed framework is compared with three standalone ensemble modelling algorithms - gradient boosting (GB), XGBoost, and random forest (RF). The feature processing by BorutaShap and ISOMAP is not used for yielding forecasts by the competing models. The respective Python libraries' default parameter values are parameter figures without using PSO for parameter tuning. Table 7 elicits the results of the evaluation by the DM test.

[INSERT TABLE 7 HERE]

The DM Test results specify the proposed framework's supremacy over the three standalone ensemble ML algorithms in predicting the future figures of AVL, BNB, POL, and SOL. The roles of both supervised and unsupervised feature processing using Boruta and ISOMAP are pivotal in significantly eliminating the possibility of overfitting and improving the quality of forecasts. The performance of competing models has no significant difference, which suggests that the parameter tuning by the PSO technique has been effective in producing stable predictions. As the propounded framework is statistically superior to existing models, we introspect its superiority over some other machine and deep learning models. The comparison is achieved using the MCS test for superior predictive ability allowing, deep neural network (DNN), decision tree (DT), least absolute shrinkage and selection operator (LASSO), long short-term memory network (LSTM), multiple regression splines (MARS), quantile regression neural network (QRNN), and support vector regression (SVR). Table 8 outlines the results.

[INSERT TABLE 8 HERE]

The MCS evaluation reveals the statistical superiority of the proposed architecture than benchmark machine and deep learning algorithms in the predictive analysis of the chosen sustainable cryptocurrencies. It is interesting to note that well-known deep learning models, DNN and LSTM, have occasionally been outclassed by classical ML models breaking the myth of their supremacy in automatic feature processing. Therefore, it is amply evident that using dedicated feature engineering modules is of paramount practical relevance in mining complex patterns with high accuracy.

5.4 Outcome of the XAI

The feature-engineered PSO-driven XGBoost model is highly efficient in drawing predictions at the expense of model interpretability. The XAI tools are used to resolve the issues. The SHAP is used to draw relative importance of the features globally, ALE plots are applied for judging the nature of the influence of the top two globally important features for respective sustainable crypto assets, and LIME is utilized to realize the local level influence of the features. Figures 5-16 depict the insights.

[INSERT FIGURE 5 HERE]

ARCA and BTC, in conjunction with three technical indicators, have appeared to be the top 5 significant features in explaining the overall movements of AVL. Positive influence infers that development in technological prowess acts as a catalyst for the growth and betterment of the financial market perception of sustainable assets. The contribution of ARCA and MTM10 is mostly positive, spanning the negative and positive figures of the respective variables. On the flip side, a steep negative impact of BTC, representing a more conventional cryptocurrency, can be observed. Investors will likely be attracted to unconventional and emerging digital currencies when the traditional ones reside in the bear phase. LAG1 transpires to exert positive influence. We now introspect the ALE plot to precisely reflect the contribution of the top two influential features.

[INSERT FIGURE 6 HERE]

The plot suggests the influence of ARCA increases steadily with its magnitude. The impact experiences a sharp dip once it crosses a value approximately in the range of 5600-5700. Hence, the pre-eminences of positive predictive power, as apparent from the ALE plot, conform with the SHAP-driven global feature evaluation. The influence pattern of the technical indicator, MTM10, exhibits diminishing negative impact with higher figures of the same. The insight helps track the AVL evolutionary pattern. We now gauge the local-level feature influence structure by invoking the LIME methodology to decode the prediction process on a randomly chosen sample. Figure 7 exhibits the output.

[INSERT FIGURE 7 HERE]

The feature influence ranking at the local level appears to be different from that of the global level. MTM10 does not feature in the top 5 spots, while LAG2 features in the list. The magnitude and direction of constituent features vary across the respective intervals. Most of the features exert a negative contribution to the given data sample. The results indicate that it is equally important to closely monitor all features to accurately estimate the forecasted figures of AVL at the local scale.

[INSERT FIGURE 8 HERE]

The SHAP-based global feature evaluation suggests the dominance of crucial macroeconomic constructs in conjunction with conventional crypto assets and technological outlook in explaining the variation of the BNB. OIL and CBOEVIX exhibit negative impacts implying the shocks in the energy market and the prevailing option market fear in the US inhibit the growth prospect of the BNB financial market. Unlike BTC, which emerged to exert negative predictive prowess on AVL, ETH demonstrates the opposite sign by positively influencing BNB. The select sustainable crypto asset largely exploits the smart contract offerings of the Ethereum blockchain and serves as an alternative platform. However, a positive vibe on ETH also ushers in the bullish phase in BNB assets. BTC's impact is marginally positive but not exceedingly high to appear in the top 5 influential feature spots. We now take a deeper look at the contribution pattern of the top two features through the lens of ALE.

[INSERT FIGURE 9 HERE]

The contribution of OIL stays positive for a brief period. Once its closing price crosses a threshold limit, a profound negative influence is felt. The magnitude of the negative impact slightly weakens over a particular interval of the closing prices of OIL, as annotated in the horizontal axis. The impact of the CBOEVIX has remained mostly negative, barring an interval wherein the extent of market fear is minimal. The sign of the stabilized negative effect is apparent as it increases. Hence, conforming to SHAP-based global feature evaluation, the ALE plots of respective features suggest turmoil in the OIL market, and the proliferation of market fear is not ideal for the overall development of the BNB blockchain and the subsequent market impression. We also assess the local-level feature influence structure.

[INSERT FIGURE 10 HERE]

The top five significant predictors to explain BNB movement at the local level differ from that of global feature ranking akin to the AVL prediction process. BTC, which emerged as not highly influential in driving the overall predictive process, has played a critical role to explain the short-run fluctuations. No technical indicator finds a position in the top five global feature list, whereas LAG1 and EMA5 are marked as significant for precisely tracking short-run movements of BNB locally.

[INSERT FIGURE 11 HERE]

Interesting insights pertinent to the global-level contribution to explaining POL dynamics have emerged. Macroeconomic and financial variables exert a significant role in uncovering the variability of POL. Barring DJIA, none of the constituent features exhibit a strong positive influence. The impact of the remaining features oscillates between the positive and negative directions with negligible magnitude. Therefore, POL shares high dependence on prevailing market sentiment in the US. If the state of financial health is sound, the said asset experiences a bullish phase. NG exerts significant predictive prowess. Using the ALE plot, we now closely inspect the role top two features - DJIA and LAG2.

[INSERT FIGURE 12 HERE]

As the market sentiment, reflected by DJIA, improves, the impact on the POL is positively sharpened. A strong dependence on market sentiment suggests close monitoring of the same for accurate estimation of POL movements. Higher values of LAG1 positively influence the POL, while low values negatively influence it. The impact of LAG1 resembles the identified persistent patterns of the POL. The local level influence map is checked next.

[INSERT FIGURE 13 HERE]

Similar to the other assets, local-level feature ranking is different from the global one for explaining the temporal pattern of the POL. ARCA is not highly significant in explaining the prediction process for the select data, whereas BTC serves a pivotal role. Most underlying features tend to contribute positively to the chosen data sample.

[INSERT FIGURE 14 HERE]

ARCA, OIL, CBOEVIX, EMA10, and DJIA feature in the top five critical feature list. Except for EMA10, the remaining four features negatively affect the temporal dynamics of the SOL. Therefore, the diversification benefits of SOL with the said features can be leveraged. The technological development and the energy demand do not positively affect the adoption of services offered by the SOL blockchain. A high quantum of market volatility during a bullish regime offsets the growth of SOL. Interestingly, BTC caters to a marginal positive impact. The influence of ARCA and OIL is further decoded through ALE plots.

[INSERT FIGURE 15 HERE]

The ALE evaluation of the impact of ARCA contradicts the SHAP-based feature assessment of SOL prediction. The ALE plot of ARCA rules out the adverse effect of the same across the entire spectrum. As ARCA closing prices surpass a threshold, a positive influence over SOL is observed. The contribution of OIL stays positive in normal circumstances. However, any unprecedented hike in closing prices of OIL due to geopolitical tensions and external events steeply declines the growth of SOL. We analyse the local level feature contribution.

[INSERT FIGURE 16 HERE]

The profound negative influence of several technical indicators alongside ETH is critical for driving the prediction of the select sample. Deciphering at the local level suggests that tracking the not-so-important features recorded at a global scale is equally important to improve forecasting accuracy.

Therefore, XAI helps to demystify the dependence structure of sustainable cryptocurrencies on the explanatory variables and draws several meaningful and actionable insights. The select digital assets are competitors of the Ethereum blockchain and facilitate the implementation of advanced virtual technologies, Web 3.0, NFT, Metaverse, etc. The most positive influence of ARCA indicates that investment and focus on key technological development are critical enablers of the digital niche assets in the long run. The success of a less energy intensive PoS protocol relies upon the state of the economic and financial health of the US. Excessive volatility and shocks in the energy market are detrimental to the flourishment of all four assets. The direction of influence across specific intervals, as specified by the respective ALE plots, can be leveraged for effective portfolio alignment and risk mitigation. Systematic tracking of the select technical indicators helps anticipate short-run fluctuations.

6. Implications

6.1 Theoretical Contribution

This study makes several theoretical contributions to cryptocurrency and financial forecasting literature. First, it extends the understanding of sustainable cryptocurrencies, a category that has received minimal academic traction compared to traditional PoW-based assets. By analyzing Polkadot, BNB Chain, Solana, and Avalanche, the study provides new insights into how environmentally friendly blockchain ecosystems respond to stress and uncertainty. Second, the study proposes an integrated methodological framework combining supervised feature selection and unsupervised feature transformation. This dual-stage feature engineering approach contributes theoretically by demonstrating how combining both techniques can enhance the modeling of complex and highly nonlinear financial time series. The use of BorutaShap, ISOMAP, PSO, and XGBoost together enriches the modelling literature by demonstrating an effective ensemble of techniques that ensures both predictive accuracy and interpretability. Third, the study advances theoretical understanding by applying global and local explainable AI techniques to decode the behavior of sustainable crypto assets. The use of SHAP, ALE, and LIME underlines the utility of the modern XAI tools in successfully interpreting machine learning models for modeling volatile and nonlinear financial markets. This helps bridge the gap between predictive analytics and interpretable finance. Overall, the study contributes to both the methodological and domain-specific literature by presenting a rigorous, interpretable, and extensible framework for studying emerging digital assets.

6.2 Managerial Contribution

The findings of this study offer meaningful and actionable insights for traders, portfolio managers, and decision-makers. The identification of long-memory dependence structures suggests that technical indicators can play a meaningful role in predicting sustainable cryptocurrency prices, which basically conforms with the nature of conventional cryptocurrencies. The practitioners can therefore leverage technical analysis for short-term and medium-term trading strategies. It is also observed that market sentiment, technology-related indices, and the options market's fear significantly influence the price movements of the sustainable crypto assets studied. Managers can use these insights to monitor key external signals and adjust their investment positions accordingly. Ultimately, the scalable framework offers a transparent and interpretable model that managers can integrate into risk assessment and decision-support systems. The use of SHAP and ALE helps practitioners understand why the model behaves in certain ways, reducing the risks associated with relying on black-box systems. This supports more informed decision-making, especially in periods of heightened volatility. In summary, the overall implications strongly support investment in eco-friendly blockchain solutions. The study highlights the potential resilience and relevance of sustainable cryptocurrencies, helping stakeholders plan strategies that balance environmental considerations with financial performance.

6.3 Future Research Directions

The natural progression of the present research will be to explore the interplay and dependence of the chosen sustainable cryptocurrencies on key macroeconomic constructs during the recent Middle East geopolitical crisis. The introspection above can reveal the nature of stability and reactions of these assets in turbulent regimes, which should provide more profound insights relevant to diversification and hedging opportunities (Acikgoz, 2025). Conventional cryptocurrencies have been recognized for their safe-haven characteristics. It is of capital importance to ascertain the same for sustainable counterparts. The present framework considers daily closing prices of two conventional cryptocurrencies as predictors. It will be interesting to unveil the dependence patterns of sustainable assets on their daily energy consumption of BTC and ETH, which has garnered growing traction in the literature (Jana et al., 2022). On the methodological front, we thoroughly explore the explainability aspect of the predictive framework; nevertheless, it is equally critical to gauge the overall compliance of the integrated structure with emerging foundations, such as SAFE AI (Ghosh et al., 2025).

7. Conclusions

The current research expounds on the market dynamics of sustainable crypto assets catering to the updated decentralized offerings at a reasonably lower energy appetite. The growing concerns about environmental sustainability will naturally see increased inceptions of similar instruments equipped to continue to momentum of digitization in running the modern-day business. The lack of cognate research to understand the DNA of the market dynamics of these emerging assets is a significant roadblock to capturing the confidence of the investors, which can hinder the viability of sustainable ecosystems. The present work is positioned to inspect the market prices of sustainable crypto assets at a deeper level to reflect granular insights, void the research gap, and draw practical insights successfully. It is the first of its kind to simultaneously forecast the future figures of sustainable crypto assets and explain the dependence structure on predictor variables.

The research findings reveal that the AVL, BNB, POL, and SOL exemplify long memory dependence structures, which explains the utility of the technical indicators in tracking them effectively. They are immune to TEU and EMV, which suggests the turmoil of the pandemic manifested in social media and news chatter during the prevailing pandemic can barely influence the market returns. It is of paramount relevance for traders willing to put a high stake in these assets in short and long-run planning. Nevertheless, the inherent fear in the options market induces significant predictive power. The upswing of ARCA tends to positively influence the market prices of four assets, indicating that the overall market outlook of technological development in the US acts as a major enabler of sustainable cryptocurrencies. The abnormal price rise of energy commodities spurs the need for alternative eco-friendly blockchain platforms and subsequent high penetration of default tokens. DJIA has shown proximity to the US market sentiment. SOL transpires to be relatively more predictable than its counterparts. The said insights can be leveraged effectively for trading operations on the chosen sustainable assets. Organizations investing heavily on sustainable business models by deploying the niche digital currencies in place of the conventional energy consuming ones, can leverage the insights for strategic decision making.

The outcome of the global and local level feature contribution analysis is beneficial for reaping diversification benefits. Thorough performance checks, statistical evaluation, and validations verify and establish the efficiency of the integrated approach. Interpreting the black box predictive structure through the XAI frameworks using SHAP, ALE plots, and LIME globally and locally are the major takeaways of the research, which uncovers several meaningful and actionable insights. Overall, the study espouses a bright future for sustainable cryptocurrencies, which can effectively balance the negative traits and adoption of the ongoing digital transformation to usher in continuous business innovation.

The scope of this research is confined to the analysis of four sustainable crypto assets during the pandemic regime. The methodological framework can easily be extended to carry out a regime-wise comparison of the predictability and dependence patterns in the future. A trade-off analysis of the PoS energy emission rate and market returns of assets built upon said protocols can be explored to explore further the efficacy of the avenues in maintaining eco-sustainability while serving investors.

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