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Explainable artificial intelligence modeling to forecast Bitcoin prices

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Abstract

Forecasting cryptocurrency behaviour is an increasingly important issue for investors. However, proposed analytical approaches typically suffer from a lack of explanatory power. In response, we propose for cryptocurrency pricing an *explainable artificial intelligence* (XAI) framework, including a new feature selection method integrated with a game-theory-based SHapley Additive exPlanations approach and an explainable forecasting framework. This new approach, extendable to other uses, improves both forecasting and model generalizability and interpretability. We demonstrate that XAI modeling is capable of predicting cryptocurrency prices during the recent cryptocurrency downturn identified as associated in part with the Russian-Ukraine war. Modeling reveals the critical inflection points of the daily financial and macroeconomic determinants of the transitions between low and high daily prices. We contribute to financial operating systems research and practice by introducing XAI techniques to enhance the transparency and interpretability of machine learning applications and to support various decision-making processes.

Keywords: Decision support systems; Explainable artificial intelligence; SHAP value; Feature selection; Cryptocurrency prices

1. Introduction

Since the inception of bitcoin and concomitant underlying blockchain technology, digital currencies and assets have expanded to thousands of assets, several blockchains, and hosts of solutions for a variety of financial and business uses. Over time, competitors have attempted to develop new digital assets that improve on Bitcoin's paradigm as a store of value and a transactional asset. However, bitcoin remains the most popular crypto asset in terms of market capitalization and so, arguably, representative of the cryptocurrency market.

Fluctuations in the prices of digital currencies naturally lead investors, scholars, and policymakers to have concerns. Anonymous, decentralized, and unregulated crypto markets may manifest bubbles that threaten financial stability (Atsalakis et al., 2019). However, the behaviour of crypto markets has been difficult to predict. Consequently, an ability to accurately forecast bitcoin prices may not only help investors

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make decisions but will also help governments design regulatory policies (Liu et al., 2021). Forecasting bitcoin prices is a serious issue when it comes to risk management, and it merits careful consideration by investors and financial institutions (Nasir et al., 2019).

Our model testing period focuses on the recent decline in the value of cryptocurrencies from February to June of 2022. This has been attributed in part to the response of stock markets to the conflict between Russia and Ukraine (Bissoondoyal-Bheenick et al., 2022; Shih et al., 2019; Boungou & Yatié, 2022; Saâdaoui et al., 2022), as well as suggest possible liquidations by prominent cryptocurrency investors Khalfaoui et al. (2022a). Khalfaoui et al. (2022a) note that the co-movements of war attention and cryptocurrency prices rely on the investment horizon and the current status of the market, documenting that war attention has a short-term negative (positive) impact on the value of cryptocurrencies. However, factors conditioning the influence of the Russian-Ukraine war on cryptocurrencies is still largely unexplored. In this regard, we investigate the predictive power of several potential conditioning factors in forecasting BTC prices related to the Russia–Ukraine war and their economic consequences. We hope to assist cryptocurrency investors in broadening their analysis of the causes behind the recent sharp drops in the values.

As traders and policymakers must develop effective warning systems to forecast asset prices including digital currencies. Large volumes of information are captured and stored on many big-data platforms for analytical purposes. However, in many cases, this large quantity of information, rather than providing advantages for optimum decision-making, instead complicates decisions. Further, gathering, storing, and processing this information is prohibitively expensive (Ghaddar & Naoum-Sawaya, 2018). Decision-makers must recognize the essential facts from this wealth of data to construct an efficient and practical prediction model without compromising the accuracy of the anticipated output. The achievement of such goals is possible through feature selection, which is an essential element in the process of data preparation in machine learning (ML) models (Simumba et al., 2022; Ben Jabeur et al., 2021).

This study contributes to the literature on forecasting bitcoin prices in several ways: First, we develop a new approach, where using an improved Shapley Additive exPlanations (SHAP) algorithm, based on feature importance selection (FS-SHAP) is proposed to forecast the prices of the financial assets including bitcoin. Our algorithm suggests that FS-SHAP can enhance the accuracy and interpretability of artificial intelligence (AI) in the prediction of BTC prices. In fact, feature selection is a critical step in many machine learning applications (Chandrashekar and Sahin, 2014). According to Labbé et al. (2022) feature selection is a necessary procedure for avoiding overfitting and reducing database size without major information loss. We carry out a number of numerical experiments using FS-SHAP, and we compare the results of these experiments to other state-of-the-art approaches that are outlined in the relevant technical literature. These experiments indicate that our methodology achieves comparable or better outcomes than the alternative methods, with the additional benefit of being simpler and easily interpretable.

Further, we build explainable artificial intelligence (XAI) models to develop and investigate the data-driven nexus between financial and macroeconomic determinants and bitcoin prices. A framework that is explainable has been presented in order to meet the interpretative requirements imposed by external stakeholders for machine models (Zhang et al., 2022). The whole process ensemble method establishes an FS-SHAP model with excellent accuracy and stability from feature selection through predictor creation. This model is supposed to search for a feature subset swiftly and efficiently with good accuracy. Through FS-SHAP, we demonstrate the utility of this modeling. We do this for both to improve forecasting of bitcoin prices and to identify factors that impact these prices, and to motivate the use of our methodology for future research in a variety of forecasting contexts.

Demonstrating the utility of XAI modeling, we highlight the inflection points of the critical macroeconomic factors above or below which the bitcoin prices will respond. Based on this utility, we demonstrate that long-term forecasting of ongoing daily bitcoin prices benefits from identifying these factors. We infer from this that other forecasting contexts will be enhanced by this modeling. We add to existing studies by providing additional determinants for predicting bitcoin prices. In this regard, key macroeconomic determinants that influence bitcoin prices, such as climate policy uncertainty, public attention to inflation and recession, and uncertainty factors (Twitter uncertainty) and new sentiments are investigated. Our study contributes to the behavioural economics theory by combining insights from psychology and economics to explain how people make decisions (Tversky and Kahneman, 1992; Kahneman and Tversky, 2013). According to this argument, individuals care more about the bad repercussions of inflation and recession than the positive ones. This article provides fresh insights into how media framing and public dialogue influence perceptions of economic news, particularly inflation and recession concerns during the Russia–Ukraine war.

Our study also provides new evidence on the role of geopolitical risks in predicting cryptocurrency prices, particularly during the Russia–Ukraine war and contributes to a growing body of literature on the financial repercussions of wars, terrorist acts, and other types of collective violence (Boubaker Glick & Taylor, 2010; Moretti et al., 2014; Pástor & Veronesi, 2013; Caldara & Iacoviello, 2022; Saâdaoui et al., 2022). Moreover, climate policy uncertainty political economy theory ((Stigler, 2021). Uncertainty around climate policy may result in uncertainty regarding regulations for a number of businesses, including the cryptocurrency industry. If investors become more risk-averse as a result of worries about the effect of climate change or the possibility of legislative changes connected to climate change, this might lead to a reduction in demand for Bitcoin, which would ultimately result in prices falling. Our research offers a thorough comprehension of the effects that global warming bitcoin market may have on the Bitcoin market.

The remainder of the paper is organized as follows: Section 2 provides background and critically discusses the literature on forecasting crypto prices; Section 3 describes the data sources across the data processing steps; Section 4 outlines the variational mode decomposition (VMD) and machine learning models adopted for this research; Section 5 reports on the causality settings, the predictive performance of ML methods, and provides discussion. Section 6 concludes.

2. Literature review

Initially, research on forecasting cryptocurrency dynamics was primarily on the potential drivers of the bitcoin prices. Early studies evidence gold, oil, natural gas, and bitcoin prices as correlated, with these assets together being portfolio diversifiers (Symitsi & Chalvatzis, 2019; Maghyereh & Abdoh, 2020; Goodell and Goutte, 2021; Zhang et al., 2022; Khalfaoui et al., 2022). Parvini et al. (2022) report that gold rates have a strong power for predicting bitcoin prices in both training and validation periods. Basher and Sadorsky (2022) evidence of the relationship between oil and the bitcoin price, finding that the oil price volatility index is a significant predictor of both the bitcoin and gold price direction, consistent with bitcoin serving as a replacement for gold in terms of diversifying this type of volatility. However, some studies dispute whether cryptocurrencies are diversifiers for equity (e.g., Goodell and Goutte, 2021).

Rehman and Kang (2021) examine the time-frequency nexus between bitcoin prices and oil. Their results revealed a significant relationship with oil over a period of 128 to 256 days. More recently, based on Granger causality testing, Li et al. (2022) investigate extreme risk transmission between bitcoin and crude oil assets. They report the existence of extreme asymmetry in the oil-bitcoin linkage, as well as time-varying causality at different timescales.

The most recent work of Basher and Sadorsky (2022) includes a set of macroeconomic factors as features in forecasting the bitcoin price, consisting of economic policy uncertainty (EPU) and inflation. Moreover, the prices of the S&P500, the volatility index, the U.S. dollar index, Ethereum, Litecoin, and Ripple were included among the predicting factors as a number of previous studies had shown a connection between bitcoin and the aforementioned commodities markets (Celeste et al., 2020; Jiang et al., 2022; Wu et al., 2022; Nguyen, 2022; Al-Shboul et al., 2022). For example, Fang et al. (2019) have stated that global EPU improves the prediction of bitcoin volatility. Demir et al. (2018) investigate the prediction power of EPU on bitcoin returns, evidencing that EPU has positive and significant impacts in both the lower and higher quantiles. In another study that employed the vector autoregressive approach, Blau et al. (2021) examine the relationship between bitcoin and inflation expectation rates, finding that changes in bitcoin cause changes in the forward inflation rate. During the recent COVID-19 pandemic, Choi and Shin (2022) examine the relationships among inflation, uncertainty, and bitcoin. Their results suggest bitcoin appreciation in with inflation shocks so that bitcoin can be a hedge against future price increases. However, considering the recent 2022 fall in cryptocurrency values during a time of global resurgence of inflation, clearly forecasting bitcoin prices requires considering a number of factors.

In terms of methodological choice, there are different approaches explored for predicting the price of Bitcoin and other cryptocurrencies. For instance, in a study based on the generalized autoregressive conditional heteroskedasticity (GARCH) model, Katsiampa (2017) report that the autoregressive component GARCH has the best goodness-of-fit to the data of any model. In another study, Sun et al. (2020) use the light gradient-boosting machine (LightGBM) and 42 features to forecast the price of cryptocurrencies. Based on their findings, LightGBM modeling is more accurate and reliable for making predictions. Han et al. (2020)

combine genetic algorithms and the NARX neural network to predict Bitcoin returns. The authors compare the hybrid model to the feed-forward model, finding that the latter is superior for predicting Bitcoin geometric returns. Mallqui and Fernandes (2019) propose recurrent neural networks and a tree classifier technique to predict bitcoin price direction. According to them, this proposed methodology leads to the best performance. There is also a suggestion that compared to GARCH models, hybrid artificial neural network modeling performs better and improves forecasting (see Kristjanpoller & Minutolo, 2018).

Focusing on intraday technical trading and using artificial neural networks for bitcoin return prediction, Nakano et al. (2018) use a deep-learning approach. They conclude that their method significantly enhances the efficiency of a buy-and-hold investment approach. Using technical analysis at high frequencies, Alonso-Monsalve et al. (2020) investigate the feasibility of neural networks with a convolutional component as an alternative to conventional multilayer perceptions in the area of trend classification of cryptocurrency exchange rates. Based on 18 technical indicators, their results indicate that the convolutional neural network LSTM performs the best, and indicated good results, especially with the bitcoin, Ether and Litecoin cryptocurrencies. Table 1 presents a summary of recent typical literature reviews on forecasting cryptocurrency prices.

(Insert Table 1)

An overview of previous research on Bitcoin forecasting suggests various contrasting approaches that suffer from a lack of explanatory power. Therefore, we are motivated to propose and demonstrate an *explainable artificial intelligence (XAI)* framework, including a new feature selection method integrated with the game-theory-based SHapley Additive exPlanations approach and an explainable frame for forecasting cryptocurrency prices. Further, this new approach can be extended to other uses as it comes with improved forecasting performance as well as improved model generalizability and interpretability. Therefore, we feel that demonstrating this novel modeling will have applications in future research beyond just being applied to cryptocurrency price forecasting.

3. Data and variables

We use daily time series covering the period from August 2016 to the end of June 2022. Our main variable of interest is the Bitcoin price series. We use the BTC price index (BTC). from *www.investing.com.* Based on previous literature, 15 predictor variables are identified for inclusion in this investigation of the effectiveness of the forecasting models, namely Litecoin (LTC), Ethereum (ETH), the S&P500 (SP500), Gold, Brent crude oil future (Oil), Volatility (VIX), the U.S. dollar index (USDI), the 5-year forward inflation expectation rate (YIFR), inflation (INF), recession (REC), the geopolitical risk index (GPR), Twitter-based economic uncertainty (TEU), the news-based sentiment index (NSI), and the infectious disease equity market volatility index (INFECTION). Table 2 provides definitions and sources of variables included in our data set, while

Fig. 1 illustrates the correlation matrix and Table 3 depicts the descriptive statistics. Moreover, the BDS of Broock et al. (1996) test is used to analyze three different types of the BTC price: level data, returns, and log-returns (test statistics: 109.65, 12.89 and 5.38. respectively, with all p-values under 10^{-5}). This implies that a more sophisticated nonlinear model may be better suited to model the data. In other words, a linear model may not accurately capture the underlying relationships between the variables in the data, and a nonlinear model may provide a better fit.

(Insert Table 2)

(Insert Table 3)

(Insert Figure 1)

Data are divided into training and out-of-sample subsets. There are several methods for splitting the sample. About 80% of the dataset is used to train the model, with the remaining 20% used for validation. This approach is similar to previous research (Parvini et al., 2022). To evaluate performance, we use out-of-sample R^2 (R^2_{OOS}) This indicator is defined as follows:

$$R^2_{OOS} = 1 - \left[\frac{\sum_{t=1}^{n}(z_t - \hat{z}_t)}{\sum_{k=1}^{n}(z_t - \bar{z}_t)^2}\right] \tag{1}$$

where z_t is the true observation, $\hat{z}_t$the predicted value of time t, $\bar{z}_t$ the historical mean of the bitcoin price and n the total number of observations in the out-of-sample dataset.

4. Methodology

4.1 Feature selection methodology

Recently, feature selection has emerged as a difficult challenge in a variety of machine-learning areas, including regression problems (Jiménez-Cordero et al., 2021). The proposed framework involves using the FS-SHAP algorithm to select the most important variables for a given model, thereby improving prediction performance. The methodology can be summarized by seven steps, including training the Extra trees model, computing the Shapley value for all features, and selecting the k highest-ranking features. Figure 2 provides a visual summary of the methodology and its key components. The following section outlines the proposed approach for selecting the most relevant features during the construction of machine learning models.

4.1.1. Shapley values for feature selection

Initial characteristics may be noisy and redundant in certain cases, negatively impacting the model training stage. As a result, efficient classification work requires the use of a strong feature extraction approach. This paper uses SHapley Additive exPlanations (SHAP), proposed by Lundberg and Lee (2017). The SHAP values are useful for illustrating how each attribute contributes to the model's final prediction (i.e., prediction). SHAP values are a relatively new metric used in machine learning to evaluate the efficacy of any decision-tree-based model. The SHAP values are determined by defining the output of a tree based on a subset of functions S, defined as $h_x(S) = [E(h(x)]$, and the SHAP values are calculated as follows:

$$\phi_{i,j} = \sum_{S \subseteq N\{i,j\}} \frac{|S|!(K-|S|-1)!}{K!} [h_x(S \cup \{i\} - h_x(S)], \quad (5)$$

where K is the number of input features.

In this paper, a SHAP value technique based on feature importance selection (FS-SHAP) is proposed to predict bitcoin prices. It is necessary to remove redundant and unneeded variables while maintaining the accuracy of different machine-learning models (Ben Jabeur et al., 2022). According to García et al. (2016), feature selection results in increased interpretability, simpler modeling, shortened learning time, and improved generalizations. To accomplish this goal, the FS-SHAP method was utilized to minimize dimensionality. This approach will not only improve forecasting performance but will also improve model generalization and interpretability. When the SHAP value is larger, the corresponding variable vector will be more important. In other words, the order of the scores should go from highest to lowest for each of the input features. We selected the top-ranked factor whose score was higher than k for the feature sets, as illustrated in Table 4.

(Insert Table 4)

(Insert Figure 2)

4.1.2. Granger causality

Granger causality, based on stochastic linear regression modeling, is often used to determine whether one economic variable may aid in the forecasting of another economic variable (Granger, 1969). It uses the Fisher test to see whether lagged information on a variable Y tells us anything important about a variable X when the lagged X is also present. If X_t, Y_t are two stationary time series, the simple causal model with autoregressive lag length p, ordinary least squares, may be used to estimate the causal relationship between X and Y as follows:

$$X_t = C_t + \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{i=1}^{P} \alpha_i Y_{t-i} + \mu_t \quad (2)$$

Based on the null hypothesis H0, that Y does not cause X (i.e., β1, β2, …, β = 0), Granger causality is a popular method for analyzing time series data in many fields, including economics and finance. Even though this framework is very popular, it has been the subject of ongoing debate about whether or not it can be used to find causal relationships between time series (Shojaie & Fox, 2022).

4.1.3. Variational mode decomposition causality

Variational mode decomposition (VMD) is considered to build non-linear and non-stationary signals into orthogonal sub-signals, known as intrinsic mode functions (IMFs) and trends, which reflect different time scales. Variational mode decomposition is a new adaptive technique for time series multi-scaled decomposition (Saâdaoui et al., 2022b); it works on the premise of adaptively breaking down an input time series X_t into a number of modes $u_t^{(m)}$. According to Wang et al. (2015), VMD is expressed as a constrained variational problem as follows:

$$X_t = \sum_{m=1}^{M} u_t^{(m)} \tag{3}$$

where M is the number of modes and $u_t^{(h)}$ is the mth intrinsic mode function (IMF).

Thus, VMD-based cross-correlation provides a multi-scaled approach for delving extensively into the scale-by-scale lead-lag connection between two signals. It is feasible to spread the VMD principle to the study of scale-by-scale causality. At each VMD scale *m* (for each IMF), the test has two possible alternative hypotheses:

$$\begin{cases} H_0: u_{t,x}^{(m)} \nRightarrow u_{t,y}^{(m)} \\ H_a: u_{t,x}^{(m)} \Rightarrow u_{t,y}^{(m)} \end{cases} \tag{4}$$

The null hypothesis in H_0 shown by the crossed-out sign suggests that component $u_{t,x}^{(m)}$ does not cause component $u_{t,y}^{(m)}$.

4.2. Machine learning models

4.2.1. Linear regression

The field of machine learning considers linear regression (LR) as a standard method. Ordinary least squares (OLS) is often used to estimate the intercept and slope regression parameters. The model may be summarized as follows:

$$\hat{Y} = \beta_0 + \sum_{i=1}^{p} \beta_i X_i + \varepsilon_i, \tag{6}$$

where *Y* represents the response variable, *Xi* represents the predictor, and β_i represents the parameter determined through OLS regression. Then, by assessing the multicollinearity, significant independent variables are chosen (Sarstedt & Mooi, 2014). According to Nolan and Ojeda-Revah (2013), OLS provides a poor fit and leads to faulty predictions in the absence of normality of the error terms. Alternatively, machine learning models may be used when errors are not normally distributed.

4.2.2. Support vector machine

Support vector regression (SVR) is a regression technique introduced in 1998 (Smola and Schölkopf, 2004). It has a powerful generalization capacity and can tackle actual issues, such as a small sample size, high dimensionality, strong nonlinearity, and local extremum. In addition, it has a high dimensionality (Huang et al., 2022). The nonlinear support vector regression (Vapnik et al., 1996) algorithm attempts to handle the following nonlinear regression problems:

$$\hat{Y} = w\emptyset(x)^H + c \tag{7}$$

where x are the input variables. $\varphi(x)$ represents a mathematical function that maps the input vector x into a higher dimensional feature space, ω are the weight vector, c and H are the intercept and transpose operator. The fundamental benefit of the SVR is that it uses the structural risk minimization concept to reduce an upper limit on the generalization error, rather than the empirical risk minimization principle to reduce the training error. As a result, it should always succeed in achieving the global optimum. In addition, even with a small data sample, the SVR may provide high generalization results.

4.2.3. Random forest

Random forest (RF) is a set of tree predictors that generate each tree by sampling an independent random vector, incorporating a regression and a classification approach. Random forest is a regression algorithm. According to Breiman (2001), in regression, numerical values are obtained from the tree predictor, in contrast to the labels obtained from the random forest classifier. According to Jabeur et al. (2021), the function can be estimated as follows:

$$\hat{Y} = \frac{1}{T}\sum_{i=1}^{T} g_k(X) \tag{8}$$

where $g(x)$ is a set of the k^{th} learner random tree, and x is the vector of the input variables. The dataset is divided into homogenous subsets at random using the bootstrap sample algorithm. Each tree is grown and trained using a random subset of the data, and its validity and accuracy are estimated using the remaining samples.

4.2.4. XGBoost regression algorithm

XGBoost, developed by Chen and Guestrin (2016) as an ensemble machine learning technique, has been used in various research fields. In XGBoost, a sequential ensemble method, also known as sequential decision tree building, is used to build a sequential decision tree. Every sample in the dataset is assigned a weight, which determines how a decision tree will choose weight for further analysis. The following equation is used to combine the data from each tree for the first productivity prediction:

$$\hat{Y} = \sum_{t=1}^{T} f_t(x_i) \tag{9}$$

where T denotes the number of trees, and $f_t(x_i)$ is the regression tree's output of the input x_i.

Appropriate hyperparameters must be determined while developing the XGBoost with improved prediction performance. In particular, the hyperparameters crucial to the initialization of the model should be validated against a range of values (Jabeur et al., 2021). Furthermore, this approach offers efficient and valuable answers to previously unresolved optimization problems.

4.2.5. Extra trees regression

As an extension of the RF method, the extra trees (ET, or extremely randomized trees) algorithm proposed by Geurts et al. (2006) is a machine learning approach that is less prone to overfit a dataset. This approach is extremely similar to the RF algorithm used to build several decision tree models. There are two significant distinctions. The primary distinction is in the full splitting of the descriptors at random at the node.

The second difference is that each tree is constructed using the whole dataset as a distinction. In the regression case, the function is computed as follows:

$$\hat{Y} = \sum_{j=1}^{T}(y_j - \bar{y}(t))^{\top}(y_j - \bar{y}(t)) \tag{10}$$

where $\bar{y}(t)$ is the sample mean of the output vector at node t, and y_j is the median of the output vector at node t. In contrast to RF, a tree is built using the whole training data set (Schmid et al., 2022). This additional degree of randomization is intended to enhance the decorrelation process, resulting in less variance and maybe even greater predicted accuracy in certain circumstances.

4.2.6. Deep neural networks

Recently there has been increasing scholarly attention to the effective implementation of deep neural networks (DNN) in a number of different contexts (Krauss et al., 2017; Jabeur et al., 2022). Deep neural networks can readily handle models with very complicated and nonlinear predictor-outcome interactions. Deep neural networks beat superior models from classical machine learning in a variety of circumstances. The model iw trained using a stochastic gradient descent training approach and a feedforward neural network architecture. Deep neural networks may be formulated by combining numerous single-layer networks to construct a DNN with k layers:

$$\text{g(x)}_{DNN} = \underbrace{g_{1NN}(g_{1NN}(\dots g_{1NN}(X)))}_{k} \tag{11}$$

where g_{1NN} is a one-layer perceptron trained using an activation function such as a sigmoid, a hyperbolic tangent, or a rectified linear unit. It is important to note that the dimensions of different layers are not always the same. Deep neural networks may include anything from two hidden layers to possibly hundreds of layers, depending on the application. This may quickly lead to networks with tens of millions of degrees of freedom when combined with the equivalent dimension of each layer.

4.2.7. Long–short term memory

An enhanced deep learning technique built on a recurrent neural network is called *Long–Short Term Memory* (LSTM). Recurrent neural networks are excellent at mining time series and semantic information from input that has sequential properties. The input layer at each instant also influences the hidden layer at that instant, as does the hidden layer at the instant before. The output values at time t are calculated as follows:

$$\hat{Y} = \delta(W_f.[h_{t-1}, x_t) + c_f) \tag{12}$$

where W_f is the weight matrix, c_f is the bias, and the operator $\delta()$ is defined as a sigmoid layer that pushes the values between 0 and 1. The bottom layer is the hidden layer represented by h_t and is the input of LSTM at day t. The training dataset is utilized to continually update the parameters in the network throughout the training process, with the model being saved after training. The rectified linear unit function performs calculations more quickly than the sigmoid and tanh functions while simultaneously solving the gradient vanishing issue in the positive interval. This function serves as the activation function for all layers.

4.3. Explainable artificial intelligence framework

In the past, researchers have used machine learning and ensemble strategies to improve the predictive performance of forecasting bitcoin prices. However, investors are still cautious about fully adopting these approaches (Zhang et al., 2022). Because of the complexity of the models, machine learning techniques do not expose the fundamental processes that they use, and it may be challenging to explain and confirm the models' predictions. In complicated models, this issue is sometimes referred to as the 'black box' problem (Adadi & Berrada, 2018). To fill this gap, researchers have developed explainable artificial intelligence or XAI. As the goal of XAI is to provide a better perception of opaque AI systems so that humans may better employ such tools to support their job, it is congruent with the notion of 'human-in-the-loop' (Zhang et al., 2022).

The novel approach of XAI consists of a complete process ensemble technique as well as an explainable framework. It was designed to satisfy the interpretative needs of traders and investors while maintaining a high level of prediction accuracy. Under the banner of XAI, there are many views and reasonings in the literature (Adadi & Berrada, 2018): interpretations to justify, interpretations to control, interpretations to discover, and explanations for better classification or regression tasks. Our research intends to provide a feature selection methodology based on the TreeExplainer for financial forecasting that improves the predictive performance of ML modeling.

TreeExplainer is a novel local feature attribution approach for trees, developed by Lundberg et al. (2020), that precisely calculates the traditional Shapley values from game theory. The Shapley values are then calculated according to Equation 1 and employed as feature attributes.

To deepen our analysis, we use explanation Local Interpretable Model-Agnostic Explanations (LIME) modeling. LIME uses a local surrogate linear regression model, which is more intuitive and understandable than an artificial intelligence method (Ribeiro et al., 2016). After the model has been trained, the prediction for an unknown sample may be explained using LIME. In essence, LIME believes that, although the overall correlations between inputs and outputs may be non-linear, linear surrogate models may be built to monitor how an individual prediction changes as the data changes are disturbed (Stevenson et al., 2021). Equation 5 was used to calculate the local linear explanation values as follows:

$$h(z') = \emptyset_0 + \sum_{i=1}^{K} \emptyset_i z'_i \tag{13}$$

where $z' \in [0,1]^K$, K is the number of simplified input variables. $\emptyset_i \in \mathbb{R}$. LIME techniques are useful because they can be integrated into many different types of machine learning. The XAI framework used to predict the BTC price is presented in Fig. 2.

5. Results and discussion

5.1. Causality test results

Cross-correlation statistics between bitcoin prices and each of the exogenous variables, all calculated in differences, are plotted in Figure 3. This preliminary visual analysis is important because it helps to determine the most important variables that can be added to a forecasting model of the bitcoin price. In addition to the cross-correlation functions, we also report the autocorrelation function of Bitcoin returns. This is also important for the preliminary identification of the autoregression order for the bitcoin variable. Most notable in these results is that two variables appear to be able to contribute to the explanation of Bitcoin returns. These are essentially LTC and ETH variables, whose cross-correlation functions show a lagging relationship with a certain regularity up to a lag of 40 days. For the rest of the variables, the cross-correlations are clearly irregular, which may be a sign that the rest of the variables are not significant for the Bitcoin forecast. However, this preliminary analysis remains insufficient to know the explanatory power that each of the variables has. It is therefore meaningful to move on to a more advanced methodology to better understand the most relevant explanatory variables.

(Insert Figure 2)

The second step of our preliminary analysis is inferential, with multi-scale causality tests being applied to the same time series. In other words, we perform a causality test between bitcoin returns and each of the 15 different variables. The choice of multi-scale causality is due to the data showing some nonlinearity with local stationarity. Their distributions are also nonstandard. The multi-resolution analysis provides a powerful tool for decomposing the series into sub-signals with more regular properties than their primitives.

(Insert Table 5)

In these tests, we employ the third-order VMD approach for the decay of the time series into intrinsic mode functions (IMFs). This technique is preferred to other methodologies such as wavelets, mainly because of its efficiency in dealing with nonlinear time series. This characteristic has been emphasized in several previous works, such as Wardana (2016) and Krishnan and Soman (2022). The results reported in Table 5 indicate that only two variables already identified in the cross-correlations, that is, LTC and ETH, are considered to cause bitcoin returns on all three scales simultaneously.

However, another finding that should be highlighted here is that three other variables are evidenced to have partial explanatory power. These variables are INF, on Scale 1 (IMF1), as well as the GPR and TEU variables on Scale 3 (IMF3). This suggests that the multi-scale VMD-based causality test makes it possible to detect what could not be observed by the cross-correlations, or by the classic single-scale Granger approach.

(Insert Figure 3 here)

(Insert Figure 4 here)

Recently, studies confirm the strong feature selection method using the SHAP value (Sigrist & Leuenberger, 2022; Jabeur et al., 2021b). SHAP employs the concept of the game theory proposed by Shapley (1953) to calculate the importance of individual independent variables. Figure 4 depicts the SHAP summary plot for all variables, which ranks factors according to their relevance in influencing the BTC price. Figure 4 is a SHAP summary graphic, with each dot representing a single data point in the dataset. A higher SHAP value indicates that the model predicts higher BTC price values and vice versa. We can observe that the top four features for XGBoost are REC, GPR, YIFR and SP 500. There are several important gaps in the literature which lead to these findings. Variables such as inflation, geopolitical risk, and recession are elements that define the economic cycle and have significant influences on the pricing of assets (Thorbecke, 1997). According to Basher et al. (2022), business cycle factors should be significant forecasters if bitcoin prices are influenced by economic circumstances.

5.2. Performance comparison

In this section, we compare machine and deep learning techniques such as linear regression (LR), random forest (RF), and eXtreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and Deep Learning Neural Networks (DL). Appendix 1 presents LSTM model details. Based on the testing dataset, the performance of the machine learning models is presented and compared in terms of the R^2_{OOS}. In this study, about 80% of the dataset was utilized to train the model, with the remaining 20% for the test dataset. The predictive accuracy of all modes was compared to the predictive accuracy of the LSTM model, with 14-day lags.

(Insert Table 6 here)

Table 6 presents the results of univariate regression for all predictors. Among the proposed predictors, LTC yields the most accurate outcomes with the highest value of R^2_{OOS} (0.896) based on the LSTM model. This finding is consistent with Elsayed et al. (2022), who posit a significant causal relationship among cryptocurrencies. In addition, REC appears to produce the second most accurate outcomes, with the highest value of R^2_{OOS} (0.865). This result is in line with García (2013) and Dias et al. (2022), who document that the capacity to forecast stock returns using the substance of the news is most prominent during recession periods. Moreover, the VIX and GPR predictors provide good performance compared to the other predictors, with R^2_{OOS} ranging from 0.525 for VIX to 0.431 for GPR, as shown in Table 6. This outcome is in line with Basher and Sadorsky (2022) which highlights that the direction of bitcoin prices may be predicted using macroeconomic factors.

According to Parvini et al. (2022), the disadvantage of univariate regression is that it does not take advantage of the synergistic and cooperative effects of numerous inputs, which are vital when utilizing machine learning algorithms. In this regard, the results of multivariate regression are presented in Table 7.

Overall, results indicate that LSTM based on the SHAP feature importance selection method (R_{OOS} = 0.689) performs better than VMD-based causality and Granger causality. As can be seen in Table 7, LSTM with FS-SHAP pulls and enhances positive territory to R_{OOS} significantly with a figure of 68.9%, averaged over all forecasting algorithms. We observe an increase in the R_{OOS} when applying FS-SHAP to all models. Meanwhile, ET based on the FS-SHAP method generates the second-best value of R_{OOS} compared to DL, SVM, LR, RF and XGBoost. LSTM and ET expand the model to accommodate nonlinear predictive relationships.

Gu et al. (2020) find that allowing for nonlinearities significantly improves predictions. Nonetheless, the forecasting performance of OLS regression is insufficiently low overall forecasting algorithms under the FS-SHAP method. When we incorporate our set of ten predictors in the OLS panel model, predictability rapidly diminishes, as indicated by the R^2_{OOS} falling deep into the negative territory of -73.7% These findings are not surprising, and are in line with the previous studies of Gu et al. (2020) and Leippold et al. (2022), who document that when there is a large number of variables, OLS regression's efficiency drops dramatically, leading to very volatile out-of-sample predictions.

(Insert Table 7 here)

The benefits of forecasting using machine learning projections are substantial. In our testing, the OLS model is statistically clearly rejected in favour of nonlinear machine learning techniques. More sophisticated statistical techniques in machine learning may be able to overcome the potentially serious limitations of these traditional approaches.

To deepen our analysis, We compared the performance of different models in terms of RMSE for each feature selection technique. The LSTM model based on FS-SHAP method provided the best RMSE of 2.031. However, for the VMD, the ET model based on IMF3 provided the best RMSE of 72.111. Overall, the findings show that the FS-SHAP feature selection strategy enhances forecasting accuracy and model generalization. In terms of RMSE, the ET model based on IMF3 beats other models, indicating that it is a promising model for predicting bitcoin values.

5.3. Model explainability

'Explainability" refers to consistency and interpretability, with explanations simple enough to understand (Chakraborty et al., 2021b; Chakraborty et al., 2021a). In this study, we utilize the SHAP and LIME based on Extra trees regression (ET) on frameworks to give straightforward, human-readable explanations, while correctly representing the real-world forecasting bitcoin price processes. In fact, Chakraborty et al (2021b) pointed out that deep learning neural networks automatically learn the input features that subsequently undergo several layers of nonlinear transformations, making them noninterpretable to the end-users. From a theoretical point of view, interpretable models such as extreme gradient boosting and extra trees regression provide certain advantages over the "black-box" type deep learning, Support Vector Machine and long short-term-memories. Moreover, based on the performance comparison, it can be concluded that the Extra Trees model provides the lowest RMSE among all the models tested, indicating that it is a promising model for predicting bitcoin values.

SHAP 'local interpretability' analysis based on FS-SHAP values is shown in Figure 5. This describes in detail how the feature values and interactions affect the model predictions. Each dot represents a data point, and the variation in height across features at any given feature value is a result of their interaction and dependence in the model. In Figure 5, we illustrate the effect of the variations in REC, GPR, YIFR, SP500, PACC and INF estimates on the models' predictions to identify the critical inflection points, above or below which bitcoin price improves.

Figure 5 highlights that REC interacts with GPR, and high REC and high GPR values drive up the SHAP values, corresponding to higher bitcoin values. Our findings are in line with Caldara and Iacoviello (2022), who highlight that the impacts of risk and uncertainty indicators on bitcoin returns are negative , while, nevertheless, bitcoin may be used as a hedge against the effects of international crises.

To further examine the critical determinants and inflection points of the important factors that drive bitcoin prices, we conduct a detailed 'local interpretability' analysis with LIME, depicted in Figure 6. These graphs provide the predictions of 12 instances from the Extra trees model to enhance their clarity. These reveal that the pertinent daily REC, GPR, YIFR, SP500, PACC, INF, TEU, ETH, Gold and INFECTION are 19.10, 62.49, 1.82, 2617.61, 32.64, 35.06, 93.06, 164.67, 1279.13, and 0.00, respectively. The VIX, USDI, NSI, LTC and Oil can be ignored, since they have a very small effect on bitcoin prices, according to the global interpretability analysis shown in Figure 9. Based on these interpretations, we can design ten different features or conditions based on these inflection points:

If REC $\leq$ 19.10, GPR $\leq$ 62.49, YIFR $\leq$ 1.82, SP 500 $\leq$ 2617.61, PACC > 32.64, INF $\leq$ 35.06, TEU $\leq$ 93.06, ETH $\leq$ 164.67, Gold $\leq$ 1279.13, and INFECTION $\leq$ 0.000, the BTC price will be low.

Regarding the effect of public attention to climate change, our result is in line with Fang and Peress, (2009) and Ouadghiri et al. (2021), who demonstrate that stocks with extensive media awareness have much lower returns. This finding could be explained by the fact that investors with different motivations, including traditional sustainable investors, neo-sustainable investors, and opportunistic self-interested investors, tend to favor the stocks of sustainable firms when there is a great deal of public attention on environmental issues.

(Insert Figure 5)

(Insert Figure 6)

5.4. Further analysis

To gain a deeper understanding of the feature importance and contribution to the model's predictions, we created SHAP force plots using the SHAP values generated by our SHAP-based ET model. Force plots are a powerful tool for visualizing the contribution of individual features to the final prediction for a single instance. To explore the relative importance of different features for predicting Bitcoin prices, we generated force plots for select observations during the Russia-Ukraine war from our dataset. Figure 7 depicts SHAP force plots for two randomly selected samples during the Russia-Ukraine war: (a) sample 2070, and (b) sample 2161, from April and July 2022 respectively, based on the ET model. The red colour highlights the features that increase the prediction, while the blue colour highlights the features that decrease the prediction. For sample number 2070, REC and infection generated a negative SHAP value, which negatively affected the BTC price. However, in the other sample (number: 2161 in Fig. 7b), the recession created a SHAP value that positively affected the BTC price value. Moreover, in both samples, ETH, INF, and GPR created SHAP values that contributed positively to the BTC value. The resulting plots helped us to identify the key features driving the model's predictions for each sample, providing a more comprehensive understanding of the underlying patterns and relationships in the data. Overall, the use of force plots enabled us to conduct a more detailed investigation and arrive at more robust conclusions regarding the relative significance of various characteristics when it comes to estimating future BTC value.

(Insert Figure 7)

6. Conclusions

Predictions of financial series are inherently difficult. However, recent developments in analytics and explainable artificial intelligence modeling suggest opportunities to overcome the difficulties associated with forecasting. Considering this context, we propose and develop an explainable artificial intelligence (XAI) framework, including a new feature selection method integrated with the game-theory-based SHapley Additive exPlanations approach and an explainable frame for forecasting. We use the cryptocurrency market to test this experimental methodology, and, in so doing, employ an improved feature selection method based on SHAP value to predict bitcoin prices.

FS-SHAP integrates the advantages of Extra trees and features important for enhancing prediction. Results demonstrate that FS-SHAP not only improves forecasting but also improves model generalization and explainability. Considering our findings, we draw several conclusions. First, based on the FS-SHAP value from the multivariate regression, we conclude that the highest Roos is ensured by LSTM followed by Extra trees among OLS regression and complex models.

The global explainability component of the SHAP framework reveals the relative importance among a set of factors impacting BTC price across the sample period. We find these factors have an order of importance of recession > geopolitical risk > 5-year forward inflation > S&P 500 > climate change > inflation > Twitter economic uncertainty > Ethereum > Gold > Infectious disease equity market volatility index.

The local interpretability of the LIME (XAI) framework allows quantification of the critical inflection points for each predictor that leads to transitions from low to high BTC prices.

From a practical standpoint, our research offers some insights for investors and policymakers. First, our work demonstrates that the combined SHAP and LIME global and local explanations accurately describe the real-world bitcoin price and explain the nonlinear ML models by offering rule-based explanations that are humanly comprehensible (Chakraborty et al., 2023). It is important to use AI models that are naturally interpretable along with XAI methods to make accurate predictions. This will help us understand how the AI approach works provide new interpretable knowledge in large datasets that would be impractical to find using traditional statistical methods. To address these issues which result from models' lack of transparency, we employ XAI models with tree-based ensembles, which are more interpretable than deep learning models (e.g., LSTM). Further, by shedding light on how economic downturn, geopolitical risk, inflation and climate change affect bitcoin prices, our findings can help investors and traders to better identify these risks and incorporate them into their investment decisions.

The FS-SHAP framework has shown promise in both theoretical and practical applications, but more work is required to ensure that it can provide accurate and reliable data for a wider range of themes and underlying factors. In the future, XAI methods might be used for other types of data (e.g., images and texts) and other ML tasks, broadening the scope of the field (e.g., unsupervised learning and semi-supervised learning). However, this work presents XAI to academics and practitioners to address the difficulty of interpreting the results of AI applications in predicting financial time series. This paper equips academics and industry experts with the information they need to develop more transparent AI applications in the financial sector.

Based on our findings, future research could investigate the impact of additional variables on BTC prices, such as social media sentiment, regulatory changes, and global economic conditions. Moreover, Future research could explore ways to enhance the interpretability and explainability of deep learning models to provide a more comprehensive understanding of their behaviour.

Appendix A. Selection of hyperparameters and training range for LSTM model.

Layer Type	Output Shape	Number of Parameters	Activation
LSTM	(None, 50)	12,400	Tanh, Sigmoid
Dense	(None, 1)	51	Sigmoid
Training Hyperparameters:			
- Loss function: Mean Squared Error (MSE)			
- Optimizer: Adam			
- Number of training epochs: 100 (early stopping with a patience of 5)			
- Batch size: 14			
- Input sequence length (lags): 14			
- Number of input features: 11			
- Number of repeats: 10			

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Table 1. The main recent studies in forecasting the bitcoin price

Studies	Time span	Data source	Methods	Variables type	Best model
Liu et al. (2021)	July 2013 to December 2019	Wind, Choice Financial Thomson Datastream	BPNN, PCA-SVR, SVR, SDAE	Cryptocurrency market, Public attention, and, macroeconomic environment	SDAE
Atsalakis et al. (2019)	September 13, 2011, to October 12, 2017	bitcoincharts.com	ANN, ANFIS, PATSOS	Bitcoin prices	PATSOS
Derbentsev et al. (2020)	August 1, 2015 to December 1, 2019	Yahoo Finance	ANN, RF, BART	Cryptocurrency market	BART
Guo et al. (2021)	2016-01-01 to 2018-12-31.	WalletExplorer, CoinMarketCap, Google Trends Data	ARIMA, ARIMAX, CNN, MLP, LSTM, Seq2Seq, BNN, SFM, WT-CATCN	Market prices data, Social interest data, Inter-exchange transaction data	WT-CATCN
Basher & Sadorsky (2022)	September 17, 2014, to December 29, 2021	Yahoo Finance, St. Louis Federal Reserve	Boost Logit, Logit, RF, Tree bag, Tune RF	Market prices data, macroeconomic variables	RF and tree bagging
Akyildirim et al. (2021a)	2 January 2020 and an end date of 10 September 2020	Chicago Mercantile Exchange	KNN, NB, Logit, RF, SVM, XGBoost, ARIMA	Bitcoin futures data	KNN and RF
Akyildirim et al. (2021b)	1 April 2013 to 23 June 2018	Kaiko digital asset store	ANN, Logit, RF, SVM, ARIMA	Cryptocurrencies traded in the global markets	SVM
Parvini et al. (2022)	August 8, 2015, to April 4, 2020	“Investing’’ website	LSTM, OLS, LASSO, AdaBoost, RF, SVR, DWT-LSTM	Market prices data	DWT-LSTM
Chen et al. (2021)		https://bitcoincharts.com/markets/			
Oyedele et al. (2023)	January 1, 2018, to December 31, 2021	Yahoo Finance	CNN, DFNN,	Cryptocurrency market	CNN

Notes: BPNN: back propagation neural network; PCA-SVR: principal component analysis-based support vector regression; SVR: support vector regression; SDAE: stacked denoising autoencoders; ANN: neural networks; ANFIS: adaptive neuro-fuzzy inference system; PATSOS: neuro-fuzzy controller forecasting system; WT-CATCN: wavelet transform-based casual multi-head attention temporal convolutional network; ARIMA: autoregressive integrated moving average; CNN: convolutional neural networks; MLP: multilayer perceptron; LSTM: Long Short-Term Memory; Seq2Seq: Sequence to Sequence; BNN: Bayesian neural networks; SFM: state-frequency memory recurrent neural networks. KNN: k-nearest neighbours, Logit: logistic regression, NB: naive Bayes, RF: random forest, SVM: support vector machine, XGBoost: extreme gradient boosting; ANN: artificial neural networks; OLS: ordinary least squares; Ridge: ridge regression; LASSO: least absolute shrinkage and selection operator; AdaBoost: adaptive boosting; SVR: support vector regression; DWT: wavelet transform. BART: Binary Autoregressive Tree model; CNN: Convolutional Neural Networks; DFNN: Deep Forward Neural Networks; GRU: Gated Recurrent Units

Table 2. Definitions of the variables.

Variable	Acronym	Source
Bitcoin	BTC	BTC is a cryptocurrency. Source: *investing.com.*
S&P500	SP500	Standard & Poor 500 index. A market-capitalization-weighted index of 500 leading publicly traded companies in the U.S. Source: Bloomberg.
Gold	Gold	Gold commodity. Source: Bloomberg.
Brent crude oil future	Oil	Brent crude oil. Source: Bloomberg.
Volatility	VIX	VIX index. Source: Federal Reserve Bank of St. Louis
U.S. dollar index	USDI	Source: Federal Reserve Bank of St. Louis
5-Year Forward Inflation Expect	YIFR	Projected inflation over a five-year period beginning five years from now. Source: Federal Reserve Bank of St. Louis.
Ethereum	ETH	ETH cryptocurrency. Source: *investing.com.*
Litecoin	LTC	LTC cryptocurrency. Source: *investing.com.*
Ripple	XRP	XRP cryptocurrency. Source: *investing.com.*
Inflation	INF	Daily normalized search volume for the term 'inflation' on Google trends in the USA. Source: Google trends.
Recession	REC	Daily normalized search volume for the term 'recession' on Google in the USA. Source: Google trends.
Geopolitical risk	GPR	The GPR index reflects automated text-search results of the electronic archives of 10 newspapers. Source: Caldara and Iacoviello (2022)
Twitter-based economic uncertainty (USA)	TEU	The TEU-USA is the total number of daily English-language tweets in the United States that include both uncertainty and economy phrases. Source: Baker et al. (2021)
New-based sentiment index	NSI	Score on a sentiment index based on newspapers dealing with topics pertaining to the economic issues. Source:(Shapiro et al. (2020).
Infectious disease equity market volatility index	INFECT	Index corresponds to newspaper-based Infectious Disease Equity Market Volatility Tracker. Source Baker et al. (2019)
Climate change	PACC	The daily normalized search volume for the term 'climate change' on Google trends in the USA. Source: Google trends.

Table 3. Descriptive statistics

	Mean	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
BTC	16240.16	8737.85	17338.0647	0.2438	1.2669	513.4	67527.9
LTC	87.9542	62.545	67.7193	1.1989	1.1425	-21.5801	386.82
SP 500	3148.612	2896.245	742.3328	-0.5327	0.7681	1775.474	5585.957
Gold	1516.442	1437.177	270.4096	-1.2032	0.3980	948.7482	2369.536
Oil	60.8540	60.215	18.0246	1.4916	0.6131	-14.56	134.7699
VIX	18.5049	16.305	9.1102	9.3730	2.2638	0.450585	89.8002
USDI	114.2861	114.3591	3.3550	0.7670	0.2527	103.4899	127.5749
YIFR	1.9764	2	0.2441	0.59400	-0.6134	0.86	2.67
ETH	888.0576	295.625	1173.9198	1.1893	1.5560	6.7	4808.38
INF	46.9106	45.30922	16.6495	5.9768	1.5795	11.2862	177.8136
REC	15.8089	12.4896	20.3228	20.9517	3.692	-20.1914	194.4609
GPR	99.4759	90.01543	57.2009	9.9916	2.2813	3.5695	539.5826
TEU	129.4994	93.05706	119.9770	12.8128	3.0591	6.3049	1134.894
INFECTION	7.6142	0.905	12.0921	9.4655	2.5237	8.88E-16	112.93
NSI	-0.0205	0.014567	0.20789	1.2870	-1.0292	-0.67612	0.333454
PACC	24.7938	21.45019	19.0926	23.2655	3.2280	-17.0035	251.6004

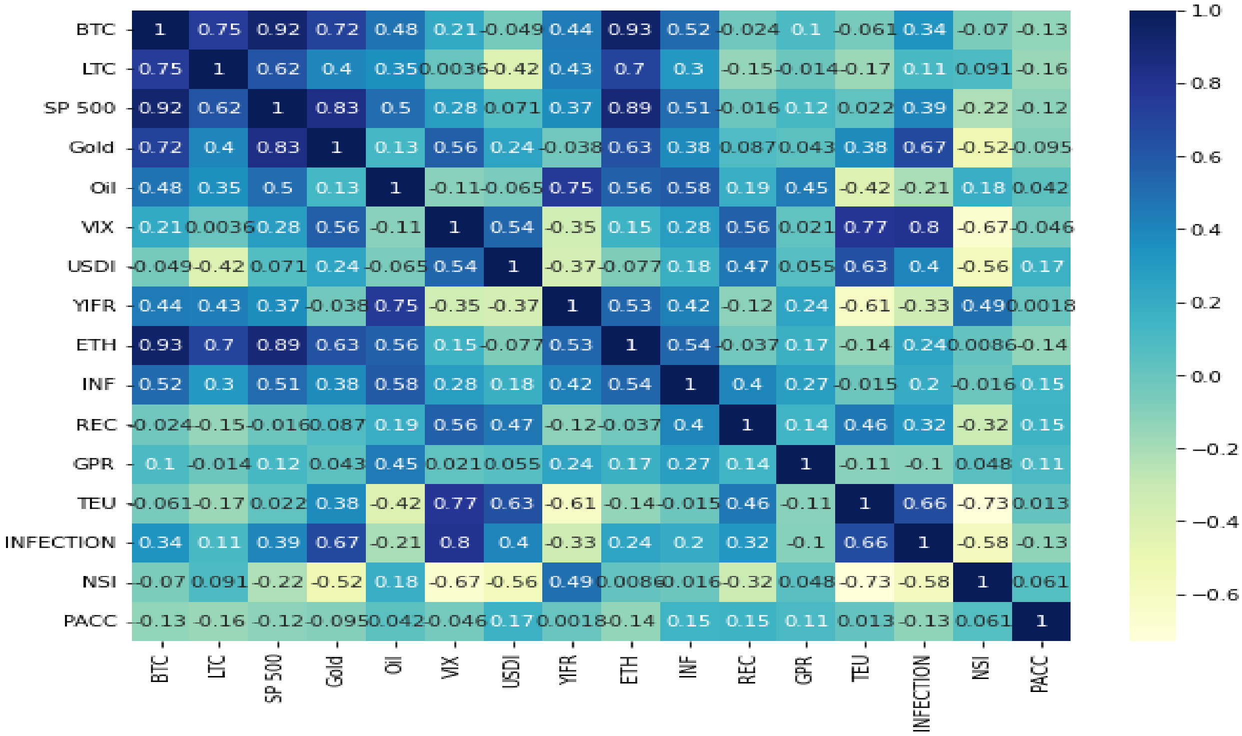

Figure 1. Correlation matrix

Table 4. FS-SHAP values algorithm based on feature importance selection

Algorithm 1: FS-SHAP value
1. Train Extra trees based on (X, Y)
2. Tune model (Extra trees) using all features
3. Compute the Shapley value for all features
4. Select the k highest-ranking features
5. Data set with key features (X, Y)
6. Model training and hyper-parameters tuning based on key features (X, Y)
7. Prediction performance evaluation

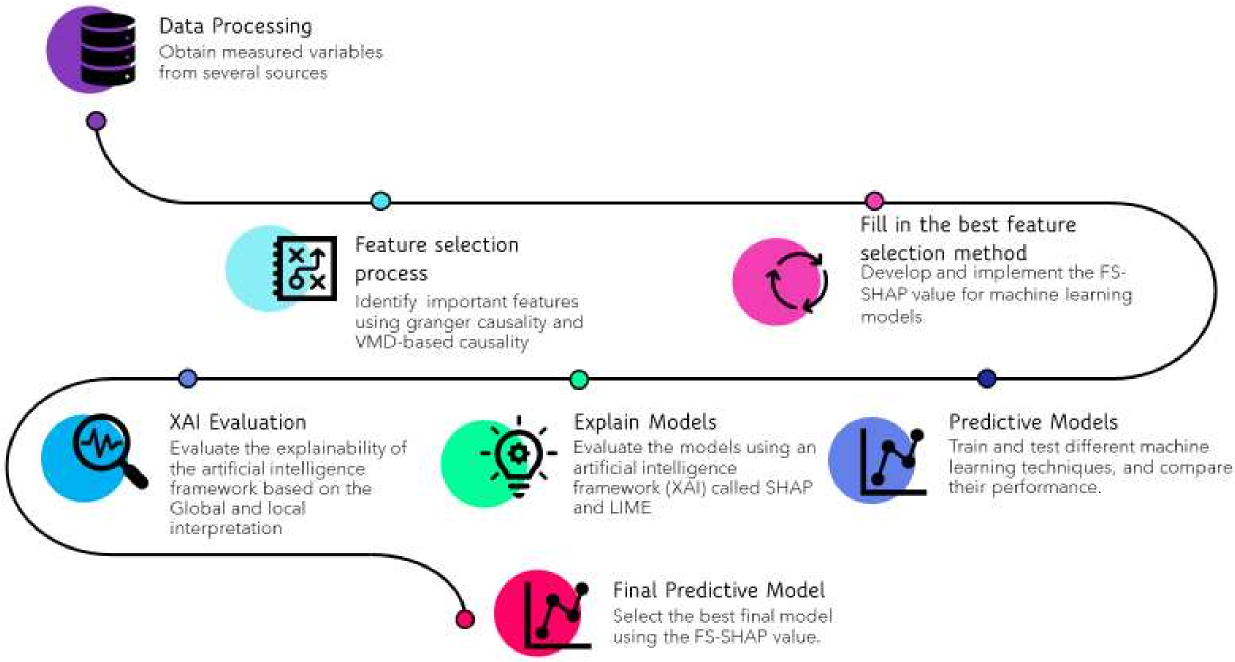

Figure 2. Conceptual representation of the research methodology based on the explainable machine learning framework

Table 5. Monoscale and multiscale (VMD-based) causality of set of exogenous variables on the bitcoin's price.

	IMF1	**IMF2**	**IMF3**	**Granger causality**		**IMF1**	**IMF2**	**IMF3**
	F-stat	**c-value**	**F-stat**	**c-value**		**F-stat**	**c-value**	**F-stat**
LTC → BTC	**10.884**	2.6090	**59.338**	2.3761	**62.6861**	2.9999	**11.711**	3.8457
S&P500 → BTC	0.1774	3.8458	1.4317	3.8458	0.9098	3.8458	1.1275	3.8457
Gold → BTC	0.0068	3.8458	0.2423	3.8458	0.3882	3.8458	0.0021	3.8457
Oïl → BTC	0.5248	3.8458	2.2635	3.8458	0.0615	3.8458	0.1888	3.8457
VIX → BTC	0.0065	3.8458	0.6779	3.8458	0.6415	3.8458	0.8784	3.8457
USDI → BTC	1.1399	3.8458	0.3227	3.8458	0.1533	3.8458	0.9124	3.8457
YIFR → BTC	2.7714	3.8458	0.0092	3.8458	0.0245	3.8458	1.3134	3.8457
ETH → BTC	**26.851**	2.2182	**75.169**	2.3761	**209.96**	2.3761	**27.302**	3.8457
INF → BTC	**5.9020**	3.8458	1.9152	3.8458	0.9289	3.8458	0.0052	3.8457
REC → BTC	0.8637	3.8458	3.6704	3.8458	0.1346	3.8458	2.0575	3.8457
GPR → BTC	0.7294	3.8458	0.1144	3.8458	**6.8142**	3.8458	0.0275	3.8457
TEU → BTC	0.1458	3.8458	0.8722	3.8458	**4.2877**	2.9999	0.9615	3.8457
INFECT → BTC	0.4189	3.8458	2.6627	3.8458	1.4720	3.8458	0.9301	3.8457
NSI → BTC	1.3053	3.8458	0.1576	3.8458	0.0583	3.8458	0.0363	3.8457
PACC → BTC	0.0005	3.8458	0.2102	3.8458	0.0053	3.8458	0.8670	3.8457
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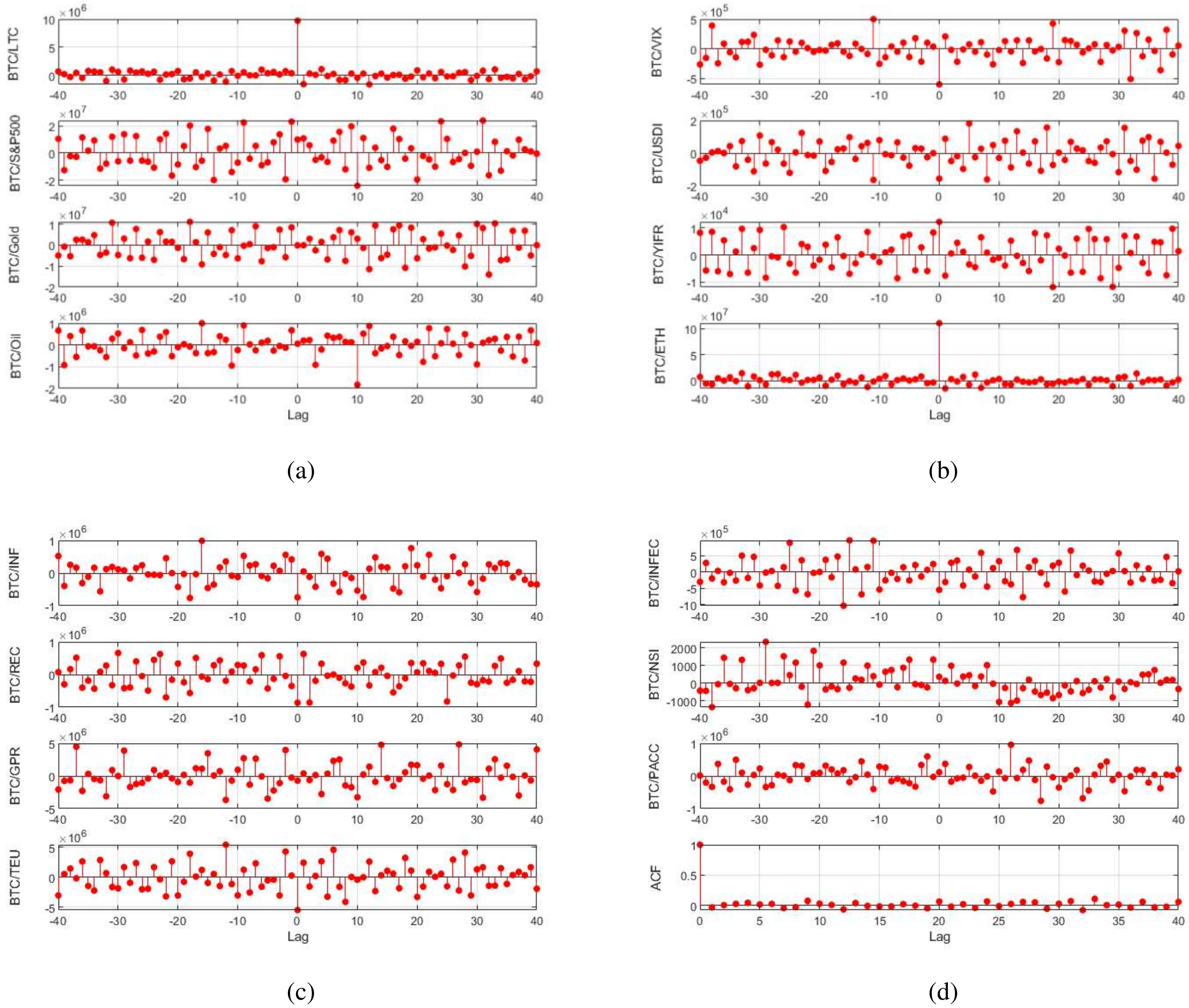


Figure 3. Cross-correlation between bitcoin and fifteen exogenous variables**.**

The last subfigure on the right-bottom represents the autocorrelation function of bitcoin.

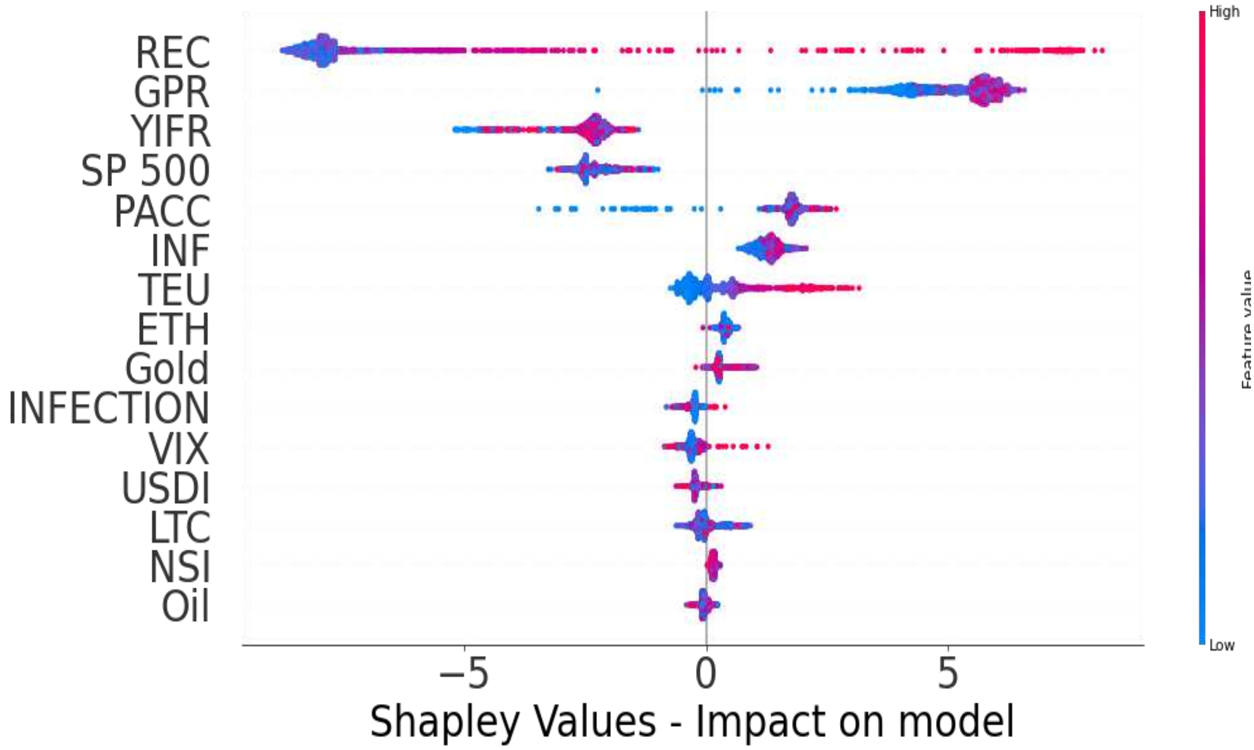


Figure 4. SHAP feature importance based on Extra Tree Regression (ET) model.

Red and blue dots indicate the positive and negative impact of the features on the outcome. The y-axis in represents the feature importance, which shows the impact of each feature on the bitcoin price of the model. The higher the value on the y-axis, the more important the feature is for predicting the outcome.

Table. 6. The performance of the univariate forecasting models								
Variables		LSTM	DL	SVM	LR	RF	XGBoost	ET
LTC	R^2_{OOS}	0.896	0.285	0.292	-0.091	0.201	0.253	0.163
	RMSE	18.819	0.508	47.312	62.004	52.988	51.315	54.582
SP 500	R^2_{OOS}	0.115	-0.591	-0.588	-0.346	-0.667	-0.606	-0.733
	RMSE	365.322	493.181	492.921	453.774	505.033	495.671	0.168
Gold	R^2_{OOS}	0.208	0.001	-0.082	-0.227	-0.349	-0.072	-0.423
	RMSE	116.488	130.811	136.319	145.169	152.166	135.647	0.168
Oil	R^2_{OOS}	-0.199	-2.321	-2.412	-2.027	-2.665	-2.677	-2.540
	RMSE	18.952	31.610	32.053	30.188	33.219	33.273	0.316
VIX	R^2_{OOS}	0.525	0.023	0.074	-0.276	-0.279	0.044	-0.435
	RMSE	4.045	5.799	5.651	6.634	6.643	5.743	0.081
USDI	R^2_{OOS}	0.059	-0.781	-1.380	-0.412	-1.109	-0.854	-1.331
	RMSE	1.6	0.025	4.001	3.448	1.454	3.753	4.187
YIFR	R^2_{OOS}	0.069	-1.813	-1.407	-2.788	-2.231	-2.182	-2.225
	RMSE	0.131	0.025	4.001	3.260	3.984	3.735	4.187
ETH	R^2_{OOS}	0.053	-2.109	-2.039	-2.119	-2.197	-2.185	-2.194
	RMSE	836.962	1536.039	1519.117	1539.038	1558.166	1555.133	0.559
INF	R^2_{OOS}	0.351	-0.585	-0.537	-0.580	-0.690	-0.664	-0.665
	RMSE	16.061	25.273	24.893	25.242	26.103	25.900	0.311
REC	R^2_{OOS}	0.865	-0.184	-0.230	-0.067	-0.210	-0.168	-0.168
	RMSE	10.220	31.119	31.729	29.548	31.459	30.914	0.006
GPR	R^2_{OOS}	0.431	-0.373	-0.311	-0.332	-0.442	-0.334	-0.444
	RMSE	66.110	102.811	100.506	101.289	105.392	101.396	0.256
TEU	R^2_{OOS}	0.051	-0.537	-0.426	-1.187	-1.502	-0.728	-1.707
	RMSE	50.024	64.102	61.904	76.665	82.004	68.149	0.072
INFECTION	R^2_{OOS}	0.545	-0.846	-0.588	-1.008	-1.201	-0.561	-1.329
	RMSE	8.358	0.048	10.138	10.776	11.281	9.50	11.590
NSI	R^2_{OOS}	0.019	-0.190	-0.237	-0.546	-0.312	-0.199	-0.339
	RMSE	0.040	0.003	0.114	0.125	0.115	0.114	0.116
PACC	R^2_{OOS}	0.814	-0.06	0.000	-0.018	-0.057	0.002	-0.082
	RMSE	10.223	0.040	27.832	28.139	28.716	27.864	28.989
Notes: Daily out-of-sample predictive R^2_{OOS} and RMSE of forecast models for different ML models								

Table 7. The performance of the multivariate forecasting										
Feature selection technique	FS-SHAP		VMD causality						Granger causality	
	FS-SHAP		IMF1		IMF2		IMF3			
Number of features	10		3		2		4		2	
Models	R^2_{OOS}	RMSE	R^2_{OOS}	RMSE	R^2_{OOS}	RMSE	R^2_{OOS}	RMSE	R^2_{OOS}	RMSE
LSTM	0.689	2.031	0.419	8.000	-0.110	876.139	-0.065	836.962	-0.110	876.139
DL	-0.274	3.811	0.350	15.496	-3.032	1572.61	-3.065	1536.039	-3.032	1572.61
SVM	-0.156	43.257	0.403	20.770	-3.251	1570.081	-0.860	1519.117	-3.251	1570.081
LR	-0.737	36.755	0.096	11.588	-2.621	1674.312	-37.503	1539.038	-2.621	1674.312
RF	-0.013	28.068	-0.363	12.258	-2.432	1581.789	-1.248	1558.166	-2.432	1581.789
XGBoost	-0.011	28.041	-0.390	12.138	-2.503	1607.513	-1.111	1555.133	-2.503	1607.513
ET	0.010	27.789	-0.331	8.924	-2.593	1637.223	-0.714	72.111	-2.593	1637.223

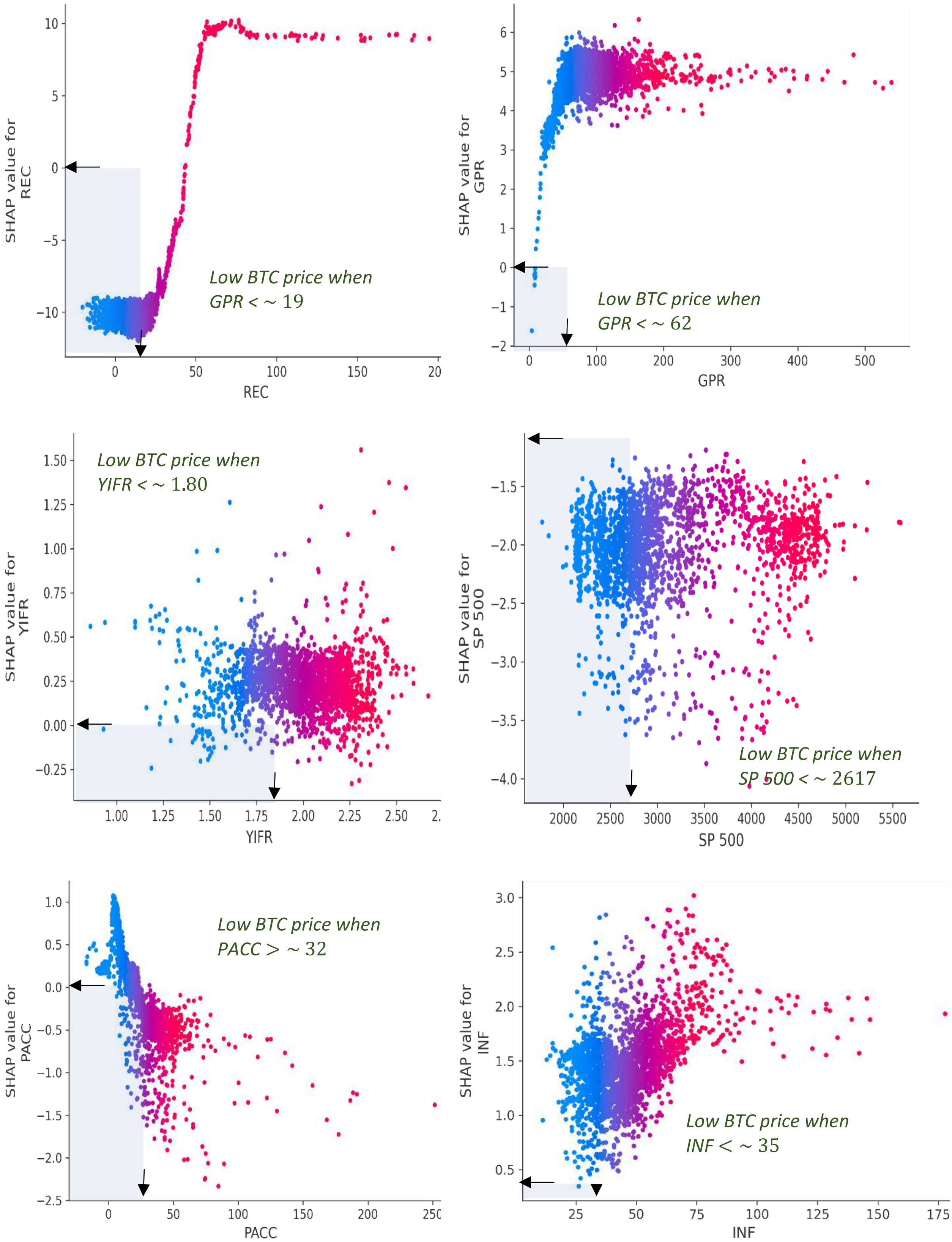


Figure 5. SHAP local dependence interpretability plots for the six important features based on Extra Trees model.

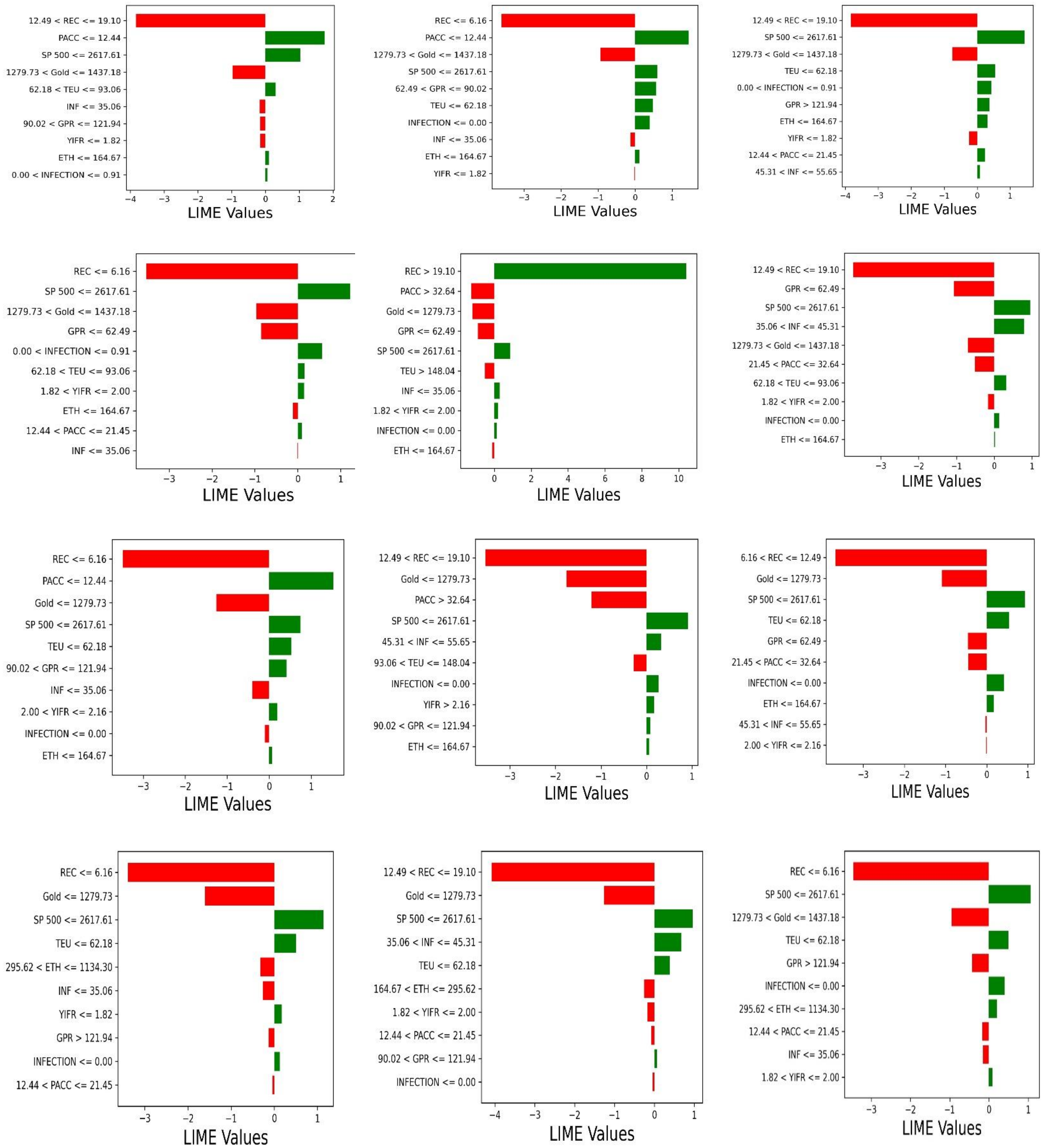
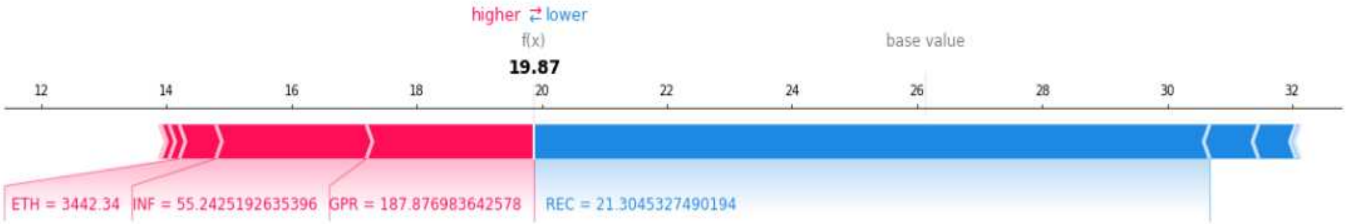
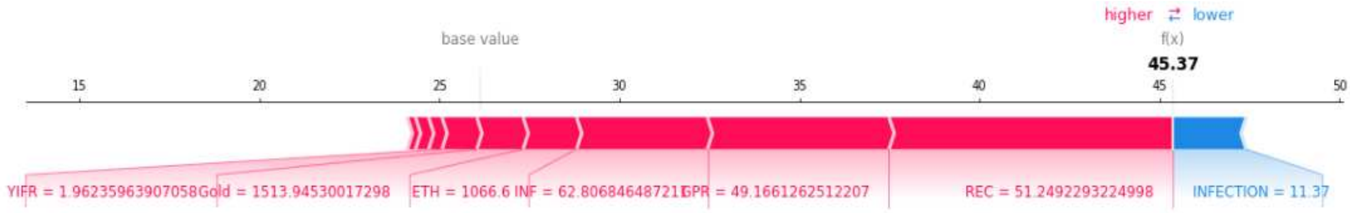


Figure 6. Local interpretation plots of the ten most important features based on FS-TreeSHAP value (ET model).



(a) sample number: 2070



(b) sample number: 2161

Figure 7. depicts SHAP force plots for two randomly selected samples during the Russia-Ukraine war: (a) sample 2070, and (b) sample 2161, from April and July 2022 respectively, based on the ET model.