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ABSTRACT

Predicting cryptocurrency prices is challenging due to their high volatility. This challenge is more pronounced during economic uncertainty, such as the 2008 financial crisis and the COVID-19 pandemic. While machine learning models can help in the prediction of cryptocurrency prices, their underlying conditions influencing the outcomes are sometimes unknown, and there is a lack of consensus on appropriate techniques to use for technical prediction and circumstances under which they may be suitable. In this paper, we apply an existing explainable artificial intelligence (XAI) framework, specifically SHAP, to identify suitable analytical techniques and the optimized set of parameters for technical trading prediction based on the two most valuable cryptocurrencies, Bitcoin and Ethereum. Rather than developing a new model, our contribution lies in systematically applying XAI techniques to uncover variable importance and model behavior in volatile market conditions. The results show that our explainable AI model is capable of efficiently forecasting closing, high, and low prices from previous days during economic uncertainties. Through our model and findings, we contribute critical insights to research and practice, especially in overcoming the challenges of the "black box" nature of machine learning models. Moreover, practitioners such as investors and regulators can utilize our model to efficiently capture changes in different cryptocurrencies' price trends toward improved decision-making during economic uncertainty.

KEYWORDS AND PHRASES

Machine learning; cryptocurrency; cryptocurrency prices; explainable AI; deep learning

Introduction

Blockchain, the foundational technology behind cryptocurrencies, enables fair, automated data trading through decentralized storage [31, 55]. This stands in contrast to the persistent issue of price volatility in the cryptocurrency market, which continues to be a pivotal factor affecting global financial markets. For instance, the global cryptocurrency markets are more volatile as compared to the US dollar, the Euro, gold, or any other type of classic financial assets (such as stocks, bonds, and derivatives). The excessive volatility of cryptocurrencies, which average 400% in their early years, leads to high uncertainty and difficulty in accurately predicting their prices. Thus, it is difficult to use traditional forecasting models in predicting cryptocurrency prices. In

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recent times, there have been attempts to use artificial intelligence (AI) techniques [38] such as machine learning (ML) to predict cryptocurrency prices. While the use of ML has been somewhat effective in predicting cryptocurrency prices [1, 57], their results are unexplainable. Meaning, we are unable to explain how ML models obtain their results, making them "black boxes" [30]. As such, it is difficult to identify the variables ML models use in predicting cryptocurrency prices as well as their decision-making process. This black box nature of ML has significant implications [30], especially during periods of economic uncertainty such as the novel coronavirus (COVID-19). Hence, there has been an increasing demand for explainable models to reveal the internal mechanisms of the ML models [2].

Explainable artificial intelligence (XAI) is a significant multidisciplinary research area that focuses on developing methods to make artificial systems understandable to human stakeholders [39]. When there are artificial systems relying on ML, XAI is highly important as very often these systems are too complex for human interpretation. Explainability approaches could be related to methods, procedures, and strategies that provide explanatory information to help humans understand artificial systems, their functions, and their outputs. Human stakeholders related to cryptocurrency could be traders, tech developers, regulators, customers of businesses, and others. These human stakeholders have varied expectations from the artificial systems (known as "stakeholders' desiderata") [32], explaining the changes in cryptocurrency price.

Despite advances in the application of ML in different financial instruments there is a lack of research on explaining the predictive power of ML in cryptocurrencies during economic uncertainty. Prior studies have focused on stable conditions [57], leaving a gap in understanding how model behavior and variable importance shift under financial stress. Our study addresses this gap by applying SHAP a widely used XAI method to interpret ML predictions across three crisis periods, using Bitcoin and Ethereum as focal assets. This contextual application offers novel insights into how feature importance varies across time, asset class, and model type, contributing to transparency and decision support in volatile markets. We have identified a study closely aligned with our research, which focuses on the application of SHAP to enhance the interpretability of cryptocurrency price predictions [14]. This study reinforces the importance of explainability in financial forecasting and supports our approach in demonstrating how SHAP can provide deeper insights into the key determinants influencing cryptocurrency market behavior.

The key gap in the literature is the lack of research on explaining the predictive power of machine learning (ML) in cryptocurrency markets during periods of economic uncertainty. While prior studies have applied ML techniques to predict cryptocurrency prices, these efforts have largely focused on stable economic conditions [57], leaving a significant gap in understanding how ML models perform under financial stress or crisis situations.

In addition, although explainability in ML forecasting is gaining attention, such as in a recent study [14], which applies SHAP to enhance interpretability, the broader challenge remains: how ML-based cryptocurrency predictions can be made more transparent and reliable specifically during uncertain economic periods, such as global financial crises or pandemics. This gap underscores the need for research that not only improves predictive accuracy, but also enhances stakeholder trust in AI-driven financial forecasting during volatile market conditions. To fill this gap in the literature, we are guided by the following question: *How can explainable AI facilitate the prediction of cryptocurrency prices during economic uncertainty?*

However, most of prior research has been restricted to the use of ML in predicting cryptocurrency prices during stable economic conditions. ML techniques are applied to predict the direction of the Bitcoin market in the form of buy and sell decisions using different technical indicators from different periods [57]. There is, however, a significant lack of research integrating macroeconomic variables, technical analysis, and explainable AI methods to predict cryptocurrency prices during times of economic uncertainty. Addressing this intersection is crucial for improving both predictive performance and stakeholder trust during volatile market conditions.

We answer this question by developing an explainable AI model that efficiently searches for the best model to predict future cryptocurrency prices during economic uncertainty while explaining the variables considered by the algorithm. Our research is an extension of the existing research on AI, where researchers prioritize human stakeholders in developing and accessing explainability approaches. These approaches are very important to use in systematically and empirically assessing the movement of prices of an asset (cryptocurrency in our study) during the time of high market uncertainty to assess the impact of it on human stakeholders and their desiderata. Thus, we developed a model that: (a) automates the search for an optimal ML model and its set of parameters, (b) evaluates the ML models across three different periods, and (c) offers an explainable framework to compute the importance of each variable in the prediction process. We validate the robustness of our model by using data on the two most valuable cryptocurrencies, BTC and Ethereum.

To realize the full potential of AI and to harness its advantages, human stakeholders need to have trust in the development, deployment, and usage of AI. Thus, stakeholders in financial markets should have a better understanding and trust in the training, evaluation, and interpretation capacity of the ML models. Moreover, during times of uncertainty, the demand for higher transparency and trustworthy explainability approaches is high among human stakeholders of the financial markets. To capture all the necessary important factors that could affect the price change during an uncertain period, we need to consider financial, technical, and macroeconomic indicators within the evolving cryptocurrency market. The methodology evaluates the contributions of individual variables to the prediction process, offering detailed insights into the factors influencing cryptocurrency price dynamics. General AI models have limited explainability capacity. Advanced AI models, especially those based on deep learning and complex algorithms, operate as "black boxes" that require clarification. Thus, XAI is crucial for building trustworthy AI systems as it can provide explanations to enhance the transparency and interpretability of these systems, fostering greater understanding, trust, and accountability. By incorporating Shapley additive explanations (SHAP), our methodology goes beyond traditional approaches of transparency or interpretability. The methodology evaluates the contributions of individual variables to the prediction process, offering detailed insights into the factors influencing cryptocurrency price dynamics. By applying this framework to three distinct periods, it helps users comprehend how AI models make decisions, thereby increasing user trust in these systems even during uncertain market conditions. This methodical strategy identifies effective predictive models while fostering trust in their outputs by combining analytical methods with actionable insights, addressing the requirements of financial modeling and decision-making.

The conceptual framework is based on the underlying concept of Game theory [33]. The reason for applying game theory is to identify how the human stakeholders associated with cryptocurrency trading could obtain a reward proportional to their contribution during uncertain times while dealing with one of the most volatile digital assets, cryptocurrency. Any model without an explainability feature cannot be trustworthy. Thus, SHAP values answers the above challenge and addresses the concern of general transparency or interpretability issues associated with existing ML models.

In this study, we find that the proposed explainable AI model is capable of efficiently forecasting closing, high, and low prices from the previous days during COVID-19. The findings show that the XAI can overcome the challenges of the “black box” nature of machine learning models. Moreover, using XAI allows human stakeholders, e.g., practitioners, investors, and regulators, to efficiently capture changes in different cryptocurrencies’ price trends toward improved decision-making during global economic uncertainty.

There are certain studies where they focus on the importance of cryptocurrency during the time of crisis, but the impact of COVID-19 on the world economy is very different from previous crises [11]. So, by examining the price of cryptocurrency during COVID-19, the study extends the forecasting literature [8]. However, there are limited studies on XAI in financial forecasting. Thus, the findings of this study contribute to the literature related to XAI [6, 24].

The rest of the paper is organized as follows: in the next section, we present a background on explainable AI and existing models and discuss the recent work on explainable AI and cryptocurrencies. Next, we present the methodology by explicating the data collection and data preprocessing steps. After this section, we outline our proposed model to then present the results and their discussion. Finally, we conclude the paper with a discussion of limitations and future research directions in the last section.

Background

Explainable AI during Uncertainty

In recent years, due to the constant questioning of the inherent opacity of AI techniques [38], the demand for explanatory models has grown among stakeholders and scholars, creating a field called explainable AI (XAI). The techniques in this field are generally recognized as an essential and needed feature for AI models’ safe and practical spread. For example, in the study on the impact of the General Data Protection Regulation (GDPR) on AI, the European Parliamentary Research Service states that an ethical framework should promote transparent algorithmic processes with traceability, explainability, and communication. In the same way, the Financial Stability Board reports a potential risk and reputational challenge if AI lacks explainability and the need to develop governance frameworks to ensure explainability and transparency to promote accountability. In addition, XAI models are used in different disciplines and by numerous well-established enterprises and start-ups, especially those challenged with uncertainty and complex scenarios. Concurrently, there is a broader discussion in the industry about AI governance, emphasizing the technical aspects and organizational practices required for successful AI deployment. Therefore, XAI can play an essential role in assisting decision-makers because it exposes how an AI model creates a decision and can develop trust among AI users when mixed with domain knowledge, but also the incorporation of both user and practitioner perspectives can further optimize the system's design and adaptability [37].

In prior research, XAI has been used to measure financial technology risk [6] and automate loan underwriting decision-making by providing textual explanations for refused loan requests [52]. Similarly, XAI has been applied to investigate the March 2020 financial meltdown [46] based on feature relevance explanations using 150 technical, fundamental, and macroeconomic variables. In addition, XAI has been used to explain the reason why clients acquire or cancel insurance coverage [16], prognostic and management of industrial assets [44], and to forecast the price movement of gold [24].

However, the application of XAI in the cryptocurrency markets is underdeveloped, with a few exceptions which provide an XAI method for variance decomposition [12] and in detecting pump-and-dump frauds using market and social signals [41]. Notwithstanding the contributions of these studies, their focus has been on XAI in stable economic periods. There is limited research on the application of XAI in technical trading prediction of cryptocurrencies, especially during economic uncertainty.

Explainable AI Models

Some models are straightforwardly understood and can be recognized as transparent; examples of these plausible models are linear regression, decision trees, and rule-based algorithms. However, it is not always possible to rely on transparent models [30] because they may not be suitable for all tasks, and some other models, like deep learning, might have better precision [28]. In addition, models based on tree structures are not good at extrapolating, therefore, scholars need to test and deal with a series of different algorithms. When it is impossible to have a transparent algorithm, a different methodology needs to be conducted to elucidate the decisions. This added procedure is commonly known as a post-hoc model, which targets to deliver a piece of comprehensible information about the predictions given by the established model at different points.

The post-hoc explainable methods can be rather specific to a particular model, usually deep learning algorithms, or it can be an agnostic method built to deal with a wide range of algorithms. The non-specific models are intended to collect information about the prediction process and can be divided into three groups [2]. The first group is the explanation by simplification and local explanations established on rule extraction techniques. The most famous model that falls into this category is the local interpretable model-agnostic explanations (LIME), which builds the explanations by perturbing and sampling the original data set and then fits a subrogate model that mirrors the unknown global model on that sample. The resulting coefficients allow obtaining a local explication of the prediction. The second group is related to visual explanation techniques (such as sensitivity analysis through Monte Carlo). The importance of individual conditional expectation (ICE) plots for supervised machine learning models has been shown [13]. This visualization method attempts to clarify the black-box machine learning model. Finaly, the third collection of post-hoc agnostic models is based on feature relevance explanations by evaluating the importance and influence of each variable in the prediction process of a given model. One successful application is SHAP, initially introduced [33] to interpret different complex ML models based on coalitional game theory [54] and is considered as the state-of-the-art technique for model-agnostic interpretation [35].

The concept in terms of game theory is to create an approach where members of a given game should obtain a reward proportional to their marginal contribution to that game. Following this analogy, we can calculate an expected reward for a feature's marginal contribution to a specific model. SHAP values will represent this contribution by averaging the permutation of each variable on the conditional expectation in a hypothetical model prediction. Through this iterative process, it is possible to compute the impact that a single variable has on the general performance of the model when it is added and combined with the rest of the variables. The SHAP values are formulated in Equation 1 [33].

$$\varphi_i(f,x) = \sum_{h \in H} \frac{1}{|n|!} \left[f_x\left(y_i^h \cup i\right) - f_x\left(y_i^h\right) \right] \tag{1}$$

where n represents the number of features, H is the set containing all the possible feature permutations, and y_i^h is the group of all features that precedes feature i in permutation h.

Explainable AI and cryptocurrencies

Since its debut in 2009, Bitcoin has soared in popularity [58], establishing itself as a pioneering and revolutionary digital currency built on blockchain technology [3, 5] and it reflects its potential to serve as an alternative currency for exchanging value, reducing risk, or influencing social and cultural change [58]. Furthermore, research into its mining incentives has revealed promising avenues for optimizing costs and strategies, underscoring Bitcoin's continued potential for shaping the future of digital finance. Gradually, several other coins, such as Ethereum and XRP, started gaining recognition in the market, especially because of higher demand from investors for alternative forms of investment channels due to the gloomy situation in the traditional financial markets following the 2008–2009 global crisis, the 2010–2012 European debt crisis and the 2019 COVID-19 pandemic. For example, on April 6, 2022, 497 exchanges[1] worldwide traded 18,737 cryptocurrencies, with a market capitalization of almost 2,065 billion US dollars, where BTC and EHT are the most preponderant in terms of market capitalization (45.3% and 17.7%, respectively), with a significant increase in prices over the last few years (see Figure 1).

Cryptocurrencies, like Bitcoin, possess a combination of properties of other traditional financial and speculative assets, which brings independence from the regional monetary policy [29, 36]. Usually, there is a low correlation between cryptocurrency and other financial instruments traded in the financial market. This lack of correlation is particularly interesting considering the fundamental differences in how cryptocurrencies function in the economy, owing to their varied attributes like identity management, consensus mechanisms, and methods of coin distribution. In addition, the cryptocurrency market is irrational and inefficient, observing herding behavior [51]. The above features in the cryptocurrency market restrict the appropriate use of forecasting models based on techniques related to fundamental analysis. In addition, the lack of efficiency in cryptocurrency markets limits the use of different prediction models based on the efficient market hypothesis [47]. These challenges are further compounded by the finding that online sentiment and discussion frequency may be more reflective of past market activities rather than useful indicators for future price movements.

[1]Top Cryptocurrency Spot Exchanges (2022, April 6) (see https://coinmarketcap.com/rankings/exchanges/).

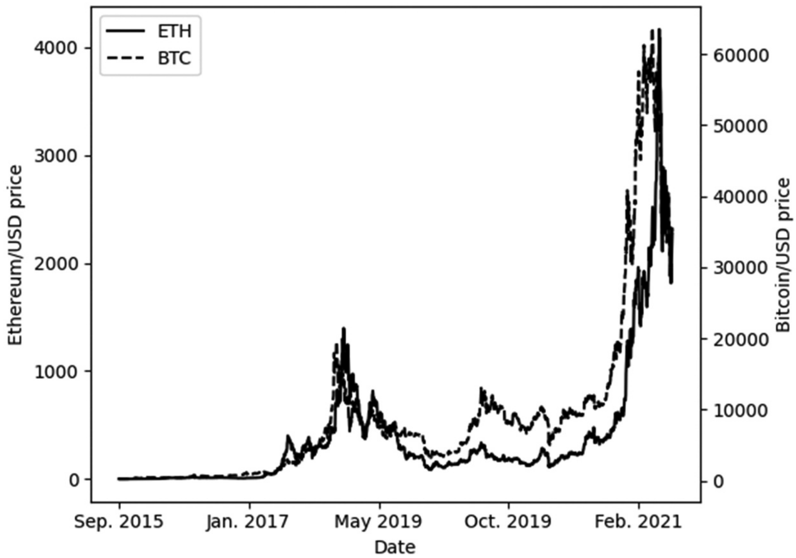

Figure 1. Price Evolution of ETH and BTC.

To overcome the deficiency of traditional models in predicting cryptocurrencies' price, we find use of ML. This technique is based on the implementation of computational algorithms that learn and improve through the experience without following a set of explicit instructions and has been a disruptive technology that radically transforms investment decisions of many financial institutions [15, 17]. Furthermore, ML algorithms show strong prediction capabilities, able to identify trading patterns in complex situations [19]. As a result, there is a flourishing adoption of ML in financial fraud detection, signaling financial distress, portfolio construction [34], predicting investor behavior [45], and price forecasting of different assets [19]. In addition, ML algorithms are more effective than other, more traditional, methods when used to predict future movements in inefficient markets with different trading horizons [57].

Despite the contributions from previous research, it is unclear, especially within the context of cryptocurrencies, how to "unblack box" and explain results from ML algorithms. So far, we observe contradictory findings when various ML algorithms are applied for trading prediction. On the one hand, some studies [7, 47] show that ML is a powerful and popular forecasting tool for the financial markets. On the other hand, other studies [6, 24] posit that ML, without explanations behaving like a "black box", is not appropriate for regulated financial services, and investors avoid it due to its lack of trust. Because of these contradictions and limited explanation of how AI algorithms reach a decision in cryptocurrency trading, there is limited trust among investors and regulators. With the growing adoption of ML algorithms in technical trading prediction, the need for an ensemble method to achieve explainability of the results of cryptocurrency trading AI algorithms is urgent. To address the limitations in existing research and practice, we seek to offer a model to examine the application of explainable AI in predicting technical trading of cryptocurrency assets during financial uncertainty.

Methodology

In this methodological framework, we explain the data collection process of different cryptocurrencies and macroeconomic variables, followed by the data pre-processing, where we calculate different technical indicators and describe the process of filling missing values to continue with the details of the model development and the hyperparameters[2] selection process. After conducting an exhaustive search for each model's ideal configuration, we choose a single model with the most optimal structure that presents the minimum prediction error, proceeding to predict. Finally, at the end of this section, we explain the algorithm procedure used to interpret the model.

Data collection

The finance literature indicates that investors exhibit asymmetry in their responses to news, often reacting to bad news that makes the financial market highly unpredictable [42]. The COVID-19 pandemic is one such bad news that affected the world financial market and the global economy. The stock market performed negatively because of COVID-19. However, cryptocurrency trading remains steady and less reactive to COVID-19 [40]. Thus, we consider the COVID-19[3] timeframe to examine our research question. The data collected in this research include the volume and the open, high, low, closing, and adjusted closing price of ETH[4] and BTC from September 1, 2015, to June 30, 2021, obtained from the Binance exchange, summing 2130 days.

During the previous crises, we find that because of the globalized nature of the financial market, there is a tendency to invest in assets that could survive a massive downfall in return [48]. Thus, from the time of global financial crisis of 2008, the popularity of cryptocurrency grew at a faster rate [11]. A similar trend of growth in cryptocurrency trading is observed even during the COVID-19 pandemic, mainly because of the feature of online trading and hedging capacity of pandemic risk. The heterogeneity feature of cryptocurrency makes it an ideal candidate to examine its price movement during COVID-19 [27].

Bitcoin transactions generate extensive datasets that can offer valuable insights, making it essential to explore big data analytical tools like machine learning for better Bitcoin price forecasting. Bitcoin combines characteristics of traditional financial and speculative assets, leading to high liquidity and has a low correlation with other financial instruments [8]. In previous research, we find evidence of dominance of Bitcoin and Ethereum during COVID-19 among different types of cryptocurrencies. So, we consider these two types of cryptocurrencies in our research.

We split our dataset into two parts: a train and test phase. The first phase is to train the ML algorithms with a set of examples that will be used to fit the parameters of the models, while the testing phase will validate the results after the

[2]In ML, a hyperparameter is a parameter used to control the learning process of an algorithm.

[3]Since the primary motivation of the study is to determine the predictability of ML during highly uncertain periods, we use the COVID-19 period as a crucial period to examine such phenomena, starting the training period for our models on the first day available in our data set until the onset of the pandemic. By following the timeline of the World Health Organization, we define the beginning of the COVID-19 pandemic as of December 31, 2019, when the organization first collected information from the media statement by the Wuhan Municipal Health Commission reporting viral pneumonia in Wuhan, People's Republic of China.

[4]In this paper ETH refer to Ether cryptocurrency of the Ethereum blockchain platform.

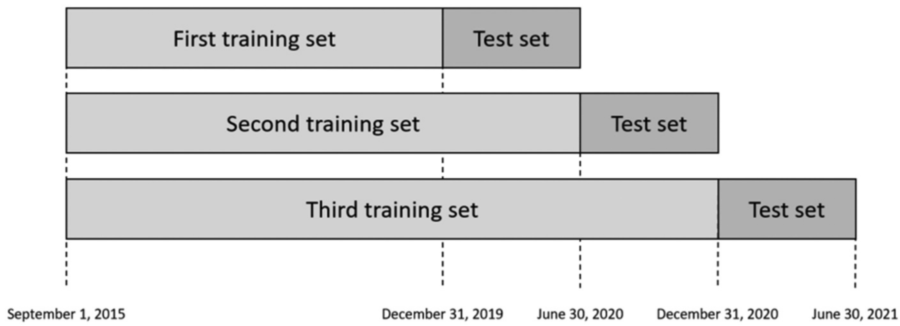

Figure 2. Train and Test Sets.

models are fitted by predicting a new set of data. Due to the fast-changing dynamics of the cryptocurrency market, we set three intervals of interest, creating three testing periods to test the ML algorithms. The initial period is the first and second quarter of the year 2020, the following period corresponds to the third and fourth quarter of the same year, and the last period covers the first and second quarter of the year 2021. The training phase for each group is the previously available data before the beginning of each phase. Figure 2 illustrates the train-test split process.

Data preprocessing

There are 2130 prices in the initial structured data set for BTC and ETH. In addition, we include the volume and the open, high, low, closing, and adjusted closing price. These values are from another 13 cryptocurrencies[5] that show significant market participation during the training or testing periods and have been used by other scholars. In addition, we include eight macroeconomic indices[6] from the Bloomberg terminal to capture the possible deterioration of economic indicators affecting the price volatility of cryptocurrencies during the pandemic [43]. We also include stablecoins such as USD Coin (USDC) and Tether (USDT) among the predictor variables. Although their prices are typically pegged to the US dollar, their inclusion is justified by their role in liquidity flows and market sentiment. Stablecoins often act as transitional assets during periods of volatility, and fluctuations in their volume and transaction patterns can signal investor repositioning or hedging behavior [40]. Prior studies have shown that even minor deviations or volume surges in stablecoins can reflect broader market stress or speculative shifts, making them relevant for predictive modelling during economic uncertainty.

It is necessary to adjust the prices of the traditional indexes to balance our data set because the cryptocurrency market does not stop any day of the year. Therefore, we fill the remaining days with the last available price, applying the same criteria in

[5]XRP, Litecoin (LTC), Dogecoin (DOGE), Peercoin (PPC), BitShares (BTS), Stellar (XLM), Nxt (NXT), MaidSafeCoin (MAID), Namecoin (NMC), Tether (USDT), Cardano (ADA), Binance coin (BNB), USD coin (USDC).

[6]Bloomberg Commodity Index (BCOM), CAC 40 Index (CAC), DAX 30 Index (DAX), S&P 500 Index, FTSE 100 Index (UKX), Volatility Index (VIX), NASDAQ-100 Index, PHLX Gold/Silver Sector Index (XAU).

cases where there is a missing value in the cryptocurrency data set. In addition, we make sure that we do not have an unbalanced data set to avoid problems with the data processing in some ML algorithms. Because there is extensive use of technical indicators in cryptocurrencies, both by investors and scholars [57], in this research, we apply seven commonly used technical indicators[7,8] into the data set as inputs (see Appendix E). After the data were separated and all the inputs correctly included, we normalized each training and testing set independently to avoid data leakage from the training set to the testing set.

Model Development

Model adoption process

We use ML techniques to capture the excessive volatility, lack of market efficiency, and high-frequency trading features of cryptocurrencies. Our goal is to predict the closing price of ETH and BTC one day ahead by utilizing these cryptocurrencies as inputs alongside technical indicators and macroeconomic variables. To achieve this, we have tested nine ML algorithms, comparing their performance to identify the most accurate and reliable model for short-term cryptocurrency price forecasting. This approach not only helps to provide valuable insights into the dynamics of the crypto market, but also serves as a helpful tool for traders and investors looking to make informed decisions in this rapidly evolving financial landscape. The algorithms in our research are implemented in the computer language Python using open-source, well-established state-of-the-art computational libraries.[9] The algorithms tested are DTR, KNNR, RFR, XGBR, LGBM, CATR, and four different neural network architectures, a simple MLP, a classical LSTM configuration, a stacked LSTM (SLSTM), and a bidirectional LSTM (BiLSTM). After considering the relevant literature (see more details in Appendix B), these algorithms and the network structure are applied. A randomized parameter optimization search is performed to choose the optimal set of hyperparameters[10] for each model. The purpose of the search is to identify the best configuration that returns the lowest prediction error. In this research, the mean squared error (MSE) metric is used to measure the overall error of a model and is expressed in Equation 2 as follows:

$$\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{2}$$

where, y_i is the predicted value, $\widehat{y_i}$ is the actual value, and n represents the number of elements.

To obtain a robust estimation of the performance of each model, we perform an independent randomized parameter optimization search in each of the three testing

[7]Moving averages (MA) (5, 10, 20, 50, 100, and 200 days), Moving average convergence divergence (MACD), indicators relative strength index (RSI), stochastic oscillator (SO), On-balance volume (OBV) and Williams %R (WR) and previous closing prices (1, 2, 3, 4, 5, 6, 7, and 8 days).

[8]The technical indicators are explained briefly in Appendix A.

[9]Python, Numpy, Scikit learn XGboost, CatBoost, Keras

[10]The set of hyperparameters for each model is shown in Appendix C.

periods. After this extensive evaluation, we select the model that shows, on average, the lowest MSE to ensure that the research is conducted with the optimal model and the prediction will have fewer errors.

Model interpretation

To know which variables are being considered by the ML algorithm at each period, we used an explainable framework to calculate the importance of each variable involved in the prediction process. After selecting the most suitable model to examine the research question, the predictions are made. We apply SHAP values using SHAP explainer[11] [33] to understand how other cryptocurrencies, technical analysis, and macroeconomic variables can help predict ETH and BTC prices over three different testing periods during the COVID-19 pandemic. In Figure 3, we explain a schema of the development and interpretation of the model and the model interpretation, where phase 1 represents the construction of a mixed data set that combines cryptocurrency prices from different currencies and macroeconomic data. Meanwhile, in phase 2, the data set created in the previous phase is normalized and split into multiple training and testing data sets to be introduced into various ML models for an exhaustive search. After the exploration in phase 3, we select the optimal model with the lowest prediction error to then, in phase 4, make a prediction. In phase 5, the freshness in unblack boxing the AI comes by calculating SHAP values using Equation one. This research presents the novelty of using SHAP values at three different periods to present the most relevant variables and transform them to calculate each variable's relative percentage, providing a practical solution to evaluate the participation of different variables in the prediction of cryptocurrencies.

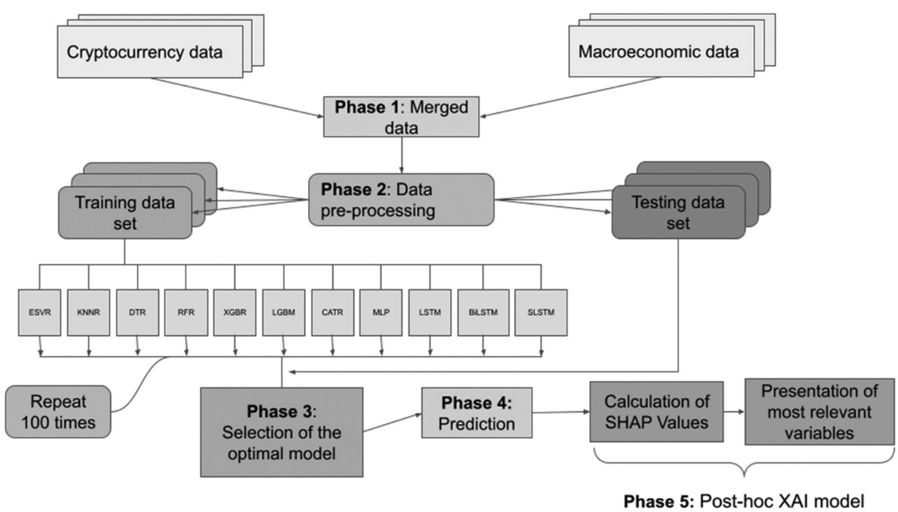

Figure 3. Explainable AI model for predicting cryptocurrency prices.

[11]Using the Python library SHAP.

Results

Model performance

After completing an extensive randomized parameter optimization search,[12] we find that the model that, on average, has the lowest MSE in the three testing periods is the RF algorithm. The RFs build multiple non-linear decision trees and then merge (bagging) their results. Therefore, this method overcomes the problem of overfitting. This is particularly important during our testing period when market conditions were rapidly changing. Thus, we argue that this ML algorithm is the best for predicting the prices of ETH and BTC during volatile economic periods. Furthermore, this model ensures that the mean of the square variations between the actual prices and the predicted values is the lowest, corroborating the lowest prediction error. A similar result was [1] shown that the RF can provide various transformations derived from the past crypto-currency price that contain predicting information of direction of price movement in future. In addition, RF methods provide insights of non-linear relationships between cryptocurrency features and macroeconomic variables [4]. So, our findings confirm the usability of RF algorithm when heterogeneity of investors is very high during economic uncertainty.

By making the predictions for ETH, we observe in Table 1 an MSE of 0.025617 in the first period, while for the second period, the MSE is 0.013093, and for the third year, we can see the lowest prediction error with an MSE of 0.009101. In order to investigate and visualize the execution of the forecast in test sets, the output and predicted values of ETH and BTC performed by the RFR algorithm can be seen in Figures 4 and 5, respectively.

In the case of BTC, we can see in Table 1 that the prediction errors are greater than those obtained with ETH. In the first set of the test data, it is possible to observe an MSE of 0.043714, while, in the second set of data, we have an MSE equal to 0.011374. Finally, it is possible to observe in Table 1 that the last testing period is a challenging phase to forecast, where the performance of the RFR algorithm shows an MSE of 0.058414. It should be noted that, in this period, all the algorithms presented the most significant difficulty in predicting the value of BTC.

Even though the RFR algorithm presents the lowest average MSE when predicting the price of cryptocurrencies, we see that other models such as MLP and BiLSTM exhibit lower error values in specific testing periods forecasting the price of ETH and BTC. According to the testing periods, this discrepancy in the results reaffirms the idea that there is no universal model capable of predicting price better under all circumstances with a fixed set

Table 1. Prediction errors from different ML algorithms

	ETH			BTC			
Algorithms	MSE 1	MSE 2	MSE 3	MSE 1	MSE 2	MSE 3	Average
Decision tree	0.039916	0.01968	0.014941	**0.022477**	0.044211	0.117307	0.043089
K-NN	0.06037	0.020451	0.029823	0.109731	0.022159	0.145628	0.064694
Random forest	0.025617	0.013093	0.009101	0.043714	0.011374	0.058414	**0.026886**
XGBoost	0.028661	0.014827	0.008415	0.04962	0.015811	0.051339	0.028112
Multilayer	**0.022562**	**0.010876**	0.039155	0.033399	0.086046	**0.039572**	0.038602
Light BM	0.028075	0.019216	**0.008272**	0.052902	0.010795	0.056746	0.029334
CAT	0.032937	0.020056	0.012241	0.037527	0.027449	0.081612	0.035304
LSTM Simple	0.04303	0.034054	0.048363	0.045041	**0.010523**	0.129956	0.051828
LSTM stack	0.07169	0.043402	0.099508	0.061454	0.014348	0.086535	0.062823
Bidirectional LSTM	0.023358	0.011756	0.011873	0.080382	0.019465	0.244418	0.065209

[12]In order to find the optimal model and its respective ideal hyperparameters, which are the parameters that control the learning process of the algorithm (Shown in Appendix D).

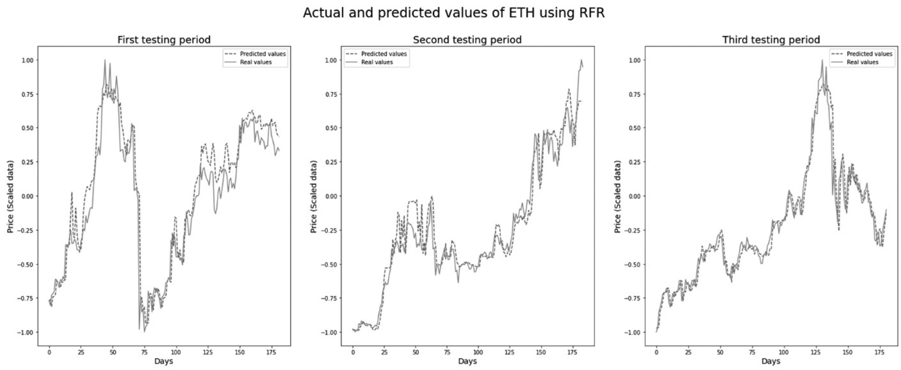

Figure 4. Prediction of ETH using RFR.

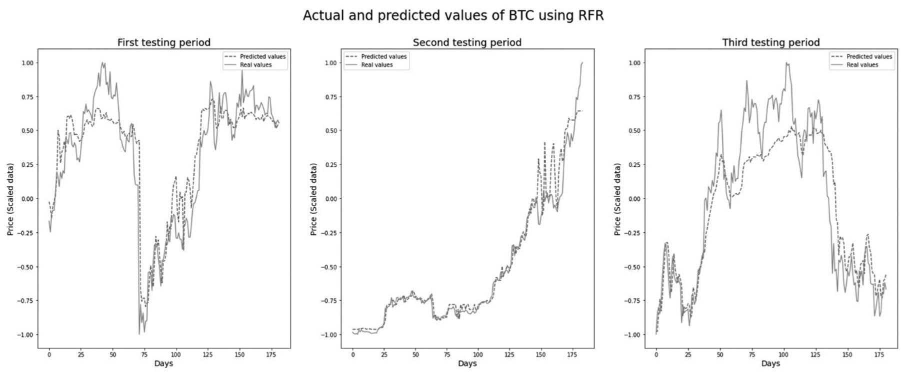

Figure 5. Prediction of BTC using RFR.

of instructions. For instance, while the random forest can address the nonlinearities and LSTM has the capabilities to remember long-term dependencies, these are computationally expensive and require fine tuning and training. In contrast, other and neural network models are excellent in capturing complex pattern in cryptocurrency data, but they are prone to overfitting if not properly regularized [18]. Most research predicting cryptocurrencies' price is uniquely focused on predicting one period, not necessarily exploring periods of economic uncertainty. However, recent research compares the performance of predicting models in different periods and during periods of uncertainty [56]. For this reason, our studies emphasize the idea of multiple tests over time to contribute to the existing literature. Therefore, a proper predicting model for cryptocurrencies needs to evolve with the dynamics of the markets as time passes. Needless to mention that to overcome the limitation of a single predicting model, it is important to employ hybrid model like bagging, boosting and stacking with traditional statistical models or hyperparameter optimization [53].

In this study, we can also confirm the evolution of ML models by seeing that the configuration of the hyperparameters for each ML algorithm changes over time to have better predictions according to a given timeframe. The constant reconfiguration of the models implies that this change over time is necessary to have accurate predictions.

Therefore, a thorough revision of the variables must be integrated into the predictive models, using an explanatory tool to measure the preponderance of each feature during specific periods.

Variable importance

This section develops a procedure that allows comprehending which variables the algorithm considers when making a predictive decision. Knowing the variables involved in the forecast is essential to avoid a black box behavior that characterizes ML to reduce the risks of uninformed decision-making and make a transparent and auditable investment decision, especially in periods of uncertainty. To obtain the preponderance of each variable after predicting with the RFR algorithm, we use the methodology based on SHAP values that has shown an outstanding execution to achieve explainability and obtain insights from the interaction of predominant features in complex datasets with multiple tasks [2]. The results of this technique are given by a matrix of size $n \times m$ that represents the SHAP values for the m variables in n periods. In this investigation, we transpose the matrix to obtain the average of the absolute values in each variable and later calculate the relative percentage of each variable. In this way, the SHAP values are shown more intuitively, and the participation of each variable in the model can be seen in percentage terms. While this method enhances interpretability, it is important to note that these SHAP-derived insights should not be interpreted as evidence of causality. Rather, they serve as a tool to improve stakeholder understanding of model behavior during turbulent market periods.

When we analyze the participation of the variables within the ETH predictions, we see that the most critical value is the previous day’s closing price in the same way as the adjusted closing price. Moreover, their participation in the prediction is nearly 50% between both features. By observing this pattern, it is possible to intuit that the primary predictor variable is the instrument’s price and not another external variable. However, in the third period, when there is a lower predictive error, the preponderance of the variables related to the closing price is lower than in the other two periods. In the same way, it is possible to see that the variables with the most significant importance are one with the high and low price of the previous day, in different ways according to the period in which it is analyzed, as can be seen in Figure 6. Here, a plain representation of SHAP is conducted before calculating the relative percentage of each variable.

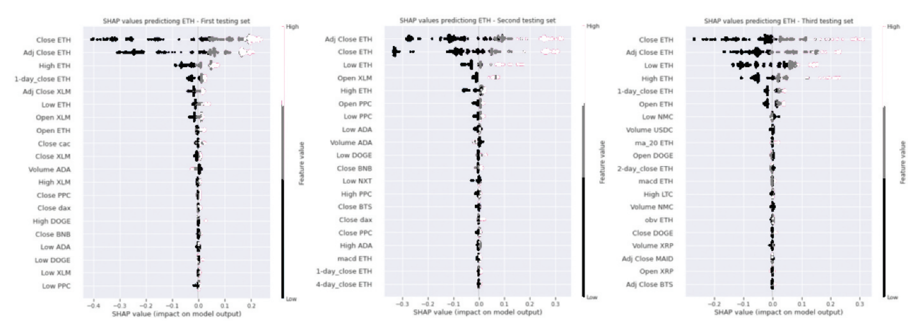

Figure 6. SHAP values representation for the prediction of ETH.

Table 2. Shapley prediction ETH with RFR.

	Percent Shapley value		
	First testing period	*Second testing period*	*Third testing period*
Close ETH	4.04	*	5.77
Adj Close ETH	27.09	33.05	22.05
Adj Close XLM	3.46	*	*
Close CAC	1.42	*	*
Close ETH	33.63	31.10	22.74
Close XLM	1.30	*	*
High ETH	8.50	4.02	15.59
Low ADA	*	1.10	*
Low DOGE	*	0.89	*
Low ETH	2.96	9.66	19.64
Low NMC	*	*	0.64
Low PPC	*	1.85	*
MA 20 ETH	*	*	0.56
Open DOGE	*	*	0.44
Open ETH	1.76	*	5.57
Open PPC	*	1.92	*
Open XLM	2.74	4.60	*
Volume ADA	*	1.02	*
Volume USDC	*	*	0.62

Note: * Features not relevant in this period

During the analysis of other variables, we can see almost no significant effect of the technical indicators in any of the periods except for the price lagged in 2 days and the moving average of 20 days in the case of the third period, as can be seen in Table 2.

Nonetheless, we can see that the algorithm considers the price of other cryptocurrencies as an essential feature, such as the closing price of XLM, which, in the first testing period, has higher participation than the closing price of ETH and has an essential contribution in the second testing period. However, this variable is no longer considered by the algorithm in the following periods, perhaps since the XLM cryptocurrency suffered a significant market correction and investors' increasing interest in other cryptocurrencies such as DOGE in the last testing period. It is also to be noted that the volume of ETH is not considered one of the most relevant variables, even when the algorithm uses the volume of two other cryptocurrencies in the second and third periods.

If we examine the ten most essential variables when predicting BTC and, just like ETH, the adjusted closing price and closing price are the most critical variables to predict. However, the prediction of BTC seems to be harder than ETH, especially in the third

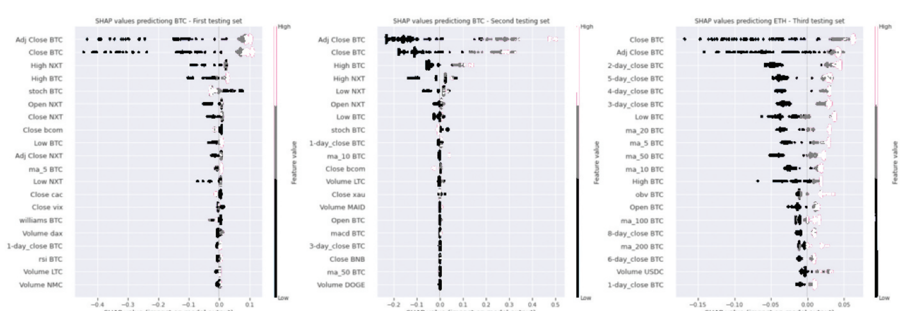

Figure 7. SHAP values representation for the prediction of BTC.

Table 3. Shapley prediction BTC with RFR.

	Percent Shapley value for BTC prediction		
	First testing period	*Second testing period*	*Third testing period*
Adj Close BTC	25.75	37.94	8.68
Close BTC	25.05	28.70	11.69
High NXT	6.84	7.51	*
High BTC	6.39	10.82	3.35
SO BTC	5.58	1.42	*
Open NXT	2.81	1.61	*
Close NXT	2.70	*	*
Close BCOM	2.10	0.97	*
Low BTC	1.79	1.52	5.29
Adj Close NXT	1.76	*	*
Low NXT	1.68	4.56	*
1-day_close BTC	0.89	1.03	1.72
MA 10 BTC	*	1.01	3.73
2-day_close BTC	*	*	8.04
5-day_close BTC	*	*	6.08
4-day_close BTC	*	*	6.06
3-day_close BTC	*	0.07	5.49
MA 20 BTC	*	*	4.98
MA 5 BTC	1.74	*	4.94
MA 50 BTC	*	0.07	4.22

Note: *Features not relevant in this period.

period, where the preponderance of the closing values is lower than in the rest of the testing periods. For example, in Figure 7, by observing the plain representation of SHAP values predicting BTC, there is no clear preponderance of the closing price over the other variables in the third period.

Nevertheless, unlike other periods, the algorithm considers lagged closing prices in the last period. Moreover, like ETH, BTC hardly considers technical indicators or macroeconomic variables as the main variables except for the first period, as shown in Table 3. In the same way, in the first trial periods, the XLM cryptocurrency has a significant degree of participation and then disappears.

ML demonstrates itself to be a suitable methodology to predict cryptocurrencies' prices with low errors. Furthermore, when we explain the optimal model by examining the feature importance using SHAP values, we see that closing, high, and low prices are the essential variables to successfully predict the price of ETH and BTC using ML during uncertain periods, followed by the prices of other cryptocurrencies. Meanwhile, technical analysis and macroeconomic features have little or no relevance in the prediction process.

Discussion

The COVID-19 pandemic marks an unprecedented milestone for testing new technologies, and in this research, we show an indispensable technological tool to overcome and adapt to the challenges imposed by high-frequency trading in an inefficient market setup. Specifically, we developed an explainable AI model for predicting cryptocurrency prices during economic uncertainty. Our model is inspired by the limitations of existing research in explaining the decision-making process [38] and the results of ML models in predicting cryptocurrency prices. Based on our model and results, we establish that ML can predict better only by using a limited set of variables [22] without the need for other tools, technical rules [21], macroeconomic features [23], or technical analysis [57]. Our results also show that deep learning algorithms will not always perform better than traditional ML algorithms [25]; meaning that the most complex models do not necessarily have a comparative advantage over traditional ML models when predicting cryptocurrencies price. Moreover, the above limitation restricted the application of the existing algorithm in times of financial uncertainty. Thus, our explainable AI model will assist practitioners such as investors to eliminate the misconceptions in the uncertain market and in developing an optimum portfolio. Furthermore, based on our trustworthy models, the regulators will be in a better situation to control the volatility in the financial market in a timely manner. Based on our model and findings, the study makes four key contributions.

First, we extend the cryptocurrency literature by unpacking the underlying decision-making process of ML models in predicting cryptocurrency prices during economic uncertainty. Whereas prior research largely focuses on predicting cryptocurrency prices during stable economic certainty [1, 21, 57], we show how to successfully implement ML models during economic uncertainty. In particular, we prove how combining multiple inputs and adding explainability to the predicting processes makes it possible to have accurate predictions and clarify which features are essential in forecasting the price movement of cryptocurrencies. Knowing which variables are involved in the predicting processes improves decision-making and trust in ML models [30], thereby providing some level of stability in the event of economic uncertainty [10]. To the best of our knowledge, this study is the first to use explainable AI to predict cryptocurrency prices during economic uncertainty. From a theoretical perspective, our research contributes to financial forecasting research by integrating explainability into ML applications under uncertainty. We show that predictive relevance is context-sensitive, migrating from closing prices in stable conditions to intraday highs, lows, and inter-coin dynamics during crises. Our study contributes to the existing theory on market efficiency and investor behavior under stress such as flight-to-safety [20, 26] by showing how information flows evolve in digital asset markets.

Second, the study develops an explainable AI model for cryptocurrency price predictions during economic uncertainty. Human behavior shifts when algorithms join prediction markets, and bad disclosure weakens deliberation and accuracy. This reinforces the importance of designing explainable and behavior-aware AI systems. Given the limited models in this domain, our model represents an important addition both to research and practice. So far, existing models have not moved beyond price prediction using ML to integrate explainable frameworks [57]. However, by integrating explainability in our model, we advance current knowledge and contribute critical insights to the development of research on cryptocurrency and AI. By enabling a mechanism that allows the explanation of the variables used in ML predictions, our model offers researchers and practitioners a medium to have a better understanding of future predictions and enriches the existing attempts to create transparent AI models [38] that help to improve fairness, confidence, and accountability in trading. For this reason, the effort to create explanations is an intrinsically valuable process, helping to meet the increasing demand from different stakeholders for white-box models, mainly due to the progressive expansion of ML in finance.

Third, the findings of this study are timely because they will help to quickly elucidate the dynamics of predictive models on new cryptocurrencies in periods of ongoing high uncertainty, helping to extend the literature of forecasting during periods of uncertainty [43, 56].

The model will explain the algorithms with a clear framework, which will allow the stakeholders of the cryptocurrency market to understand the relevance of certain variables affecting their trading outcomes and how these change over specific periods. The results of the research have immense practical implications. Investors would be in a better-off situation to make an informed operational decision by mitigating the risk. By capturing timely information on the price movement of high-frequency cryptocurrency trading, reducing market inefficiency will generate a fair return to the economy. Firms using blockchain [50] based cryptocurrencies in their strategic, operational activities will observe economic stability. The ML-based model will assist regulators in getting enough scope to examine the suitability of existing governance mechanisms in the cryptocurrency trading ecosystem. In addition, the findings will guide investors [36], and policymakers in determining which variables to pay attention to while modifying the existing policy around transparency and trust in cryptocurrency trading.

Moreover, our findings suggest that predictive relevance is not fixed but migrates with market conditions. For instance, closing prices dominate in stable periods but give way to intraday ranges and short-term momentum during high-volatility episodes. Transient inter-coin dynamics, such as NXT's early influence on BTC, appear and fade, highlighting the need for a temporal lens. Macro and stable-coin variables surface sporadically, pointing to shifting markets. By re-estimating our models across windows, we capture these evolving patterns that static correlation methods overlook. These patterns are not unique to cryptocurrency as they reflect broader dynamics in financial forecasting under uncertainty. Our framework for evaluating variable importance using SHAP can be adapted to other asset classes, such as equities or commodities, and applied in domains like credit risk modelling, insurance pricing, and macroeconomic forecasting. While our analysis centers on BTC and ETH, the XAI framework is broadly transferable and can be applied to other cryptocurrencies and traditional financial assets.

Moreover, our findings recognize the asymmetric relationship between BTC and altcoins. BTC, which accounts for approximately 45% of global cryptocurrency trading volume, often exerts a dominant influence on other cryptocurrencies. We explicitly address this dynamic by interpreting altcoin variables not as independent drivers but as reflective of broader market sentiment responding to Bitcoin movements. This contextual clarification reinforces the robustness of our variable selection and provides a more accurate foundation for interpreting the predictive results.

For practitioners, our framework offers actionable insights. Fund managers can use SHAP-derived feature importance to stress-test portfolios by identifying which variables dominate in crisis-like conditions. For example, had our model been applied during the 2008 financial crisis, it could have revealed shifts from stable predictors (closing prices) to short-term volatility signals (intraday highs and lows), helping investors rebalance portfolios or increase hedge positions. Private investors may use the explainable outputs to improve transparency in decision-making and avoid over-reliance on black-box predictions. Regulators can further apply this framework to monitor systemic risks arising from interdependence among crypto assets during downturns.

Finally, the results of the research signal that the prediction process of cryptocurrencies' prices must frequently evolve because the complexity of models will change if the nature of the data starts changing. The unique contribution of this study is to indicate to researchers and practitioners the crucial importance of adapting hyperparameters in critically forecasting the price of cryptocurrencies instead of following a herd. As a caution, it is important to note that, even though most cryptocurrencies have a high correlation and usually move almost identically, it is unlikely that a unique algorithm with a single configuration will successfully always predict all cryptocurrencies. As seen in this research, there are specific periods where cryptocurrencies such as NXT are relevant to predict Bitcoin and Ethereum, but in the following periods, they are not. Therefore, due to the rapid change in the dynamics of digital assets and the constant appearance of new cryptocurrencies, it is crucial to consider periodic adjustments of the hyperparameters and the integration of new variables for a better prediction. In summary, by demonstrating how explainable AI can uncover context-sensitive variable behavior across crisis periods, we contribute to a growing body of literature on model transparency and stakeholder trust in volatile environment. This generalizable insight supports future research in regulated financial services, policy modelling, and ESG analytics, where interpretability is essential.

Conclusion and Future Research

In this research, our primary objective is to examine the capability of XAI algorithms in forecasting cryptocurrency prices during periods of economic uncertainty. We recognize the importance of discovering how algorithms can assist stakeholders in predicting price movements during turbulent times, with the COVID-19 pandemic serving as a relevant instance to test the suitability of ML algorithms and has fast-tracked the implementation of AI and ML solutions across various sectors, demonstrating their potential in addressing complex, time-sensitive issues [49]. To address this objective, we are developing an XAI model to predict cryptocurrency prices that can successfully forecast during uncertain times. Incorporating explainable AI features can also promote inclusivity by offering greater transparency, which in turn helps in mitigating biases [9].

The insights we obtain from our experimentation offer valuable contributions to research and application in the financial and economic fields. The findings from this study can be leveraged by stakeholders to develop AI-driven investment platforms that utilize XAI models for transparent and bias-aware financial forecasting. Financial institutions could integrate these models into real-time risk assessment tools, enabling investors to make more informed decisions during periods of economic uncertainty. In addition, regulatory bodies could apply XAI frameworks to strengthen market surveillance, ensuring ethical trading practices and identifying irregularities in cryptocurrency price movements. However, it is critical to acknowledge the limitations inherent in this research endeavor. Primarily, our dataset is limited to the most predominant cryptocurrencies, which opens up opportunities for future research to expand the data set by including future periods covering forthcoming uncertain economic environments. In addition, the data set can be enhanced by incorporating a broader range of economic indicators or different assets. In this way, researchers can improve the robustness and generalizability of the model, making it more adaptable to multiple real-world scenarios.

We acknowledge that our current model does not explicitly incorporate regulatory and institutional variables such as taxation policies, capital controls, or exchange regulations, which significantly affect investor behavior and the risk profile of cryptocurrencies. Furthermor, the study examines only a defined historical window, and this temporal scope should be recognized as a constraint when interpreting the results. Future research should expand our framework by integrating these institutional dimensions, thereby enhancing the explanatory power and robustness of predictive models in contexts where policy interventions and governance structures play a critical role.

Furthermore, our study concentrates exclusively on the top two cryptocurrencies, which have emerged as the most widely used and innovative forms of digital currency in recent times [3] enhancing our findings' credibility. However, it would be of interest for future research to employ our model to analyze additional cryptocurrencies, thereby broadening the range and practicality of the framework. Through this approach, scholars can investigate the efficacy of the XAI paradigm across a broader spectrum of digital assets, providing insights into the unique characteristics and dynamics of different cryptocurrencies. Our research assists in expanding the body of knowledge on forecasting in times of unpredictability [43, 56] by developing a model that aims to deliver accurate prediction even amid high uncertainty in the financial sector, which regularly faces similar challenges. Therefore, future research endeavors may seek to validate our model with traditional financial assets during periods of economic uncertainty. This extension allows for a comparative study of cryptocurrencies and traditional finance, deepening understanding of the model's performance and role in investment decisions. It also opens up possibilities for using new natural language processing techniques to broaden this implementation.

In conclusion, our research offers critical insights into using XAI algorithms for forecasting digital asset prices during economic uncertainty. While acknowledging the limitations of our study, these findings provide a solid foundation for future research directions. The proposed model can be applied to other cryptocurrencies and financial instruments by expanding the dataset to include a wider range of assets and economic indicators, thereby improving its generalizability and robustness. Future research could explore its efficacy across diverse digital currencies and traditional financial assets, allowing for a comparative analysis of their behavior during economic uncertainty. Moreover, incorporating new AI techniques, such as advanced natural language processing methods, could enhance predictive accuracy and adaptability in various financial contexts.

Availability of Data and Material

The methods implemented in this study are publicly accessible and can be found in a GitHub repository: https://github.com/gonzalezcortes/Explainable-Artificial-Intelligence-in-predicting-digital-asset-prices

A subset of data used in this research is available for academic purposes. However, some data are proprietary and sourced from Bloomberg; thus, they are not publicly available.

It should be noted that despite the unavailability of the complete data set, the methods and results have been rigorously validated, and the partial data set still serves to demonstrate the proof of concept for the study effectively.

Authors' contributions

All authors contributed equally to this work. They were involved in the conception and design of the study, the acquisition of data, the analysis and interpretation of data, and the drafting and revising of the manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

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