Explainable Artificial Intelligence Modelling for Bitcoin Price Forecasting

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ABSTRACT

Precise forecasting of Bitcoin prices has been an essential yet a thought-provoking task in the jurisdiction of cryptocurrency trading. Explainable Artificial Intelligence (XAI) has emerged as a tool which has been widely used by researchers in different fields. In this chapter, an XAI Modelling approach for Bitcoin price forecasting, integrating robust methodologies for data analysis and model development has been proposed. The method starts with importing the essential libraries like matplotlib, pandas, numpy, and scikit-learn, expediting continuous visualization, data manipulation, and model construction. For comprehensive analysis, historical Bitcoin price data is sourced from trustworthy platforms and then it has been loaded into a structured format. After data loading, the realization of the structure and characteristics of dataset is performed by exploratory data analysis (EDA. To address the issues of missing values, techniques like imputation or removal are engaged while for underlying trends, patterns, and seasonality, time series visualization methods are engaged in Bitcoin prices. Descriptive statistics and correlation analysis are employed to further enrich the understanding, offering insights into price distributions and relationships with significant variables. Afterwards, the data go through the preprocessing to prepare for model training. MinMaxScaler is employed for scaling the features, safeguarding the uniformity across input variables. According to the sequential nature of time series data, the model architecture is designed precisely. For their efficacy in time series forecasting, Long Short-Term Memory (LSTM) was deliberated. The model is compiled with an appropriate loss function and optimizer, optimizing predictive accuracy during training. Experimentation with hyperparameters further refines the model's performance, enhancing its generalization ability..

Keyword: *Explainable AI, Bitcoin, Price Forecasting, Exploratory Data Analysis, Model Building, Long Short-Term Memory (LSTM).*

INTRODUCTION

Last four decades have witnessed an excitement in researchers and scientists with emergence of artificial intelligence and its variants like machine learning, deep learning. The applicability of AI and its variants in different fields (Tripathi et al 2022, 2023, 2024; Kumar et al. 2024, 2024; Mishra et al. 2024; Rai, et al. 2023,) have opened paths for applications of XAI. Digital currencies and assets have grown exponentially since bitcoin and the blockchain technology it relies on were first introduced. There are now thousands of assets, many blockchains, and a plethora of solutions catering to different industries and financial needs. There have been ongoing efforts by Bitcoin's rivals to create new digital assets that outperform Bitcoin in both its monetary value storage and transactional capabilities. Having said that, if we were to look at the cryptocurrency industry as a whole, we would see that bitcoin is still the most valuable and widely used cryptocurrency (Angelov et al., 2021).

There is understandable anxiety among investors, academics, and lawmakers due to the volatility of digital currency pricing. Financial stability might be jeopardized if anonymous, decentralized, and uncontrolled crypto marketplaces experience bubbles. But the crypto markets' actions have been hard to foresee. So, governments will be able to better craft regulatory rules and investors will be able to make more informed judgments if they can reliably predict bitcoin values. Investors and financial organizations should give forecasting bitcoin prices a lot of thought since it's a big deal for risk management.

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For the reason that regulators and traders alike need reliable early warning systems to predict the value of digital currency and other assets. Many big-data systems collect and store massive amounts of data for analysis. But instead of helping with optimal decision-making, this mountain of data often makes things more complicated. It is also very costly to collect, store, and analyze this data. Deciders need to glean the essential details from this deluge of data so they can construct a practical and effective prediction model without sacrificing the precision of the anticipated results. Feature selection enables the fulfillment of such goals and is an essential component of data preparation in ML models. (Ahmed et al. 2022)

Bitcoin, a decentralized digital currency not controlled by any central bank or government, is protected by cryptography. Bitcoin was created by an individual or group of individuals in 2008 in a paper titled "Bitcoin: A Peer-to-Peer (P2P) Electronic Cash System" under the pseudonym Satoshi Nakamoto. Due to its recording on a public database known as the blockchain, the transaction history of any particular Bitcoin may be seen by anyone. Due to its decentralized nature, Bitcoin may be instantly transferred around the globe and operates independently of central banks. Recent years have seen a rise in its use as both a medium of exchange and a means of storing wealth. There have been several price swings over the last decade, but in November 2021, the overall price reached over USD 1.2 trillion, and a single coin topped USD 68,000.

Yet, Bitcoin's tremendous volatility is a problem when it comes to the commodity status of Bitcoin. Bitcoin had a daily return rate standard deviation of 3.85% from April 2015 to April 2022, a duration of seven years. This outpaced both the S&P 500 and the return rate standard deviation of gold by a factor of 2.68 and 3.36, respectively. The extreme volatility of Bitcoin's value has cast doubt on its use as a medium of trade and a means of storing wealth. (Gunning and Aha, 2019)

The challenge of understanding Bitcoin's trend in order to reduce the danger of Bitcoin floating has emerged as a significant obstacle to the widespread adoption of Bitcoin and its decentralized nature. The link between Bitcoin's price and the prices of other commodities is a common way that scholars attempt to understand the trend of Bitcoin. Previous research has shown that there is a modest association between Bitcoin and commonly used benchmarks such as gold, stock market indices, and crude oil prices. One other line of inquiry into Bitcoin's price movement has been to use artificial intelligence (AI) algorithms and the processing power of computers to foretell the cryptocurrency's future value. As computing power has increased in the modern era, machine learning has emerged as a promising area of study. The stock market, crude oil markets, gold markets, and futures markets are among the most common places where machine learning has found application.

This study uses the LSTM model of neural networks and the random forest regression technique of machine learning to forecast Bitcoin's price, with the need to mitigate Bitcoin's price risk serving as a backdrop. Using LSTM's prediction results as a benchmark, I primarily examine how well random forest regression does in predicting Bitcoin prices. Regression using random forest is known as random forest regression. Machine learning techniques like random forest regression, in contrast to neural networks' opaque nature, may reveal the relative weight of each explanatory variable in Bitcoin prediction by analyzing the output of its weak-learners.

Stock price direction predictions using random forest have proved successful. While random forest classifiers aim to identify price increases and decreases, few publications have used random forest regression to examine the cryptocurrency market (Saxena et al., 2022).

Thanks to advancements in machine learning, data processing and handling technology, and the capacity to store and analyze massive volumes of data, algorithmic trading has been booming in the last several decades. Market players compete not only with one another but also with those who do not utilize automated systems, which in turn increases the complexity of the algorithms employed by these systems. Given these tendencies, it is critical to investigate whether machine learning algorithms can solve algorithmic trading issues. This is essential for academics and algorithmic trading organizations like hedge funds. The reason behind this is that it provides them the understanding capability for construction of automated trading systems for cryptocurrency markets by means of state-of-the-art machine learning algorithms(Kenny et al, 2020). Thus, the cryptocurrency value prediction applying deep learning and ensemble learning are dealt with. Two methods namely deep learning neural networks and ensembles of base predictors have been developed for mimicking real Bitcoin traders.

The aim of this chapter is the development of a predictive model based on LSTM for Bitcoin prices and investigation of the impact of different input features on accuracy of prediction. The fruitfulness of the model is observed in prediction of Bitcoin prices.

Long Short-Term Memory (LSTM)

LSTM is a variant of recurrent neural network (RNN). The basic difference between LSTM and RNNs is that RNNs are restricted to memorizing short-term information. LSTM is an Artificial RNN which is widely employed in deep learning. LSTM uses feedback connections unlike other neural networks. Both the discrete data points and whole data streams may be processed by LSTM. Also, RNN models suffer from the vanishing gradient problem in trading with data of lengthy sequence. This issue can be resolved using LSTM. Another beauty of LSTM models lie in automatically governing the retaining of essential characteristics and the neglecting the irrelevant features in the cell state as well as remembering past long-term time-series data. An LSTM model is composed of the input, forget, and output gates and it regulates the features (Lahmiri and Bekiros, 2019).

LSTM network is a variant of RNN having the ability to learn sequence prediction problems with order dependency. Realms containing complex problems, like voice recognition and machine translation requisite this behavior. A cell state is absent in vanilla RNNs. There are only concealed states acting as the memory for RNNs. While in LSTM, cell states and hidden states both are present (McNally et al., 2018).

Applications of LSTM

LSTM has widely been used in several fields. Here, we list some of the applications:

Language Modelling

LSTMs have widely been employed in many natural language activities like text summarization, Machine translation, language Modelling , etc. Grammatically accurate and coherent sentences can be produced by revising the interactions between words in a phrase.

Speech Recognition

LSTMs have been employed in many activities like text-to-speech transcription, speech patterns and command recognition of speech recognition.

Time Series Forecasting

LSTMs have been employed in many time series forecasting activities like Stock price, energy consumption, and weather predictions (Ulumuddin et al., 2020).

Anomaly Detection

LSTMs have been employed in many anomaly detection activities like fraud and network intrusion detection. LSTMs may learn to spot unusual data patterns and point them as possible outliers.

Recommender Systems

LSTMs have been employed in many recommender systems. They can observe trends in user actions can be observed by LSTMs and tailored suggestions can be provided by employing this information.

Video Analysis

LSTMs have been employed in many video analysis activities like activity recognition, object identification, action categorization, etc. LSTMs in combination with other neural networks can sift through video data and pull-out valuable insights.

Explainable Artificial intelligence (XAI)

Explainable artificial intelligence (XAI) is a set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms. In order to enable the creation of new systems, the XAI program focuses on two explicit areas of machine learning: i) the classification of events of interest in heterogeneous multimedia data, and ii) the construction of decision policies for an autonomous system to carry out a number of simulated missions (Arrieta et al., 2020). The two selected challenge issue areas: intelligence analysis and autonomous systems, represent the meeting point of two major machine learning techniques (classification and reinforcement learning). The easiest kind of XAI to get is explainable data. The vast amounts of data that may be used to train an AI system make the term "attainable" appear deceptively simple. One extreme example is the GPT-3 algorithm for natural language processing. The model may be able to imitate human speech, but it trained on a lot of harmful material on the internet. For an AI system, "the underlying training data and training method, as well as the resultant AI model" are the most important parts, according to Google. The capacity to extensively analyze the dataset that was used to train an AI model, even after a long period of time has passed, and to successfully map a trained model to that dataset is essential for this comprehension (Babaei et al., 2022; Das and Rad, 2020).

Because of the potential impact on actual humans, developing AI systems that can be understood and explained is of utmost importance now. An essential part of developing an AI system from the 1970s and beyond has been AI's explainability. The symbolic reasoning system MYCIN created in 1972 explained the reasoning behind diagnostic tasks like treatment of blood infections. Truth maintenance systems (TMSs) were created in 1980s & 1990s to expand AI reasoning capabilities. Inference systems relying on rules and logic use them. Applying rules, operations and logical inferences, a TMS follows an AI's thinking to its conclusions. Every AI reasoning is supplemented by an explanation produced by this method. The public's exposure to explainable AI systems has grown during the 2010s. The emergence of racial and other biases in AI systems prompted researchers to devote more resources to finding methods to identify AI prejudice (Minh et al., 2022).

When an AI model, its expected outcomes, and any inherent biases can be described in detail, we say that it has explainable AI (Došilović et al., 2018). The accuracy, fairness, transparency, and outcomes of AI models may be better described using this (Khosravi et al. 2022). Building trust and confidence via explainable AI is the first step for any organization looking to put AI models into production. Organizations may better develop AI responsibly with the help of AI explainability. Humans will have a harder and harder time trying to decipher the algorithms' thought processes as they produce more complex AI. The whole computation becomes an incomprehensible "black box" that no one can decipher. It is from the data that these "black box" models are constructed. Not even the algorithms' original developers, who are often engineers or data scientists, have any idea what's going on within these AI programs or how they got the results they did. (Carbó and Gorjón, 2022).

There are several benefits to knowing the steps that an AI-powered system takes to get a certain result. Developers may benefit from explainability while testing the system's functionality, it's vital for compliance with regulations, and it gives those impacted by decisions a chance to contest or alter their results. In the future, machine-learning systems will be able to justify their actions, highlight their best and worst traits, and predict their own behavior. To get there, we'll be creating or improving upon machine-learning methods that provide models that are easier to understand and explain. Figure 1 shows the ultimate result of combining these models with cutting-edge human-computer interaction approaches that can translate models into explanation dialogues that the end user can comprehend and make use of. (Nassar et al, 2020)

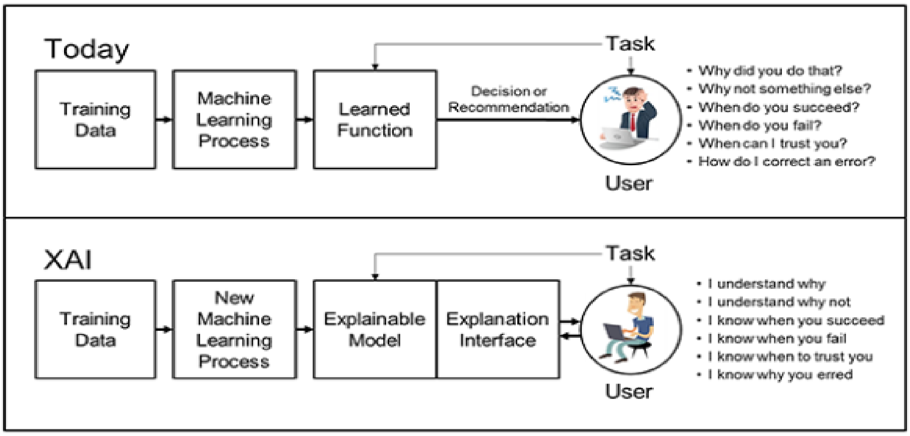

Figure 1: XAI concept

Working of explainable

To help its development teams build its AI model, a company might establish an AI governance committee right from the start. The purpose of this group should be to establish guidelines for the explainability of AI. One of the guiding concepts of the organization's responsible AI standards is explainability, which is achieved by doing this from the beginning (Li and Dai, 2020).

An explainable AI model relies, at its most fundamental level, on the training data. Developers should be very careful that the training data used to build an AI model is free of bias. It is the responsibility of the developers to investigate potential measures to reduce the impact of skewed data (Vilone and Longo, 2020; 2021). Furthermore, training should not include any data that is not relevant. Making an AI model that can be explained might take a variety of forms, depending on the AI in question. For instance, it's possible that certain AIs are programmed to provide context for the data they generate by explaining their origins. It is crucial to create a model that can have its algorithms explained and its forecasts explained (Islam et al., 2021). Each model layer should be transparent about how it contributes to the result if the algorithm is to be designed in an explainable way. Similarly, for a forecast to be explainable, it is necessary to precisely specify the model elements that were used. n fields where the immediate impact on someone's life is high, XAI takes on further significance. One potential use of AI in healthcare is the automatic detection of fractures in patients using X-rays (Tjoa and Guan, 2020). If medical professionals do not have faith in AI or understand how it determines a patient's diagnosis, they may be hesitant to use the technology, even after an initial investment in AI. Doctors and other medical professionals may go over the diagnosis and draw their own conclusions about the patient's prognosis when using an explainable method (Zaman et al., 2021; Ghosh and Jana, 2024).

Benefits of explainable AI

More openness and responsibility in AI systems is provided by XAI in general. Here are some of its advantages: Increases confidence in AI. People may be hesitant to put their faith in an AI system if they cannot understand its reasoning process. XAI's goal is to provide end users with clear justifications for its actions. Enhances the AI system as a whole. Thanks to the increased visibility, developers will have an easier time finding and fixing problems. Defends against hostile assaults by offering knowledge. By feeding a model intentionally manipulated data, adversarial ML assaults hope to trick it into making a wrong judgment. Unusual justifications for XAI system's judgments might indicate an aggressive assault. Provides measures to prevent bias in AI. Attributes and decision-making procedures in ML algorithms are what XAI aims to shed light on. Unfair results caused by biased developers or poor-quality training data may be better identified using this method. (Babaei, 2022)

Limitations of explainable AI

The following are some of XAI's limitations:

Simplifying things too much. A discussion on how to build AI systems with better interpretable models—or models that can more effectively correlate causes to effects—may ensue if a XAI system oversimplifies and misrepresents a complex system in comparison to other transparency approaches.

- Decreased efficiency of the model. The performance of XAI systems is often inferior to that of black box versions.
- Training is challenging. Compared to black box models, it is more complex to create an AI system that also explains its rationale.
- Having no personal space. Because XAI is inherently open and transparent, any sensitive data processed by a XAI system runs the risk of becoming public knowledge.
- A decline in mutual comprehension and confidence. While it is expected that XAI would enhance users' faith in AI, it is possible that certain users may remain skeptical of the system even after being provided with a clear explanation of its reasoning. (Zaman, 2021)

Principles of explainable AI

These ideas are illustrated by the following instances.

Give background information about an algorithm. A clear illustration of this would be the rationale behind the approval or rejection of a loan.

Increase public faith in artificial intelligence. Some explanations aim to build confidence by justifying the paradigm and technique utilized, rather than explaining specific results. Some examples of such information include the algorithm's goals, development process, data utilized and its sources, and the algorithm's advantages and disadvantages.

Meet all legal or government requirements. Artificial intelligence algorithms must be able to prove compliance with rules as they gain significance in regulated businesses. For instance, self-driving AI systems need to detail their compliance with relevant traffic laws.

Help further the system's development. When developing AI, technical professionals must identify the sources of incorrect output and determine how to fix them. Help the owner of the algorithm. Businesses are using AI systems in every sector with the expectation of substantial returns. An example would be a streaming service that uses suggestions that are easy to understand to maintain subscribers. (Ulumuddin, 2020)

Meaningful

If the user can grasp the explanation, then the meaningfulness principle has been met. There could be a variety of consumers who need clarification for a certain AI system. An explanation that satisfies the driver of the self-driving car—for instance, "the AI classed the plastic bag in the road as a rock, and thus took action to avoid striking it"—would not meet the demands of an AI engineer trying to fix the issue. The developer should investigate the misclassification of the plastic bag. (Kenny, 2020)

Explanation accuracy

The correctness of explanations is distinct from that of outputs. An AI algorithm must provide a precise justification for its results. It would be misleading for a loan acceptance algorithm to claim that an applicant's income and debt were the deciding factors when in fact the zip code was the determining factor. (Saxena, 2022)

Knowledge limits

There are two paths an AI system might take to exhaust its store of information. The input may not be within the system's area of competence. A system developed to categorize bird species is used as an example by NIST. A image of an apple should prompt the system to clarify that it is not a bird. Another option is to provide the system with a hazy photo. It should either not be able to identify the bird or declare a very low confidence in its identification. (Das, 2020)

Bitcoin price prediction using deep learning methods

To determine whether the gold price can predict the Bitcoin price, CNN, LSTM, and GRU have been used. A comparison of the three models' prediction accuracy reveals that the LSTM model outperforms the others; in contrast, the model that relies only on gold price diverges from the real Bitcoin price (Rizwan et al., 2019). A total of forty elements were identified by Liu and Zhang (2021) as potential determinants of Bitcoin price, with the inclusion of search indexes, cryptocurrency markets, and macro market indices such as the stock market index, crude oil price, exchange rate, and so on. When compared to BPNN, PCA-SVR, and SVR, the SDAE method produces superior predictions. Time series and machine learning are the two main categories of approaches used in Bitcoin price prediction research. Several research have shown that ARIMA's prediction accuracy is worse than machine learning's (McNally et al., 2018).

Phaladisailoed and Numnonda (2018) employed four deep learning algorithms including LSTM to predict Bitcoin values. LSTM algorithm produced the highest accuracy of 52.78%. Tandon et al. (2019) trained LSTMs employing 10-fold cross-validation. The accuracy increased by 14.7%. with the same set of explanatory variables. Aggarwal et al. (2019) included the price of Bitcoin and gold to the list of explanatory variables. The experimental outcomes established that in comparison to CNN and GRU, the LSTM algorithm achieved better results with an RMSE of 47.91. In order to predict the price of Bitcoin, McNally, et al. (2018) included Bitcoin-related factors like hash rate and difficulty and observed that LSTM produced a better result with prediction accuracy of 52.78% in comparison to ARIMA and RNN.

Chen et al. (2020), sandwiched LSTM layers with Dropout layers in between to alleviate overlearning. The study conducted by Jagannath et al. (2021) focuses on the core factors of the Bitcoin blockchain, such as users, miners, and exchanges, as opposed to the macroeconomic variables that have been extensively employed in previous publications. Bitcoin price predictions using technical indicators have been successful. Although the study claims that the self-adaptive LSTM achieves high prediction performance, it does not provide any experimental results comparing the model with and without macroeconomic factors. García-Medina and Duc Huynh (2021) developed a fresh approach by investigating how factors like social media and Tesla stock price may explain Bitcoin price. As 2020 progressed, it became clear that these factors, which were very relevant at the time, did not have the ability to explain the observed fluctuations. In their appendix, Carbó and Gorjón (2022) examine the impact of including the Bitcoin price from the prior period alongside the LSTM algorithm-based explanatory variables. After include the historical Bitcoin price as an explanatory variable, the model's RMSE accuracy dropped from 21% to 11%, a considerable improvement.

Many scholars have also examined the process of choosing time unit pricing. The standard unit of measurement in most studies is minutes or days. Lamothe-Fernández et al. (2020) found that DSVR, DNDT, and DRCNN all achieved more than 60% prediction accuracy in their quarterly study. However, the lengthy quarterly units and Bitcoin's overall climb from 2011 to 2019 in the sample might be contributing factors to this high accuracy. The LSTM model, with sample units in minutes, hours, and days, is the foundation of Shin et al.'s (2021) study. The results demonstrate that the hour-unit model is outperformed by both the day model and the minute model in terms of prediction accuracy.

Cryptocurrencies' theoretical worth is directly proportional to their exponential growth in value over the last decade as a means of trade. Early research in this field mostly concentrated on cryptocurrency volatilities, which have been substantial and difficult to forecast so far (Klein et al., 2018), due to the growing significance of cryptocurrencies for financial institutions. In addition, the data suggests that: The distributions of returns on cryptocurrency investments are heavily tailed, the decay rates of relative and absolute return autocorrelations are different, cryptocurrencies show a strong leverage effect and volatility clustering, returns and volatility are dependent on one another over long distances, and the correlation between price and volatility is power-law. Because of these characteristics, the value of cryptocurrencies is very unpredictable, and investing in them is riskier than in more traditional forms of money. The absence of a correlation between cryptocurrency assets and any underlying fundamentals has made it hard to predict the value changes of these assets. This has led many to speculate that market mood plays a significant role in determining these fluctuations. Bitcoin and other cryptocurrency prices have followed cyclical patterns (often called bubbles) in the last several years, according to the literature (Confalonieri, 2021).

Traditional statistical approaches have been the primary focus of studies attempting to predict the future value of cryptocurrencies (Vilone and Longo, 2020). For their 2019 prediction, Ethereum, Bitcoin, Ripple, and Litecoin were the four most talked-about cryptocurrencies that was analyzed using a variety of VAR models, including both multivariate and univariate ones. Remarkably, data showed that predicting accuracy was much enhanced by integrating several univariate forecasting models. Conrad et al. (2018) found that the S&P 500's volatility significantly affected Bitcoin's long-term volatility after using the GARCH-MIDAS model to disentangle the two types of cryptocurrency volatility. Similarly, Walther et al. (2019) employed the GARCH-MIDAS framework for forecasting the volatility of the CRIX cryptocurrency index with notable market capitalization, all of which were influenced by Global Real Economic Activity (GREA). GREA is a vital issue in the long-term volatility of cryptocurrencies. Walther et al. (2019) observed that the models with individual exogenous factors performed better than the classic GARCH model in prediction of the volatility of cryptocurrencies in unfavourable markets.

ML algorithms have been proved as the effective standard in prediction of bitcoin prices during the last decade. By signifying a model combining MLP neural network and GARCH for predicting the volatility of the Bitcoin price, Kristjanpoller and Minutolo (2018) obtained a considerable addition in the area of Bitcoin price volatility. Hybrid models comprising of linear and nonlinear models were proved very beneficial for predicting. This was concluded after performing comprehensive investigation on a number of GARCH models. Nakano et al. (2018) employed an MLP neural network for predicting the Bitcoin returns applying a collection of technical indicators. The MLP predicting model bettered the baseline buy-and-hold strategy, as per the experimental results. In comparison to ARIMA, Prophet, and random forest, MLP performed better when it came to movement direction. Very recently, recurrent neural networks like LSTM and GRU were employed to derive automatically the broad temporal trends from bitcoin time series. As proposed by Zhang et al. (2021), GRU performed much better than standard ML approaches and LSTM-based approaches in prediction of the values of four main cryptocurrencies. The major drawback of these models was their relying on deep learning which do glowing in univariate contexts, but it used to become very complicated and could not learn the difficult temporal patterns.

Ensemble learning techniques have been used as a substitute for deep learning models having the capabilities to alleviate the bias and the volatility of individual ML techniques employing other techniques such as random forest and boosting (Derbentsev et al., 2020). It has been observed that bias reduction was more vital in comparison to variance reduction in context of cryptocurrency prices. This was concluded from the fact that the LightGBM (light gradient boosting machine) model performed better than the random forest model in prediction of the market's price. In sum, the aforementioned research shows that predicting models based on machine learning perform better than those based on traditional statistical approaches. This is because ML models can readily build generic models that capture complicated nonlinear patterns in bitcoin data. Machine learning algorithms for bitcoin price predictions have been the subject of two recent systematic reviews. Given its capacity to identify long-term time-series connections, LSTM is deemed the optimal approach for forecasting bitcoin price time series by Khedr et al. (2021).

Bitcoin and other cryptocurrency prices have followed cyclical patterns (often called bubbles) in the last several years, according to the literature (Confalonieri et al., 2021). Zhu and Ugunsakin (2023) established the relationship between XAI and Bitcoin price prediction. Guo, et al. (2018) proposed Bitcoin price prediction in perspective of blockchain.

METHODLOGY

Description of Dataset: The Bitcoin BTC-USD data is used in our study. This dataset contains daily historical price data for Bitcoin (BTC) against the US Dollar (USD).

- Data Source: Yahoo Finance
- Time Period: September 17, 2014 - February 5, 2024

- Frequency: Daily
- Asset: Bitcoin (BTC)
- Currency: US Dollar (USD)

Data Fields:

- Date: Date in YYYY-MM-DD format.
- Open: Opening price of BTC on the date.
- High: Highest price of BTC on the date.
- Low: Lowest price of BTC on the date.
- Close: Closing price of BTC on the date.
- Adj Close: Adjusted closing price of BTC, considering stock splits and dividends.
- Volume: Trading volume for BTC on the date.

Description of programming languages and frameworks used

The implementation will be carried out using Python programming language and the TensorFlow framework for deep learning.

Practical Implementation

Installing & importing essential libraries

We load necessary libraries for time series analysis, data manipulation, machine learning, and visualization to start our data science journey and forecast Bitcoin volatility.

Essential Libraries:

Numpy, Pandas, Matplotlib, Scikit-learn and TensorFlow.

Importing Data

Data Acquisition and Exploration for Bitcoin Volatility Prediction is the most crucial step. Authenticity of the data is essential for predicting valuable insights and results.

Data Source:

Chosen Source: Yahoo Finance

Data Type: BTC-USD

Format: CSV

Data Loading and Cleaning:

Programming Environment: Jupyter Notebook

Data Reading and Structuring: pandas DataFrames for efficient analysis

Data Integrity Checks:

Confirm presence of necessary columns (date, open, high, low, close) Identify and handle missing data, irregularities, or outliers.

Figure 2: Stock Analysis

Checking for Null Values

To generate accurate and dependable outcomes, any data-driven project must ensure that thedata is full and of high quality. We made sure that the data was accurate because time-series forecasting depends on it. Missing values could have introduced biases that were substantial and affected the underlying patterns that the algorithm learns from.

```
In [7]:  df.isnull().sum()

Out[7]:  Open         0
         High         0
         Low          0
         Close        0
         Adj Close    0
         Volume       0
         dtype: int64
```

Figure 3: **Null values**

Split Data

Dividing the Bitcoin price data into training and testing sets is crucial for simulating real-world scenarios where models must predict unseen data based on what they've learned. This step essentially simulates a real-world scenario where the model has never seen the testing data before and its performance is solely based on the knowledge it has gained from the training set.

- Training Set (80%): The majority component acts as the foundation for the model's learning.
- Test Set (20%): This data, which is kept secret from the model throughout training, acts as the real-world testing ground.

Scale Data

- Every model used to predict Bitcoin volatility is affected by the problem of feature ranges with noticeably different scales.

- When data includes attributes, such as trading volume (thousands) and closing price (hundreds). When models are trained directly on such data, they may prioritize minimizing errors for features with higher absolute values, thereby missing out on important information found in smaller-range features. This leads to:
- Erroneous Predictions: Models may produce projections for certain features that are wrong because they overemphasize larger features.
- Learning Inefficiency: Ignoring the interdependencies between all aspects by concentrating on a small number of "loud" features makes learning more difficult.
- Using scaling methods like StandardScaler or Min-Max scaling, all features are converted to a common range (such as 0-1). This guarantees:
- Equal Opportunity: Regardless of their initial scale, all features have an equal opportunity to participate during training.
- Holistic Focus: To promote the identification of hidden links, models are encouraged to minimize errors across all features.
- LSTM: Scaling enables LSTMs to learn from all features efficiently, leading to predictions that are more reliable and accurate.
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Model Building

LSTM: LSTMs, or long short-term memory networks, are a unique class of RNNs that can learn long-term dependencies. LSTMs are expressly designed to prevent the long-term reliance problem. They don't struggle to learn as RNNs do—in fact, remembering information for extended periods of time is practically their default habit.

- Every recurrent neural network is composed of a series of neural network modules that repeat. This repeating module in conventional RNNs will have a very basic structure, like a single tanh layer. Furthermore, they are not affected by issues such as vanishing/exploding gradient descent.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 60, 50)            10400

 dropout (Dropout)           (None, 60, 50)            0

 lstm_1 (LSTM)               (None, 60, 50)            20200

 dropout_1 (Dropout)         (None, 60, 50)            0

 lstm_2 (LSTM)               (None, 60, 50)            20200

 dropout_2 (Dropout)         (None, 60, 50)            0

 lstm_3 (LSTM)               (None, 50)                20200

 dropout_3 (Dropout)         (None, 50)                0

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 71,051
Trainable params: 71,051
Non-trainable params: 0
_________________________________________________________________
```

Figure 4: **LSTM Model Building**

RESULT AND DISCUSSION

This prediction model relies heavily on memory. With its powerful memory, the LSTM network thoroughly analyzes every data point in historical data by delving deep into it. It makes use of its knowledge of previous sequences, correlations between characteristics, and hidden patterns to forecast the next value in the testing data. The LSTM keeps up this complex dance by giving its own forecasts back into the network to create a detailed chronology of expected Bitcoin prices.

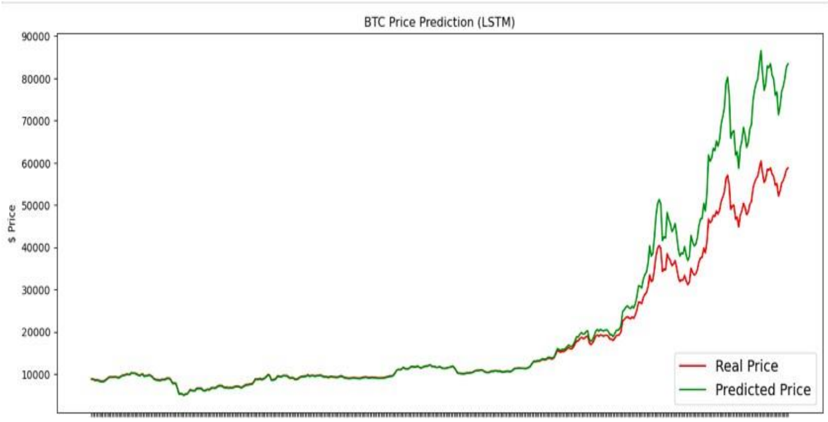

Figure 5: **LSTM prediction plot**

Figure 5: This indicates that the information pertains to a specific figure (most likely a graph or chart) numbered 11 within a larger document or presentation.

LSTM prediction plot: This suggests that the figure depicts the results of a prediction made using a Long Short-Term Memory (LSTM) network, a type of artificial neural network adept at handling sequential data. The plot likely visualizes the predicted values over time.

Error: Employing the deep learning proficiency, LSTM acquired pretty low root mean square error (RMSE) of **2.279**, indicated its grander capability in identifying the intricate patterns and predicting the volatility of Bitcoin.

CONCLUSIONS

Advantageous comprehensions have been multiplied into the underlying forces of the cryptocurrency business from our investigation of Bitcoin price forecast employing the LSTM models during the period 2018-22. Our conception of Bitcoin's price fluctuations has been heightened by the LSTM's capability to identify patterns and connections in time-series data over the long term. The important factors that influenced significantly the fluctuations of Bitcoin values were legislative changes, Market sentiments, macroeconomic trends and technical breakthroughs. Regardless of the promising predictive capacities of LSTM models, the intrinsic volatility and unpredictability nature of the cryptocurrency market proned towards impossibility for reliably estimating the price of Bitcoin. Though so many complexities convoluted, yet the study accentuates the capabilities of LSTM models in apprehending essential trends and temporal dependencies within the data of Bitcoin price. Additionally, our outcomes highlight the significance of integrating multiple data sources and filtering model designs to enrich prediction accuracy. Also, unrelenting progressions in machine learning techniques, combined with comprehensive data analysis, embrace potential for enlightening the accurateness of Bitcoin price predictions. Nevertheless, it is indispensible to identify the inherent risks and uncertainties connected to cryptocurrency investments and to workout caution when construing the outputs of predictive models. It can be concluded from this study that LSTM-based analysis affords valuable intuitions into Bitcoin price dynamics but, for cautious execution in cryptocurrency investments, it is necessary to have a complete understanding of risk management strategies and market fundamentals in addition to prediction from algorithm.

REFERENCES

Aggarwal, A., Gupta, I., Garg, N.,Goel, A. "Deep Learning Approach to Determine the Impact of Socio Economic Factors on Bitcoin Price Prediction", *2019 Twelfth International Conference on Contemporary Computing (IC3)*, pp. 1-5, 2019.

Ahmed, I., Jeon, G., & Piccialli, F. (2022). From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where. IEEE Transactions on Industrial Informatics, 18(8), 5031-5042.

Angelov, P. P., Soares, E. A., Jiang, R., Arnold, N. I., & Atkinson, P. M. (2021). Explainable artificial intelligence: an analytical review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 11(5), e1424.

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information fusion, 58, 82-115.

Babaei, G., Giudici, P., & Raffinetti, E. (2022). Explainable artificial intelligence for crypto asset allocation. Finance Research Letters, 47, 102941.

Carbó, J. M., & Gorjón, S. (2022). Application of machine learning models and interpretability techniques to identify the determinants of the price of bitcoin.

Chen, W., Xu, H., Lifen Jia, L., Gao, Y. (2020). Machine learning model for Bitcoin exchange rate prediction using economic and technology determinants. International Journal of Forecasting 37: 28–43.

Confalonieri, R., Coba, L., Wagner, B., & Besold, T. R. (2021). A historical perspective of explainable Artificial Intelligence. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 11(1), e1391.

Conrad, C., Custovic, A., Ghysels, E. (2018). Long- and Short-Term Cryptocurrency Volatility Components: A GARCH-MIDAS Analysis. J. Risk Financial Manag. 2018, 11, 23; doi:10.3390/jrfm11020023.

Das, A., & Rad, P. (2020). Opportunities and challenges in explainable artificial intelligence (xai): A survey. arXiv preprint arXiv:2006.11371.

Derbentsev, V., Datsenko, N., Babenko, V., Pushko, O., Pursky, O. (2020). Forecasting Cryptocurrency Prices Using Ensembles-Based Machine Learning Approach. 707-712. 10.1109/PICST51311.2020.9468090.

Došilović, F. K., Brčić, M., & Hlupić, N. (2018, May). Explainable artificial intelligence: A survey. In 2018 41st International convention on information and communication technology, electronics and microelectronics (MIPRO) (pp. 0210-0215). IEEE.

García-Medina, A.; Luu Duc Huynh, T. (2021). What Drives Bitcoin? An Approach from Continuous Local Transfer Entropy and Deep Learning Classification Models. *Entropy* , *23*, 1582. https://doi.org/10.3390/e23121582

Ghosh, I., & Jana, R. K. (2024). Clean energy stock price forecasting and response to macroeconomic variables: A novel framework using Facebook's Prophet, NeuralProphet and explainable AI. Technological Forecasting and Social Change, 200, 123148.

Goodell, J. W., Jabeur, S. B., Saâdaoui, F., & Nasir, M. A. (2023). Explainable artificial intelligence Modelling to forecast bitcoin prices. International Review of Financial Analysis, 88, 102702.

Gunning, D., & Aha, D. (2019). DARPA's explainable artificial intelligence (XAI) program. AI magazine, 40(2), 44-58.

Guo, H., Zhang, D., Liu, S., Wang, L., & Ding, Y. (2021). Bitcoin price forecasting: A perspective of underlying blockchain transactions. Decision Support Systems, 151, 113650.

Islam, S. R., Eberle, W., Ghafoor, S. K., & Ahmed, M. (2021). Explainable artificial intelligence approaches: A survey. arXiv preprint arXiv:2101.09429.

Jagannath, N., Barbulescu, T., Sallam, K.M., Elgendi, I., Okon, A.A. McGrath, B., Jamalipour, A., Munasinghe. K. (2021). A Self-Adaptive Deep Learning-Based Algorithm for Predictive Analysis of Bitcoin Price. IEEE Access 9: 34054–66.

Kenny, M. (2020). Investigating the Predictability of a Chaotic Time-Series Data using Reservoir Computing, Deep-Learning and Machine-Learning on the Short-, Medium-and Long-Term Pricing of Bitcoin and Ethereum.

Khedr, A., Arif, I., Pravija P.V., El-Bannany, M., Alhashmi, M., Sreedharan, M.. (2021). Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey. Intelligent Systems in Accounting, Finance and Management. 28. 10.1002/isaf.1488.

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., ... & Gašević, D. (2022). Explainable artificial intelligence in education. Computers and Education: Artificial Intelligence, 3, 100074.

Klein, T., Thu, H.P. & Walther, T. (2018). Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. International Review of Financial Analysis. 59. 105-116. 10.1016/j.irfa.2018.07.010.

Kristjanpoller, W. & Minutolo, M. (2018). A hybrid volatility forecasting framework integrating GARCH, Artificial Neural network, Technical Analysis and Principal Components Analysis. Expert Systems with Applications. 109. 10.1016/j.eswa.2018.05.011.

Kumar, N., Tripathi, P., Nanda, R.P., Tiwari, S., Sharma, S. (2024). Machine Learning for Smart Health Services in the Framework of Industry 5.0. In M. Khan, R. Khan, P. Praveen, A. R. Verma & M.K. Panda (Eds.), Infrastructure Possibilities and Human-Centered Approaches With Industry 5.0 (pp. 215-230). IGI Global.

Kumar, N., Agarwal, P., Gupta, G., Tiwari, S., Tripathi, P. (2024). AI-Driven Financial Forecasting: The Power of Soft Computing. In Bansal, S., Kumar, N., Agarwal, P. (Eds.), Intelligent Optimization Techniques for Business Analytics, pp. 146-170, IGI, Global, USA.

Lahmiri, S., & Bekiros, S. (2019). Cryptocurrency forecasting with deep learning chaotic neural networks. Chaos, Solitons & Fractals, 118, 35-40.

Lamothe-Fernández, P., Alaminos, D., Lamothe-López, P., Fernández-Gámez, M. (2020). Deep Learning Methods for Modelling Bitcoin Price. Mathematics. 8. 1245. 10.3390/math8081245.

Li, Y., & Dai, W. (2020). Bitcoin price forecasting method based on CNN-LSTM hybrid neural network model. The journal of engineering, 2020(13), 344-347.

Liu, Y., & Zhang, L. (2023, July). Cryptocurrency valuation: An explainable ai approach. In Science and Information Conference (pp. 785-807). Cham: Springer Nature Switzerland.

McNally, S., Roche, J., & Caton, S. (2018, March). Predicting the price of bitcoin using machine learning. In 2018 26th euromicro international conference on parallel, distributed and network-based processing (PDP) (pp. 339-343). IEEE.

Minh, D., Wang, H. X., Li, Y. F., & Nguyen, T. N. (2022). Explainable artificial intelligence: a comprehensive review. Artificial Intelligence Review, 1-66.

Mishra, R., Tripathi, P., Kumar, N. (2024). Future Directions in the Applications of Machine Learning and Intelligent Optimization in Business Analytics. In Bansal, S., Kumar, N., Agarwal, P. (Eds.), Intelligent Optimization Techniques for Business Analytics, pp. 49-76, IGI, Global, USA.

Nakano, M., Takahashi, A., Takahashi, S. (2018). Bitcoin technical trading with artificial neural network. Physica A: Statistical Mechanics and its Applications. 510. 587-609. 10.1016/j.physa.2018.07.017.

Nassar, M., Salah, K., ur Rehman, M. H., & Svetinovic, D. (2020). Blockchain for explainable and trustworthy artificial intelligence. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10(1), e1340.

Phaladisailoed, T. Numnonda, T. "Machine Learning Models Comparison for Bitcoin Price Prediction," *2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE)*, Bali, Indonesia, 2018, pp. 506-511, doi: 10.1109/ICITEED.2018.8534911.

Rai, M., Tyagi, N., Tripathi, P., Kumar, N., & Kumari, P. (2023). Advancement in Agricultural Techniques With the Introduction of Artificial Intelligence and Image Processing. In M. Khan, B. Gupta, A. Verma, P. Praveen, & C. Peoples (Eds.), *Smart Village Infrastructure and Sustainable Rural Communities* (pp. 47-68).

Rizwan, M., Narejo, S., & Javed, M. (2019, December). Bitcoin price prediction using deep learning algorithm. In 2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS) (pp. 1-7). IEEE.

Saxena, R., Dubey, D., Kaur, A., & Kaur, S. (2022). An Efficient Artificial Intelligence Model to Predict the Values of Cryptocurrencies. Mathematical Statistician and Engineering Applications, 71(4), 6351-6365.

Shin, M., David M., and Joongheon K. (2021). Bitcoin Price Forecasting via Ensemble-based LSTM Deep Learning Networks. Paper presented at 2021 International Conference on Information Networking (ICOIN), Jeju Island, Republic of Korea, January 13–16; pp. 603–8.

Tandon, S., Tripathi, S., Saraswat, P. Dabas, C. (2019). Bitcoin Price Forecasting using LSTM and 10-Fold Cross validation. Paper presented at 2019 International Conference on Signal Processing and Communication (ICSC), Noida, India, March 7–9; pp. 323–28.

Tjoa, E., & Guan, C. (2020). A survey on explainable artificial intelligence (xai): Toward medical xai. IEEE transactions on neural networks and learning systems, 32(11), 4793-4813.

Todorovska, A., Peshov, H., Rusevski, I., Vodenska, I., Chitkushev, L. T., & Trajanov, D. (2023). Using ML and Explainable AI to understand the interdependency networks between classical economic indicators and crypto-markets. Physica A: Statistical Mechanics and its Applications, 624, 128900.

Tripathi, P., Kumar, N., Paroha, K.K., Rai, M., Panda, M.K. (2024). Applications of Deep Learning in Healthcare in the Framework of Industry 5.0. In M. Khan, R. Khan, P. Praveen, A. R. Verma & M.K. Panda (Eds.), Infrastructure Possibilities and Human-Centered Approaches With Industry 5.0 (pp. 69-85).

Tripathi, P., Kumar, N., Rai, M and Khan, A. (2022) “Applications of Deep Learning in Agriculture” in Artificial Intelligence Applications in Agriculture and Food Quality Improvement, IGI Global, USA, pp 17-28.

Tripathi, P., Kumar, N., Rai, M., Shukla, P. K., & Verma, K. N. (2023). Applications of Machine Learning in Agriculture. In M. Khan, B. Gupta, A. Verma, P. Praveen, & C. Peoples (Eds.), *Smart Village Infrastructure and Sustainable Rural Communities* (pp. 99-118)

Ulumuddin, I., Sunardi, S., & Fadlil, A. (2020). Bitcoin Price Prediction Using Long Short Term Memory (LSTM): Bitcoin Price Prediction Using Long Short Term Memory (LSTM). Jurnal Mantik, 4(2), 1090-1095.

Vilone, G., & Longo, L. (2020). Explainable artificial intelligence: a systematic review. arXiv preprint arXiv:2006.00093.

Vilone, G., & Longo, L. (2021). Notions of explainability and evaluation approaches for explainable artificial intelligence. Information Fusion, 76, 89-106.

Walther, T., Klein, T., Bouri, E., 2019. Exogenous drivers of Bitcoin and Cryptocurrency volatility – mixed data sampling approach to forecasting. J. of International Financial Markets, Institutions and Money 63, 101133

Zaman, M. S. I., Kamal, M. I., Ishan, S. M., Khan, S. Z., & Hossain, S. (2021). Cryptocurrency price prediction and forecasting using machine learning algorithm and long-short term memory mapping (Doctoral dissertation, Brac University).

Zhang, D.H.; Lou, S. The application research of neural network and BP algorithm in stock price pattern classification and prediction. *Futur. Gener. Comp. Syst.* **2021**, *115*, 872–879.

Zhu, Q., & Ogunsakin, R. (2023, September). Towards Explainable AI: Relationship Between Twitter Sentiment, User Behaviour, and Bitcoin Price Prediction. In Intelligent Systems Conference (pp. 433-447). Cham: Springer Nature Switzerland.

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