ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/360042317

A Prediction Model for Bitcoin Cryptocurrency Prices

Chapter · January 2022

DOI: 10.1007/978-3-030-89546-4_7

CITATIONS
5

READS
397

4 authors:



Micheal Arowolo
University of Missouri
85 PUBLICATIONS **943** CITATIONS
SEE PROFILE



Peace Ayegba
Landmark University
19 PUBLICATIONS **162** CITATIONS
SEE PROFILE



Shakirat Ronke Yusuff
Kwara State University
3 PUBLICATIONS **10** CITATIONS
SEE PROFILE



Sanjay Misra
Institute for Energy Technology
854 PUBLICATIONS **11,525** CITATIONS
SEE PROFILE

All content following this page was uploaded by Sanjay Misra on 23 February 2023.

The user has requested enhancement of the downloaded file.

A Prediction Model for Bitcoin Cryptocurrency Prices

Micheal Olaolu Arowolo[1[0000-0002-9418-5346]], Peace Ayegba[2[0000-0002-0830-7811]], Shakirat Ronke Yusuf [3] and Sanjay Misra [4[0000-0002-3556-9331]]

[1,2] Department of Computer Science, Landmark University, Omu-Aran, Nigeria
[3] Department of Computer Science, Kwara State University, Malete, Nigeria.
[4] Department of Electrical and Information Engineering, Covenant University, Ota, Nigeria.
arowolo.olaolu@lmu.edu.ng; peace.ayegba@lmu.edu.ng;
shakirat.yusuff@kwasu.edu.ng;
Sanjay.misra@covenantuniversity.edu.ng

Abstract.

Cryptocurrencies like Bitcoin are a contentious and difficult technological innovation in today's financial system. With huge improvements in financial markets, machine learning and Artificial Intelligence aided trading have piqued interest in recent years. This study suggests a predicting model for blockchain bitcoin cryptocurrency prices and its profitability trading strategies using machine learning algorithms (ICA-Firefly and SVMs). For the prediction analysis of Bitcoin cryptocurrency data, this study combines ICA-Firefly with SVM algorithms. The model was tested on a large dataset of 2,194 samples, and its performance was analyzed in terms of evaluation metrics. In evaluation to state of the art, the ICA-Firefly with L-SVM and Sigmoid SVM classification approach performs well on the bitcoin sample dataset, with an accuracy of 95% and 97%, respectively. The ICA-Firefly with the SVM model can be adopted as a viable financial system sustainability management strategy.

Keywords: Blockchain, ICA, Firefly, SVM, Machine Learning.

1 Background of the Study

Owing to its potential applications in finance, stock chain management, and cybersecurity, blockchain is quickly gaining popularity. Significant advancement of blockchain technology has the latent for users to directly exchange ownership of digital resources (such as cryptocurrencies) to one another inside a dispersed and distributed peer-to-peer network lacking the assistance of a third party (e.g., financial institution). Transactions change the global state of the blockchain network by transferring ownership of resources. Respective transaction published to the blockchain network necessitates digital autographs by the user, using a digital signature technique [1]. Bitcoin is a decentralized virtual integrated financial management information solution that allows peer-to-peer transactions without any centralized authority. Cryptography is used to secure network transactions and liquidity. Presently, the system has a vibrant open-source community and payment network. Bitcoin's ecosystem is attracting a lot of

interest from enterprises, individuals, and financiers due to the distinct payment protocol and its rising popularity. To succeed, financial products and services that are presently accessible in our conventional, fiat money world must be replicated and customized to Bitcoin and other developing cryptocurrencies [2].

Among the most contentious and unclear breakthroughs in the current economic environment has been the rapid development of digital currencies during the last decade. The organization of the economy, capital industry, and payment systems are all changing as technology advances. Financial markets around the world have become more digitized than ever before, and a cashless society is on the horizon. People can now produce their own money (digital cryptocurrency) thanks to modern technology, and the role of central banks as lenders of last resort is being debated [3]. Bitcoin, like some other cryptocurrencies, is a finance phenomenon in which data is viewed as money. Users (referred to as "miners") transmit and receive cryptocurrencies (data) electronically from their workstations in peer-to-peer information systems to purchase goods and services if other parties are willing to accept these transactions. In 2019, the market valuation of 2957 cryptocurrencies and the number of miners hit $221 billion (Bitcoin $147) and 42 million, respectively. From its inception in 2009 to Late august 2020, the price of Bitcoin has risen dramatically, from $0.0008 to $10,168 per single coin [4].

Cryptocurrencies like Bitcoin are among the most contentious and difficult technological advancements in today's financial system. Given that Bitcoin is still an emerging technology with such a highly volatile market value, current valuation prediction models are scarce and ineffective in a production setting [5]. Investors in the Cryptocurrency market establish trust connections by creating Blockchains based on cryptography and hash algorithms. Bitcoin's inherent qualities, obtained from Blockchain technology, have sparked a wide range of analytical concerns, with economics and cybersecurity and machine learning [6]. Machine learning techniques are being used since they do not need explicit principles and divide datasets into training and testing sets for learning. It enables machines to "learn" and predict the future [7][8][9].

Several studies have lately been directed on modeling Bitcoin pricing as a growing market element with accurate, relevant rules. Machine learning techniques, for example, recurrent neural networks (RNNs) and long short-term memory (LSTM) are used to price bitcoin, and the results are compared to those obtained with autoregressive integrated moving average (ARIMA) models, among other studies on data analysis or economic characteristics and representations of Bitcoin prices relate directly to its features and functionality as a financial asset. They exhibit low predictive performance accuracy through binomial logistic regression, support vector machine, and random forest [9][10]. With the advancement of machine intelligence, forecasting Bitcoin has gained a lot of attention, a lot of studies have evolved yet more improvement needs to be carried out using machine learning algorithms for prediction of cryptocurrency system, in terms of the technical input parameters, existing continuous dataset, machine learning algorithms for forecasting the performance. To provide improved projections, many studies have been used in modeling and forecasting stock prices. This work is, in fact, a crucial phase in financial decision-making involving portfolio optimization, risk assessment, and trading. The use of machine learning to analyze and predict cryptocurrency prices is one of the hottest topics in financial markets.

This study uses an innovative strategy based on machine learning to predict the price of bitcoin cryptocurrency. In order to analyze the processes, an ICA with the Firefly method is used to choose relevant information from the given sample dataset and classify it using SVM kernels, the evaluation of the performance is investigated in terms of accuracy, sensitivity, specificity, among others.

The paper is structured in five sections. The next section discusses about the related works. Section 3 discusses on the materials and methods used. In Section 4, the results are discussed. Section 5 summarizes and discusses the conclusion of the paper.

2 Review of Related Works

Machine learning algorithms are being used for predicting Bitcoin price fluctuations [4], Artificial Neural Networks, Support Vector Machines, Naïve Bayes, and Random Forest, in addition to the logistic regression model, were used to evaluate algorithm performance utilizing continuous and discrete datasets. The results of the ANN, SVM, NB, and RF were compared to the results of the LR using the t-test. According to empirical studies, the RF has the best prediction accuracy in the continuous dataset, whereas the NB has the worst. However, the ANN has the best performance in the discrete dataset, and the NB has the worst. Also, the algorithms (models) evaluated the discrete dataset and enhanced overall predicting performance.

A micro-credit scoring method using machine learning was suggested [11], evaluating different machine learning techniques on actual fintech information to see how effective they are in categorizing debtors into different credit classifications. They showed that using readily available information about customers, off-the-shelf multiclass classifier like decision tree methods may do excellently (such as age, occupation, and location). This provides micro-lending organizations in developing countries with a low-cost and effective means to evaluate creditworthiness in the lack of credit record or centralized credit repositories.

The use of Google trends and keywords in a deep learning model for global financial prognostication was suggested [12]; using Google Trend for Internet searches, they looked at the relationship involving google movements and the Taiwan Weighted Stock Index. In the correlation test and the regression analysis, Google Trend's search terms volume was employed. The terms were then investigated in two studies: the first was machine learning, and the other was searching trends. Following empirical analysis, it was discovered that the neural network outperformed the support vector machine and decision trees in the experimental one. As a result, in the conducted test, the neural network was chosen in comparison with the search trend.

An empirical strategy to analyzing machine learning classification for stock markets was proposed [13]; through a series of exchange imitations in the FOREX marketplace, we examine the significance of simple machine learning models in achieving profitable trading. It assesses the models' effectiveness and the extent to which specific model parameters produce methodical trade projections. The use of extracting features, frequently occurring retraining, and training set size is addressed in to get a combination

of such parameters proficient with not only creating positive cumulative yields for machine learning models, and also demonstrating that simple algorithms initially prevented cash flow forecast. The study outlines how such an integration of features, in related to technological markers which have been used as input data to machine learning-based predictive variables, such like cost-based information, seasonal fluctuations characteristics, and lagged values used in classical time series analysis, can be used to improve classification capacities that directly affect ultimate profitability.

Over the use of machine learning techniques in significant financial and banking industries, a study and classification of neural networks in financial services was presented [14], including an emphasis on modeling preparation, inputs, and parameter estimation. Furthermore, relevant components that would have an impact on the outcomes of economic deep neural networks are examined. This study informs scientists and professionals about the state-of-the-art in the usage of machine learning techniques in investment banking.

Several cryptos prediction using machine learning and professional trading metrics [15], modeling cryptocurrency price increases with a neural network approach having lowest method damage of over 100 epochs in training and Technical Trade Pointers charts that depict a actual BTC price of 5 to 10 times in 300 days of the recent economic year has bolstered trader confidence and shifted the universal cryptocurrency chart by predicted BTC values. In a similar vein, employing Machine Learning and Sentiment Analysis to analyze bitcoin pricing. They looked at stock market movements to see whether they could forecast bitcoin prices quantitatively. In addition, researchers investigated the impact of international currencies, including the American dollars and currency exchange rates on Bitcoin rates, including whether Bitcoin really does have the consistency to depose world monetary systems and be the sole monetary system. The research seemed to be satisfactory to assist in prediction models, with findings acquired that indicate an accuracy to predict price of bitcoin and to use a machine learning-based neural network obtaining an accuracy of 94.89 % in all constraints of conceptual market sign during estimation, significantly reducing its current value over 13.7 % 2020 solely.

Machine learning is used to predict and trade cryptocurrencies amid shifting economic conditions [16], The predictability of significant cryptocurrencies such as Bitcoin, Ethereum, and Litecoin, and also the financial performance of investment strategies based on machine learning, are explored in this research (e.g., linear models, random forests, and support vector machines). The results are developed in a time of profound upheaval and evaluated in a time frame of market corrections, enabling for evaluation of whether the estimations are accurate and when business trajectory shifts among analysis and testing. The classification and regression methodologies utilize buying and selling and network connections qualities from August 2015 to March 2019, with the sample test starting in April 2018. Five of the 18 specific models tested had less than 50% success rates during the testing period. The exchange strategies depend on the assembly of models. For Ethereum and Litecoin, the ensemble that assumes five models yield undistinguishable signs (Ensemble 5) and attains the best results, with annualized Sharpe ratios of 80% and 91%, respectively, and annualized revenues (subsequently relative round-trip exchange costs of 0.5%) of 9.62% and 5.73%. These

encouraging findings back up the claim that machine learning can be used to investigate the predictability of cryptocurrencies and devise profitable trading strategies in these markets, even in the face of adversity.

Multiple machine learning technologies for predicting cryptocurrency price complexities were suggested [17], The case diagram of cryptocurrencies is incredibly complicated, predicting the future hard. They used two popular machine learning algorithms, the adequately Artificial Neural Network and the Long-Short-Term-Memory, to model the value of numerous prevalent cryptocurrencies and Bitcoin, Ethereum, Ripple, Stellar Lumens, Litecoin, and Monero, in this study. They analyzed the model's performance and proceeded to run an analysis to learn more about our model's performance. They discovered that, while LSTM appears to be more relevant for time sequence prediction problems, ANN outperforms LSTM in general in our experiments. The use of price data from other cryptocurrencies for simultaneous training and prediction could make BTC prediction much easier. Furthermore, the predictive inaccuracy of the model is greatly dependent on the time scale of interest.

Data analysis in crypto exchanges was proposed [18], proposing a retraining machine learning-based actively traded model and applying it to five main cryptocurrencies in flux; they showed how, compared to a purchase strategy, this model generates greater risk returns and lowers downside risk. When actual transaction costs are taken into account, these conclusions hold true. They concluded that the model could be used in real-world asset management, but efficiency will vary depending on how it will be validated in test samples.

Financial markets and machine learning for cryptocurrency were suggested [19], determining how machine learning is used in the financial markets Despite the fact that much artificial intelligence research has been published, they are concentrating on recent financial market studies with possible applicability to blockchain-based cryptocurrencies. While different machine learning techniques have varied goals, they all aim to make money and anticipate future pricing. Their conclusion demonstrates the advantages of employing such models to account for a variety of financial market occurrences. They come to the conclusion that artificial intelligence techniques for financial markets, namely machine learnings, cannot acquire all features of the given data in the same way that general artificial intelligence can. As a result, depending on the dataset's structure and hierarchy, it's only natural to choose a desirable strategy. In addition, the researcher's perspective on the market influences the approach he or she takes.

Machine learning-based models for bitcoin value predictions was proposed [20], by evaluating the efficiency of one-stage methodologies based on a single machine learning approach, such as the Bayesian Neural Network, Feed Forward, and Long Short Term Memory Neural Networks, and two-stage bases constructed by the neural networks listed above in succession to Support Vector Regression. The results show that the two-stage frameworks outperform the corresponding one-stage frameworks, except for the Bayesian Neural Network. The performance of the one-stage Bayesian Neural Network system is the best, and the demand of magnitude of the mean absolute percentage error calculated on the anticipated value by this framework agrees with those provided.

Using machine learning to analyze cryptocurrency values was proposed [21], this method was presented to test the notion that the bitcoin market's inefficiencies might be used to produce extraordinary gains. Between November 2015 and April 2018, they examined daily data for 1681 coins. They showed that established benchmarks are outperformed by simple trading techniques aided by cutting-edge machine learning methods. Their findings suggest that nontrivial but ultimately straightforward algorithmic processes can aid in forecasting the bitcoin market's short-term evolution.

Predicting with deep learning in cryptocurrency elevated trades was suggested [22], With 65,535 samples, they used a deep forward neural network (DFFNN) to analyze and forecast Bitcoin high-frequency price data. To see how standard numerical training procedures, such as the conjugate gradient with Powell-Beale resumes, the robust method, and the Levenberg-Marquardt method, affect the accuracy of DFFNN. The simulation findings demonstrate that DFFNN trained with the Levenberg-Marquardt significantly outperforms DFFNN trained with Powell-Beale restarts and DFFNN trained with robust methods when using root mean squared errors (RMSEs). Furthermore, the robust method is quick, implying that it could be useful in online training and trading.

A review of huge developments and research gaps in blockchain-enabled IIoT networks supervised learning in blockchain-enabled IIoT networks was conducted [23]; though blockchain-enabled IIoT networks have the ability to meet the services and expectations of next-generation networks, the gap study offered in this paper identifies key areas that require development. The essay then proposes the use of reinforcement learning (RL) approaches to resolve some of the major difficulties of blockchain-enabled IIoT networks, for example, block time minimization and transaction throughput enhancement, based on these discoveries. A complete case study follows, in which a Q-learning methodology is utilized to reduce the transmission delays for a miner, hence limiting the occurrence of forking occurrences. Extensive simulations were carried out, and the results for the average transmission delay relating to forking events were obtained. The collected findings show that the Q-learning strategy beats the greedy policy while remaining relatively simple. Some future research directions are also documented in order to further create blockchain-enabled IIoT networks. While this research focuses on the use of RL approaches in blockchain-enabled IIoT networks, the insights and results presented could help accelerate the adoption of blockchain technology.

A targeted anomaly detection method based on machine learning for efficient blockchain transaction authentication was proposed [1]. Digitally signed transactions are used to store blockchain-related data in distributed ledgers. Its ledger data is saved once users with digital identities conduct a digital signing process. This procedure takes a long time and is not user-friendly. This paper presents a machine learning-based solution for automating the signing of blockchain transactions, as well as tailored anomaly detection. For testing the performance, an experiment and analysis were conducted using data from the Ethereum public main network, with positive findings paving the way for future integration of such a mechanism in specialized digital signing software for blockchain transactions.

The limitations of machine learning integration in blockchain-based smart technologies, and a way forward [24]. Blockchain technology (BT) has emerged as a one-of-

a-kind, disruptive, and trending technology. Data security and privacy are prioritized in BT's decentralized database. It also has a consensus system that ensures data security and legitimacy. Nonetheless, it introduces new security concerns, such as majority attack and double-spending. Data analytics on blockchain-based secure data is required to address the aforementioned concerns. The value of emerging technology Machine Learning is highlighted through analytics on these data (ML). To create precise choices, machine learning uses a reasonable amount of data. In order to improve the accuracy of outcomes, data reliability and exchange are critical. When these two technologies (ML and BT) are combined, they can produce extremely exact results. We give a detailed analysis on machine learning adoption for making BT-based smart applications more resilient to attacks in this paper. Support Vector Machines (SVM), clustering, bagging, and Deep Learning (DL)algorithms like Convolutional Neural Network (CNN) and Long short-term memory (LSTM) can all be used to analyze assaults on a blockchain-based network. They also discussed how knowledge could be utilized in various smart applications, including unmanned aerial vehicles (UAVs), smart grids, healthcare, and smart cities.

Security and privacy for blockchain technology in cyber-physical systems utilizing artificial intelligence: technologies, approaches, and issues were suggested [25], Blockchain (BC) and Cyber-Physical Systems (CPS) applications are growing at a rapid pace. However, because of the intricacy involved, defining durable and correct smart contracts (SCs) for these smart applications is a difficult undertaking. Traditional industrial, technological, and business processes are being modernized by SC. It is self-executing, self-verifiable, and fixed into the BC, obviating the necessity for trustworthy third-party systems and, as a result, saving both administration and service expenses. It also increases system efficiency while lowering security risks. SCs, on the other hand, are enthusiastic about Industry 4.0's new technology innovations, but there are still a number of security and privacy concerns to be solved. A study of SC security flaws in software encryption that might be readily hacked by a hostile operator or franchise the whole BC network is described in this study. According to the literature, the difficulties of SC safety and discretion are not well examined by investigators. According to the prevailing recommendations, constructing a complicated SC will not be able to address the privacy and security concerns. As a result, this study looks into several Artificial Intelligence (AI) methodologies and methods for protecting SC privacy. Then, for AI-based SC, open topics and problems are examined. Finally, a retail marketing case study was proposed, which employs AI and SC to maintain security and privacy.

Networking systems for blockchain and machine learning were suggested [26]. Infrastructural facilities, services, edge devices, and programs in communication and networking systems have become increasingly complex and varied as information and communication technologies advance at a breakneck pace. Furthermore, the vast amount of data and end devices could pose major privacy, security, service delivery, and network security issues. The combined evaluation of blockchain and machine learning with considerable profits has piqued the interest of both academics and industry to achieve distributed, encrypted, smart, and modern information systems management and operation. On the one hand, blockchain can greatly facilitate the sharing of training data and machine learning models and decentralized intelligence, security,

privacy, and trustworthy Computational decision-making. On the other side, machine learning will have a big impact on the advancement of blockchain in infrastructures and networking systems, especially in terms of energy and resource competence, scalability, safety, confidentiality, and intelligent smart agreements. However, numerous critical outstanding issues and problems, such as resource management, data processing, scalable operation, and security concerns, must be resolved before the widespread use of blockchain and machine learning. They offered a survey of existing works on the block chain and machine learning technologies in this paper. We identify numerous key characteristics of combining blockchain and machine learning, including an overview, benefits, and applications. Then we go over some of the open topics, obstacles, and broad views that must be solved in order to explore blockchain and machine learning for communications and networking systems together.

Integration of blockchain, IoT, and machine learning in industrial automation for multistage quality safety and access was carried out [27]. The demand for predictive equipment reliability and quality is driving the growth of smart manufacturing systems. To that goal, a variety of machine learning techniques are being investigated. Data security and management is another issue that is becoming increasingly significant in the industry. To address the issues raised above, we used a combination of blockchain and machine learning techniques to protect system transactions and handle a dataset to combat the false dataset. Big data approaches were employed to organize and evaluate the obtained dataset. The private Hyperledger Fabric platform was used to create the blockchain system. Consequently, the hybrid prediction methodology was used to assess the fault diagnosis prediction component. The system's worth control was assessed using non-linear machine learning techniques, which represented the complex environment and determined the genuine positive rate of the quality control methodology used by the system.

Machine learning-based prediction of the bitcoin prices in a short period was proposed [28]. They looked at the bitcoin market's predictability over time horizons ranging from 1 to 60 minutes. They investigated a variety of machine learning models and discovered that, while all models outdo a random classifier, recurrent neural networks and gradient boosting classifiers are particularly well-suited for the prediction tasks under consideration. They employed a diverse feature set that included technical, blockchain-based, sentiment/interest-based, and asset-based elements. Their findings suggest that for most techniques, technical factors are the most important, followed by selected blockchain-based and sentiment/interest-based elements. They also discovered that predictability improves with longer prediction horizons. Although a quantile-based long-short trading strategy generates monthly profits of up to 39% before transaction costs, after transaction costs are factored in, the approach provides negative returns due to the extremely short holding periods.

Predictions of the Ethereum blockchain cryptocurrency value in a system of economic financing were suggested [29]. In the last decade, cryptocurrency has grown in popularity. Cryptocurrency's untraceable and uncontrollable nature appeals to millions of people all over the world. The goal of cryptocurrency research is to locate the ether and anticipate its price based on the coin's previous price inflations. Using a time series of daily ether cryptocurrency closing prices, price prediction is accomplished using two

machine learning algorithms, namely linear regression (LR) and support vector machine (SVM). By applying filters with varying weight coefficients, multiple window lengths are used in ether cryptocurrency price prediction. A cross-validation method is used in the training phase to build a high-performance model that is independent of the data set. Two machine learning approaches are used to implement the suggested model. The SVM approach has greater accuracy (96.06%) than the LR approach when utilizing the proposed model (85.46%). Furthermore, by adding features to the SVM approach, the proposed model's accuracy score can be enhanced to 99%.

3 Materials and Methods

3.1 Blockchain, Cryptocurrency, and Bitcoin

Blockchain has sparked an influx of intrigue in both academia and industry. As a decentralized, immutable, shareable, and time-ordered ledger, it is a new technology. Transactions are saved in blocks with timestamps and references (i.e., the hash of the previous block) that are kept in a chain. Transactions, which indicate money transfers, are generated by anonymous individuals and competitively gathered by a worker to construct a new block in Bitcoin. The worker who creates a fresh and valid block can earn a reward, so the chain is continually lengthened by workers [30].

The blockchain systems, including Bitcoin and Ethereum, vary in various ways, including transaction mechanism and latency. The advantage of using this approach is that you can rest assured that the information you store is safe. Blockchain technology is the primary means of achieving this goal, as it distributes digital information lacking granting copy permission and administers the time-stamp dataset in the network that connects the services and the system. The permissioned blockchain will be used to achieve this strategy [27]. In present networks, blockchain opens up new possibilities for coordinating several untrustworthy parties and enabling decentralized governance. The following are the main characteristics of blockchain: decentralization, transparency, immutability, security, suitability, anonymity, and autonomy [26]. Since growing Blockchain size corresponds with more investors conducting Bitcoin transactions, and Bitcoin market price is highly driven by consumer demand and interest, we selected blockchain size as a useful representative feature for our model.

Cryptocurrency is digital money that uses encryption to ensure that network transfers and exchanges are secure. As one of the most well-known cryptocurrencies, Bitcoin creates a distributed ledger that is preserved through a network. Decentralization is one of the most fundamental characteristics of Bitcoin, which distinguishes it from centralized, traditional currencies in that Bitcoin transactions and management are not governed by any central body. As a result, people solely trade between customers and vendors, rather than relying on a third-party trusted platform or other financial institutions. Bitcoin is also secure thanks to cryptographic encryption technology. Even if some information is unnecessary, all transaction information is logged and cannot be changed [17].

Bitcoin (₿) is a sort of electronic money that is based on digital currency. It is a distributed advanced exchange without a central bank or a solitary chairman that can

be directed from one client to another across the Bitcoin network without the necessity for a middleman. System hubs use cryptography to verify exchanges, which are then stored in an openly disseminated record known as a blockchain. Bitcoin was created by an unidentified individual or cluster of persons under the name Satoshi Nakamoto and unconfined as open-source programming in 2009. Bitcoins are created as a reward for performing a task known as mining. They can be applied to a variety of financial structures, items, and organizations. According to research by the University of Cambridge, there were 2.9 to 5.8 million notable clients using a digital currency wallet in 2017, with the most of them using Bitcoin [31].

3.2 Dataset

In this investigation, one of the most popular blockchain currencies in existence, bitcoin (BTC), was used with a sampling period from June 2015 to June 2021 (1447 data points) and was obtained from the Yahoo finance current data for bitcoin from the Coin Market Cap website [32]. The dataset includes the day-to-day price in US dollars, market capitalization, and the trading volume for 2,194 cryptocurrencies, where market capitalization is the merchandise of price and circulating stock, with the volume number of coins traded every day. Figure 1 shows the Bitcoin current Price data.

Date	Open	High	Low	Close*	Adj. close**	Volume
02-Jun-2021	36,628.57	37,906.16	36,036.41	37,906.16	37,906.16	32,08,28,98,944
01-Jun-2021	37,293.79	37,896.73	35,787.09	36,684.93	36,684.93	34,63,94,23,297
31-May-2021	35,658.59	37,468.25	34,241.95	37,332.86	37,332.86	39,00,98,47,639
30-May-2021	34,607.41	36,400.67	33,520.74	35,678.13	35,678.13	31,64,60,80,921
29-May-2021	35,684.16	37,234.50	33,693.93	34,616.07	34,616.07	45,23,10,13,335
28-May-2021	38,507.08	38,856.97	34,779.04	35,697.61	35,697.61	55,20,01,91,952

Fig. 1. Bitcoin Current Price Data

3.3 Machine Learning, Independent Component Analysis (ICA), Firefly Algorithm and Support Vector Machine Classifier

3.3.1 Machine Learning

In the last 15 years, machine learning has become one of the most rapidly increasing technologies. It has a wide variety of applications in industries, for example, computer vision, bioinformatics, business analytics, healthcare, finance, fraud detection, and trend prediction, to name a few. Machine learning is a technique that permits a computer to learn from large data samples and predict patterns in the data. In various study fields, machine learning algorithms are used to anticipate and classify test data in order to produce reliable results. Machine Learning classifier models are becoming increasingly popular, and they have proven to be extremely useful in a variety of financial datasets [33][8].

To aid with executive and business decisions, machine learning algorithms are employed to extract important dataset patterns. Because it can infer data associations that are frequently not readily visible by humans, machine learning is an effective technique for designing Bit-coin and other cryptocurrency trading techniques [34]. Machine Learning, at its most basic level, is based on the definition of two fundamental components: input features and objective function. Dimensionality reduction techniques like Independent Component Analysis and Firefly can drastically reduce the time complexity of the training phase of machine learning algorithms, lowering the strain on the algorithms [35]. The primary goal of this research is to see how dimensionality reduction techniques affect the performance of the commonly used Support Vector Machine classifier with the Bitcoin Blockchain price prediction from Yahoo Finance.

3.3.2 Independent Component Analysis (ICA) Algorithm

ICA is considered an extension of the principal component analysis (PCA) approach. On the other hand, ICA optimizes higher-order statistics like kurtosis, while PCA optimizes the data's covariance matrix, which represents second-order statistics. As a result, PCA identifies uncorrelated components, whereas ICA identifies independent components. As a result, when the higher-order correlations of mixture data are minimal or insignificant, PCA can recover separate sources. Fast-ICA, projection pursuit, and Infomax are only a few of the ICA algorithms. These algorithms' main purpose is to extract independent components by; maximizing non-Gaussian, reducing mutual information, or employing the maximum likelihood (ML) estimation approach. However, ICA has a number of flaws, including over-complete and under-complete ICA [36].

Independent component analysis is a technique for recovering the original independent variables from observations that have been transformed linearly. The majority of ICA methods are formulated as an optimization of a contrast function that minimizes component cross-dependency [37]. The observable stochastic signal x is assumed to obey the model $x = As$, where s is the unidentified source signal, its components are independent of one another, and A is an unknown mixing matrix. The ICA's objective is to estimate the mixing matrix A and the source signal s solely by looking at x.

3.3.3 Firefly Algorithm

The Firefly algorithm uses flashing lights to simulate the mating system and data. The behavior of fireflies, binary fireflies, the artificial Firefly algorithm, and the Firefly algorithm are explored. There are about 2,000 kinds of fireflies on the planet, and the great majority of them produce brief, pattern flames. The interest of accomplices in mating, such as correspondence, potential, and a component of mechanism, is the major cause of this debt.

Most fireflies can only be seen at a given distance, away from the bat, due to two factors: the brightness of a source at a specific distance conforms to the law of the opposing square, implying that the power of light with expansion decays somewhere $I \propto /1/r^2$. The assimilation of light, which is recognized surrounding it, is the next factor, which reduces the force as the separation rises.

The Firefly algorithm is a "nature-inspired" algorithm that is based on flies' behavior. Nature-inspired algorithms are widely employed in the machine learning process at various stages. The natural lights that fireflies emanate from their bodies aid them in attracting or finding other flying mates. It also aids them in catching prey and defending themselves against predators. Three main assumptions underpin the algorithm [38] [39]:

i. The Firefly Algorithm is a versatile capacity that promotes population growth's advantages.
ii. The Firefly Algorithm can effectively deal with multi-model problems in a few steps by dividing the population and gradually limiting the vision of each leaflet to provide them subdivisions in the study region.
iii. Setting random and enchantment limits for the FA throughout the stress cycle can boost the calculation's collection rate.

This algorithm 1's core architecture is as follows:

Algorithm 1: Firefly Pseudocode

```
Input: X = Sample populations of Fireflies
       X Iterations = Samples of Optimizing the Iterations
       β0 = attraction criterion
       ∝ = criterion selection
Output: Best Fireflies Algorithm fit
       create a colony of x fireflies using the arbitrary firefly algorithm
       identify the optimal fitness-related option
       While stop parameters not met do
          For individual Firefly a do
          For individual Firefly b do
             If Firefly b is better than Firefly a then
                Move Firefly a to Firefly b
                   Update Intensity of Firefly
                End
                   Evaluate each Firefly best stand
                End
          End
       Loop
```

3.3.4 Support Vector Machine (SVM)

The SVM was created to solve complicated pattern recognition problems. For two-dimensional classification, SVMs were provided, and for high-dimensional difficulties, they were improved [40][41]. SVM (Support Vector Machine) is a discriminative classifier that creates a separating hyper-plane. In the case of inseparable class data, an error tolerance budget is introduced to make the separating hyperplane robust. Kernel

implementation transforms linear decision boundaries into more complicated boundary shapes (e.g., polynomial, Gaussian and radial kernel). SVMs have gotten a lot of attention because of their remarkable classification performance.

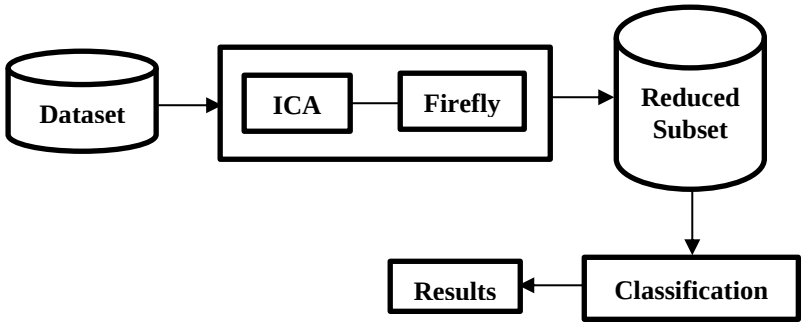


Fig. 2. Model Workflow of the Study

3.4 Evaluation Metrics for the Model and the System Configuration

The performance of the suggested model using ICA-Firefly with SVM classification for blockchain bitcoin price prediction was assessed using some assessment indicators. The most basic evaluation metric is accuracy, which is a percentage of correctly identified messages, among additional metrics like sensitivity, specificity, recall, precision, and f-score [7][42].

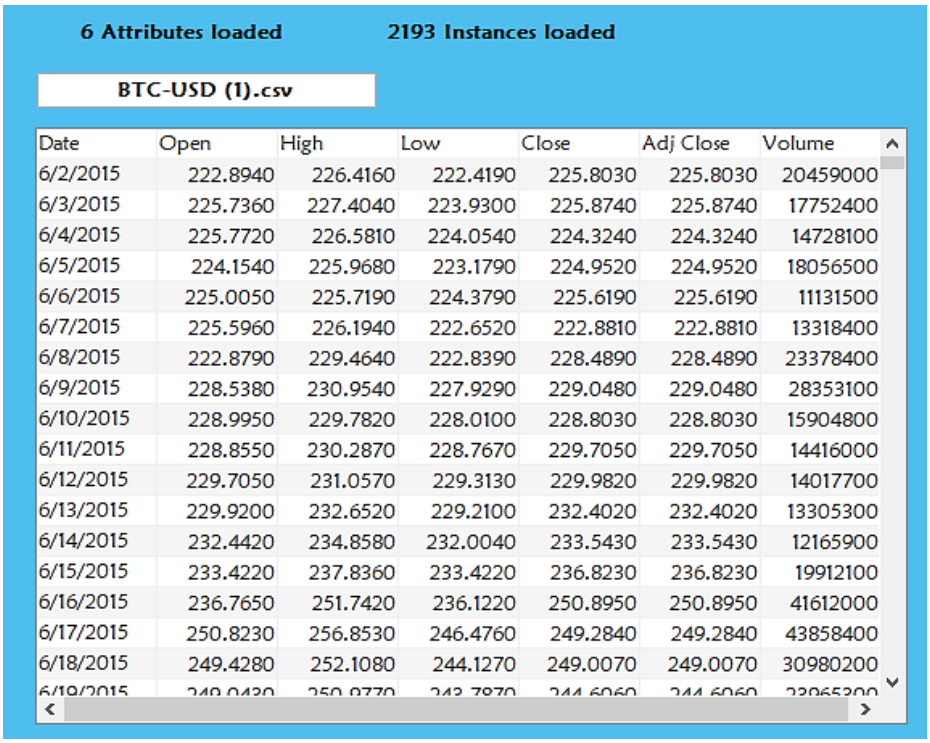
The Yahoo Finance repository provided access to the Blockchain BTC dataset. As a result, the suggested research is carried out on the MATLAB environment. The MATLAB platform's significantly increased computational power and data handling capabilities aided in processing dataset inputs for the application of machine learning algorithms.

4 Results and Discussions

An ICA-Firefly algorithm was used to generate a prediction for Blockchain bitcoin price prediction in this study. The data sets were divided into two portions in the proposed models: training and testing. The proposed models with six attributes were built using a total of 2193 sample data; Figure 3 shows the dataset features. By comparing the corresponding values of the evaluation performance, the models' performances were determined. An adaptive search technique employing the ICA-Firefly algorithm is applied to overcome missing data in a dataset and select the most appropriate imputation value. The general result demonstrated that the model algorithm is an efficient methodology based on the simulation results from the datasets employed.

Figures 4 and 5 shows confusion matrix of how the Linear SVM and Sigmoid SVM classifiers performed on the Blockchain Bitcoin Price dataset when combined with the

ICA-Firefly algorithms. Performance evaluations in terms of accuracy, sensitivity, and specificity, among other metrics, are the most commonly used metrics to analyze the performance of machine learning algorithms. The evaluation metrics of the proposed ICA-Firefly and SVM kernel classification models are compared in Table 1.



6 Attributes loaded **2193 Instances loaded**

BTC-USD (1).csv

Date	Open	High	Low	Close	Adj Close	Volume
6/2/2015	222.8940	226.4160	222.4190	225.8030	225.8030	20459000
6/3/2015	225.7360	227.4040	223.9300	225.8740	225.8740	17752400
6/4/2015	225.7720	226.5810	224.0540	224.3240	224.3240	14728100
6/5/2015	224.1540	225.9680	223.1790	224.9520	224.9520	18056500
6/6/2015	225.0050	225.7190	224.3790	225.6190	225.6190	11131500
6/7/2015	225.5960	226.1940	222.6520	222.8810	222.8810	13318400
6/8/2015	222.8790	229.4640	222.8390	228.4890	228.4890	23378400
6/9/2015	228.5380	230.9540	227.9290	229.0480	229.0480	28353100
6/10/2015	228.9950	229.7820	228.0100	228.8030	228.8030	15904800
6/11/2015	228.8550	230.2870	228.7670	229.7050	229.7050	14416000
6/12/2015	229.7050	231.0570	229.3130	229.9820	229.9820	14017700
6/13/2015	229.9200	232.6520	229.2100	232.4020	232.4020	13305300
6/14/2015	232.4420	234.8580	232.0040	233.5430	233.5430	12165900
6/15/2015	233.4220	237.8360	233.4220	236.8230	236.8230	19912100
6/16/2015	236.7650	251.7420	236.1220	250.8950	250.8950	41612000
6/17/2015	250.8230	256.8530	246.4760	249.2840	249.2840	43858400
6/18/2015	249.4280	252.1080	244.1270	249.0070	249.0070	30980200
6/19/2015	249.0430	250.9770	243.7870	244.6060	244.6060	23965300

Fig. 3. The Dataset Features

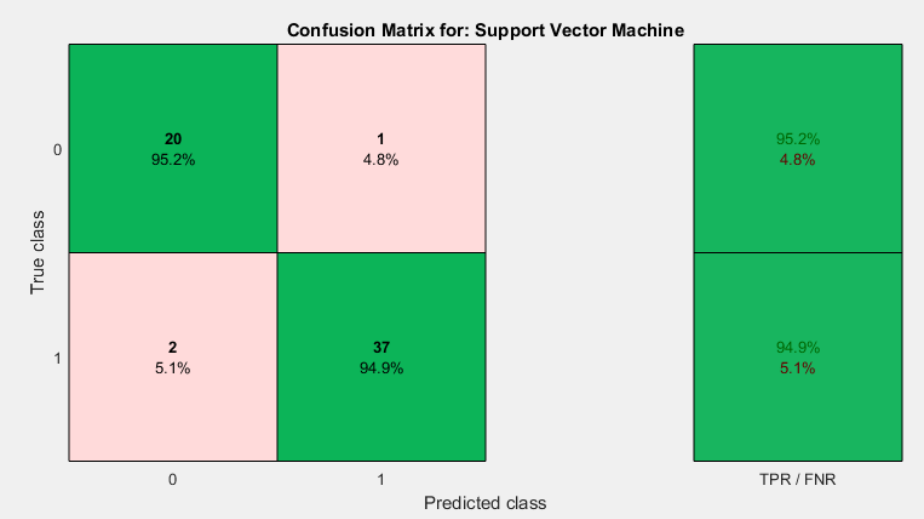


Fig. 4. ICA-Firefly with L-SVM Classification TP=37 TN=20 FP=2 FN=1

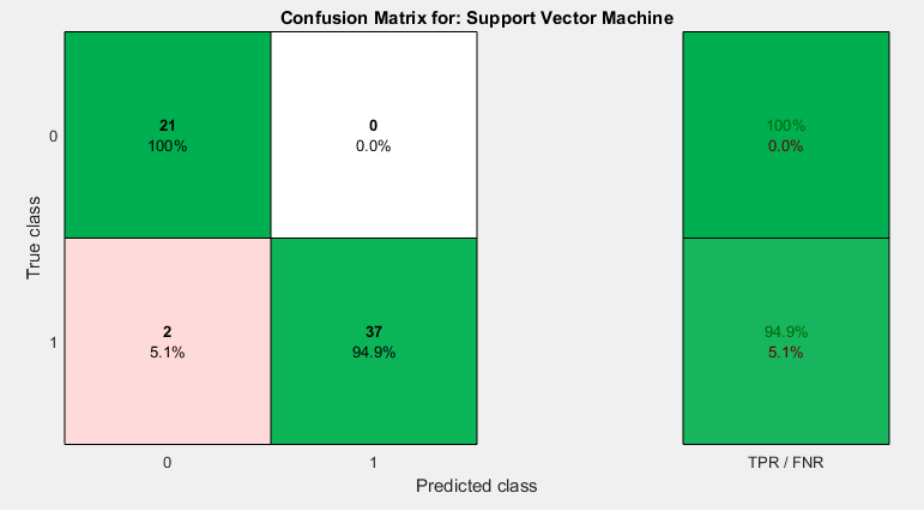


Fig. 5. ICA-Firefly with L-SVM Classification TP=37 TN=21 FP=2 FN=0

Table 1. Performance Evaluation.

Performance Metrics (%)	ICA-Firefly-L-SVM (%)	ICA-Firefly-Sigmiod-SVM (%)
Accuracy	95.00	96.67
Sensitivity	97.37	100
Specificity	90.91	91.30
Precision	94.87	94.87

F1-Score	96.1	97.37
Matthews Correlation Coefficient	89.19	93.07

Table 1 summarizes the findings of this study's experimentation. SVM kernels were used further to investigate the performance of ICA-Firefly on the datasets. The Sigmoid SVM outperformed the LSVM by around 97% Accuracy. Several studies have been conducted in literature; Table 2 compares the results of this study with existing models.

The effects of using ICA-Firefly for dimensionality reduction were measured in this study. The components of ICA-Firefly were utilized to forecast BTC price increases and decreases by capturing variances in the data. The categorization models, on the other hand, outperformed various other models shown in Table 2. For example, the accuracy of Sigmoid SVM was 97%, and L-SVM was 95%. The classification metrics revealed that Sigmoid-SVM is quite similar to the models in Table.

Table 2**.** Comparison with Existing Models.

Authors	Work Done	Accuracy Results (%)
Mohammed et.al., [43]	ANN, SANN, SVM and LSTM	65
Yan and Dai., [44]	CNN-LSTM	64
Sebastiao and Godinho, [16]	linear models, RF, and SVMs	80.17
Zhengyang et.al., [17]	Artificial Neural Network (ANN) and the Long-Short-Term-Memory (LSTM)	90

The increase and decrease of the price, as well as the factual price, are two components of the BTC pricing model. Internal and external criteria were used to classify the increase/decrease in BTC price in this study. BTC prices are stochastic, and no single set of characteristics can be used to predict the future. Nonetheless, researchers have had varying degrees of success estimating BTC values based on various feature sets. We have included characteristics that are directly related to the blockchain in this article. If numerous individuals are using it for transactions, then the relevant features such as dynamic addresses and number of transactions would be high.

5 Conclusion

BTC price estimates utilizing Machine models were carried out in this study using BTC price estimates from 2015 to 2021. The best overall performance was achieved with ICA-Firefly with SVM kernels and ICA-Firefly algorithm with Sigmoid SVM. All of the models developed are satisfactory and perform well, with classification models recording up to 97% accuracy for next-day forecasting. The findings show that the

provided models are unproductive and undependable cryptocurrency price forecasters, owing to the complexity of the problem, which even advanced deep learning techniques like LSTM and CNNs are unable to address efficiently. According to our findings and investigations into the cryptocurrency pricing problem, cryptocurrency prices follow a nearly random walk process, with a few underlying patterns that an intelligence framework must uncover in order for a prediction model to create accurate and dependable projections. As a result, novel algorithmic methodologies, alternative methodologies, and new validation measures should be investigated.

The findings reveal that while it is easy to estimate the real BTC price with very low error rates, forecasting its rise and decrease is far more difficult. The performance scores for the classification models offered are the top in the works. Having said that, more research on Bitcoin classification models is required. Hourly BTC prices and technical indicators, as well as Decision tree models that mix several types of models for forecasting, could be used in future work. Artificial intelligence can be used to model the price of cryptocurrencies as a basis for calculating the risk issue associated with the financial use of blockchain technology.

References

1. Podgorelec, B., Turkanović, M., Karakatič, S.: A Machine Learning-Based Method for Automated Blockchain Transaction Signing Including Personalized Anomaly Detection. Sensors. 20, 147 (2019). https://doi.org/10.3390/s20010147.
2. Żbikowski, K.: Application of Machine Learning Algorithms for Bitcoin Automated Trading. Presented at the (2016). https://doi.org/10.1007/978-3-319-30315-4_14.
3. Gulihar, P., Gupta, B.B.: A Taxonomy of Bitcoin Security Issues and Defense Mechanisms. In: Machine Learning for Computer and Cyber Security. pp. 209–232. CRC Press, Boca Raton, FL : Taylor & Francis Group, [2019] | "A science publishers book." (2019). https://doi.org/10.1201/9780429504044-9.
4. Pabuçcu, H., Ongan, S., Ongan, A.: Forecasting the movements of Bitcoin prices: an application of machine learning algorithms. Quant. Financ. Econ. 4, 679–692 (2020). https://doi.org/10.3934/QFE.2020031.
5. Li, X., Wang, C.A.: The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. Decis. Support Syst. 95, 49–60 (2017). https://doi.org/10.1016/j.dss.2016.12.001.
6. Casino, F., Dasaklis, T.K., Patsakis, C.: A systematic literature review of blockchain-based applications: Current status, classification and open issues. Telemat. Informatics. 36, 55–81 (2019). https://doi.org/10.1016/j.tele.2018.11.006.
7. Arowolo, M.O., Adebiyi, M.O., Ariyo, A.A., Okesola, O.J.: A genetic algorithm approach for predicting ribonucleic acid sequencing data classification using KNN and decision tree. TELKOMNIKA (Telecommunication Comput. Electron. Control. 19, 310 (2021). https://doi.org/10.12928/telkomnika.v19i1.16381.
8. Alabi, K.O., Abdulsalam, S.O., Ogundokun, R.O., Arowolo, M.O.: Credit Risk Prediction in Commercial Bank Using Chi-Square with SVM-RBF. Presented at the (2021). https://doi.org/10.1007/978-3-030-69143-1_13.

9. Jang, H., Lee, J.: An Empirical Study on Modeling and Prediction of Bitcoin Prices With Bayesian Neural Networks Based on Blockchain Information. IEEE Access. 6, 5427–5437 (2018). https://doi.org/10.1109/ACCESS.2017.2779181.
10. Gupta, A., Nain, H.: Bitcoin Price Prediction Using Time Series Analysis and Machine Learning Techniques. Presented at the (2021). https://doi.org/10.1007/978-981-15-7106-0_54.
11. Ampountolas, A., Nyarko Nde, T., Date, P., Constantinescu, C.: A Machine Learning Approach for Micro-Credit Scoring. Risks. 9, 50 (2021). https://doi.org/10.3390/risks9030050.
12. Fan, M.-H., Chen, M.-Y., Liao, E.-C.: A deep learning approach for financial market prediction: utilization of Google trends and keywords. Granul. Comput. 6, 207–216 (2021). https://doi.org/10.1007/s41066-019-00181-7.
13. Gerlein, E.A., McGinnity, M., Belatreche, A., Coleman, S.: Evaluating machine learning classification for financial trading: An empirical approach. Expert Syst. Appl. 54, 193–207 (2016). https://doi.org/10.1016/j.eswa.2016.01.018.
14. Huang, J., Chai, J., Cho, S.: Deep learning in finance and banking: A literature review and classification. Front. Bus. Res. China. 14, 13 (2020). https://doi.org/10.1186/s11782-020-00082-6.
15. khalid salman, M., Abdu Ibrahim, A.: PRICE PREDICTION OF DIFFERENT CRYPTOCURRENCIES USING TECHNICAL TRADE INDICATORS AND MACHINE LEARNING. IOP Conf. Ser. Mater. Sci. Eng. 928, 032007 (2020). https://doi.org/10.1088/1757-899X/928/3/032007.
16. Sebastião, H., Godinho, P.: Forecasting and trading cryptocurrencies with machine learning under changing market conditions. Financ. Innov. 7, 3 (2021). https://doi.org/10.1186/s40854-020-00217-x.
17. Zhengyang, W., Xingzhou, L., Jinjin, R., Jiaqing, K.: Prediction of Cryptocurrency Price Dynamics with Multiple Machine Learning Techniques. In: Proceedings of the 2019 4th International Conference on Machine Learning Technologies - ICMLT 2019. pp. 15–19. ACM Press, New York, New York, USA (2019). https://doi.org/10.1145/3340997.3341008.
18. Koker, T.E., Koutmos, D.: Cryptocurrency Trading Using Machine Learning. J. Risk Financ. Manag. 13, 178 (2020). https://doi.org/10.3390/jrfm13080178.
19. Cho, H., Lee, K.-H., Kim, C.: Machine Learning and Cryptocurrency in the Financial Markets. Presented at the (2021). https://doi.org/10.1007/978-981-33-6137-9_13.
20. Cocco, L., Tonelli, R., Marchesi, M.: Predictions of bitcoin prices through machine learning based frameworks. PeerJ Comput. Sci. 7, e413 (2021). https://doi.org/10.7717/peerj-cs.413.
21. Alessandretti, L., ElBahrawy, A., Aiello, L.M., Baronchelli, A.: Anticipating Cryptocurrency Prices Using Machine Learning. Complexity. 2018, 1–16 (2018). https://doi.org/10.1155/2018/8983590.
22. Lahmiri, S., Bekiros, S.: Deep Learning Forecasting in Cryptocurrency High-Frequency Trading. Cognit. Comput. 13, 485–487 (2021). https://doi.org/10.1007/s12559-021-09841-w.
23. Jameel, F., Javaid, U., Khan, W.U., Aman, M.N., Pervaiz, H., Jäntti, R.: Reinforcement Learning in Blockchain-Enabled IIoT Networks: A Survey of Recent Advances and

Open Challenges. Sustainability. 12, 5161 (2020). https://doi.org/10.3390/su12125161.
24. Tanwar, S., Bhatia, Q., Patel, P., Kumari, A., Singh, P.K., Hong, W.-C.: Machine Learning Adoption in Blockchain-Based Smart Applications: The Challenges, and a Way Forward. IEEE Access. 8, 474–488 (2020). https://doi.org/10.1109/ACCESS.2019.2961372.
25. Gupta, R., Tanwar, S., Al-Turjman, F., Italiya, P., Nauman, A., Kim, S.W.: Smart Contract Privacy Protection Using AI in Cyber-Physical Systems: Tools, Techniques and Challenges. IEEE Access. 8, 24746–24772 (2020). https://doi.org/10.1109/ACCESS.2020.2970576.
26. Liu, Y., Yu, F.R., Li, X., Ji, H., Leung, V.C.M.: Blockchain and Machine Learning for Communications and Networking Systems. IEEE Commun. Surv. Tutorials. 22, 1392–1431 (2020). https://doi.org/10.1109/COMST.2020.2975911.
27. Shahbazi, Z., Byun, Y.-C.: Integration of Blockchain, IoT and Machine Learning for Multistage Quality Control and Enhancing Security in Smart Manufacturing. Sensors. 21, 1467 (2021). https://doi.org/10.3390/s21041467.
28. Jaquart, P., Dann, D., Weinhardt, C.: Short-term bitcoin market prediction via machine learning. J. Financ. Data Sci. 7, 45–66 (2021). https://doi.org/10.1016/j.jfds.2021.03.001.
29. M., P., Sharma, A., V., V., Bhardwaj, V., Sharma, A.P., Iqbal, R., Kumar, R.: Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system. Comput. Electr. Eng. 81, 106527 (2020). https://doi.org/10.1016/j.compeleceng.2019.106527.
30. Weng, J., Weng, J., Zhang, J., Li, M., Zhang, Y., Luo, W.: DeepChain: Auditable and Privacy-Preserving Deep Learning with Blockchain-based Incentive. IEEE Trans. Dependable Secur. Comput. 1–1 (2019). https://doi.org/10.1109/TDSC.2019.2952332.
31. Negar, M., Alireza, N., Masoud, R., Yasser, Z.: Bitcoin Price Prediction Based on Other Cryptocurrencies Using Machine Learning and Time Series Analysis. Sci. Iran. Int. J. Sci. Technol. (2020). https://doi.org/10.24200/SCI.2020.55034.4040.
32. Yahoo, F.: Bitcoin Price Prediction, https://in.finance.yahoo.com/quote/BTC-USD/history?p=BTC-USD&guce_referrer=aHR0cHM6Ly9naXRodWIuY29tL3N1cmFqYmFoYWR1cjU5MS9CaXRjb2luLVByaWNlLVByZWRpY3Rpb24tVXNpbmctUk5OLS0tTFNUTQ&guce_referrer_sig=AQAAAHL6O0g7rnrvKBzzqIlA6B4fdHCk0Vp_mdcZPKO9V7W9d0d6cMkBLA1DxSSlcvb49Oq_m9nOh9y-Ay6s73nEk31hxma615IMw9okiq3sqeK9L9rUxlqvPMrhvOjARP7X96ckdYbjO0HzbsPe9VXZXn4YqkOZe-dkS-dia7qDMB-3&guccounter=2.
33. Reddy, G.T., Reddy, M.P.K., Lakshmanna, K., Kaluri, R., Rajput, D.S., Srivastava, G., Baker, T.: Analysis of Dimensionality Reduction Techniques on Big Data. IEEE Access. 8, 54776–54788 (2020). https://doi.org/10.1109/ACCESS.2020.2980942.
34. Awotunde, J.B., Ogundokun, R.O., Jimoh, R.G., Misra, S., Aro, T.O.: Machine Learning Algorithm for Cryptocurrencies Price Prediction. Presented at the (2021). https://doi.org/10.1007/978-3-030-72236-4_17.
35. Vaddi, L.: Predicting Crypto Currency Prices Using Machine Learning and Deep Learning Techniques. Int. J. Adv. Trends Comput. Sci. Eng. 9, 6603–6608 (2020). https://doi.org/10.30534/ijatcse/2020/351942020.

36. Tharwat, A.: Independent component analysis: An introduction. Appl. Comput. Informatics. 17, 222–249 (2021). https://doi.org/10.1016/j.aci.2018.08.006.
37. Maghrebi, H., Prouff, E.: On the Use of Independent Component Analysis to Denoise Side-Channel Measurements. Presented at the (2018). https://doi.org/10.1007/978-3-319-89641-0_4.
38. Gadekallu, T.R., Khare, N., Bhattacharya, S., Singh, S., Maddikunta, P.K.R., Ra, I.-H., Alazab, M.: Early Detection of Diabetic Retinopathy Using PCA-Firefly Based Deep Learning Model. Electronics. 9, 274 (2020). https://doi.org/10.3390/electronics9020274.
39. Veysel, A., Ahmet, Nusret, T., Farah, Hatem, K., Bashar, Ahmed, K.: Wrapper Feature Selection Approach Based on Binary Firefly Algorithm for Spam E-mail Filtering. J. Soft Comput. Data Min. 1, 44–52 (2020). https://doi.org/10.30880/jscdm.2020.01.02.005.
40. Ferdiansyah, F., Negara, E.S., Widyanti, Y.: BITCOIN-USD TRADING USING SVM TO DETECT THE CURRENT DAY'S TREND IN THE MARKET. J. Inf. Syst. Informatics. 1, 70–77 (2019). https://doi.org/10.33557/journal-isi.v1i1.7.
41. Ali Alahmari, S.: PREDICTING THE PRICE OF CRYPTOCURRENCY USING SUPPORT VECTOR REGRESSION METHODS. J. Mech. Contin. Math. Sci. 15, (2020). https://doi.org/10.26782/jmcms.2020.04.00023.
42. Majeed, Y., Zhang, S.,Ren.: A big data-driven framework for sustainable and smart additive manufacturing. Robotics and Computer-Integrated Manufacturing 67, 102026 (2021). https://doi.org/10.1016/j.rcim.2020.102026.
43. Mudassir, M., Bennbaia, S., Unal, D., Hammoudeh, M.: Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach. Neural Comput. Appl. (2020). https://doi.org/10.1007/s00521-020-05129-6.
44. Li, Y., Dai, W.: Bitcoin price forecasting method based on CNN-LSTM hybrid neural network model. J. Eng. 2020, 344–347 (2020). https://doi.org/10.1049/joe.2019.1203.

View publication stats