Harnessing Machine Learning for Crypto-Currency Price Prediction: A Review

Zeravan Arif Ali[1, a)], Adnan M. Abdulazeez[1]

[1]*IT Department, Duhok Technical College, Duhok Polytechnic University, Duhok, Iraq*

[a)]*email: zeravan.ali@dpu.edu.krd*

Abstract

Despite their recent inception, cryptocurrencies have become globally recognized for their dispersal, diversity, and high market capitalization. This volatility developed into a challenge for investors looking to predict price movements. Thus, it has become an attractive investment opportunity. To increase prediction accuracy, researchers integrate machine learning algorithms with technical indicators. In this review, a systematic comparison has been employed to identify efficient algorithms, and researchers have employed statistical measures to make short- and long-term forecasts of decentralized money prices. Moreover, the paper highlights the results of researchers based on machine learning and deep learning methodologies on multiple types of cryptocurrencies like Bitcoin, Ethereum, Monero, etc. Lastly, the work emphasizes the limitations, gaps, and challenges facing researchers to take advantage of existing literature for future works.

Keywords: Cryptocurrencies, Deep Learning, Machine Learning, Technical Indicators

Introduction

Predicting market behavior for maximizing profit is incredibly challenging in cryptocurrency, a decentralized digital currency based on peer-to-peer transactions. The altcoins market, characterized by rapid information flow and many transactions, has rapidly gained acceptance, leading many hedge funds and asset managers to incorporate these assets into their portfolios [1]. Despite their recent inception, alternative currencies have become globally recognized for their volatility, diversity, and high market capitalizations. These virtual currencies' appeal lies in decentralization, immutability, security, and trust in their technological infrastructure, offering anonymity, speed, and convenience in transactions without central oversight.

Predicting cryptocurrency prices can help businesses by allowing them to navigate the volatile market effectively, maximizing returns while minimizing risks. Accurate forecasts enable companies to make informed investment decisions, capitalize on favorable market conditions, and adjust their strategies as needed. This ability to anticipate price movements is crucial in a rapidly evolving market, where informed decision-making can significantly impact profitability [2]. Additionally, businesses can leverage these insights to enhance their risk management practices, ensuring stability and resilience in the face of market fluctuations.

Researchers used precise approaches like Machine Learning (ML) to anticipate cryptocurrency values. ML has an enormous measure of calculations, which can make errands simpler, including altcoin prices. Besides, regression techniques can be used to predict the future price of a cryptocurrency and predict forthcoming results - this review covers different machine learning algorithms and techniques that have also been taken these days into account to obtain abnormal profits by prognosing the inefficiency of the cryptocurrency market [3]. Different modelling techniques are applied to datasets with varying data structures and dimensional features to predict daily and high-frequency Bitcoin prices by Chen, et al. [4]. Further, analyze price variations and predict Ethereum's closing price by developing statistical and machine-learning techniques have been carried out [5]. A hybrid model using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) for predicting the prices of lesser-known cryptocurrencies like Litecoin and Monero already been discussed [6]. On the other hand, paper [7] yield a significant concentrate on the impacts of machine learning approaches and their supports in cryptocurrency transaction and digital pricing for achieving further research opportunity.

The article reviews various algorithms regarding machine learning for forecasting future prices of multiple types of cryptocurrencies such as Bitcoin, Ethereum, Cardano, Monero, etc. Furthermore, the review aims to analyze and evaluate the findings, methodologies, inconsistencies, and theories related to different techniques. In addition, we focus on identifying trends for developing and assessing learning models for foreseeing superior prices and minimizing risks regarding the cryptocurrency market. At last, our addition is to identify the pros, cons, and gaps regarding each approach, revealing disagreements related to the previous work.

Methods

1. Machine Learning

Machine learning is a subgroup of well-known artificial intelligence that targets developing algorithms and statistical models that enable computers to operate tasks without explicit instructions, depending instead on inference and patterns. It is a model of data analysis that computerize penetrating model construction [8]. Algorithms concerning machine learning learn from and make decisions or forecasts based on data, enhancing their performance as they are revealed to more data over time. This field intersects with computational statistics and relies on probability theory, computer science, and optimization techniques, enabling systems to independently learn from and adapt to new experiences [9].

Variables that identify the process of learning are called hyperparameters. These variables in machine learning are crucial external settings that guide algorithms in learning and predicting. Unlike internal parameters learned from data, hyperparameters are preset based on prior knowledge or experimentation. Key to model performance include settings like learning rate and tree depth, which significantly affect model behavior and accuracy [10]. Figure 1 illustrate the machine learning models key diagram related to process of training and testing [11].

1.1. Multiple Linear Regression (MLR) algorithm

The MLR is a statistical approach employed to examine the relationship between two or more independent variables (predictors) and a dependent variable (outcome). It extends simple linear regression to multiple predictors and is frequently found in economics, business, social sciences, and the natural sciences[12]. Figure 2 illustrate the steps regarding the MLR.

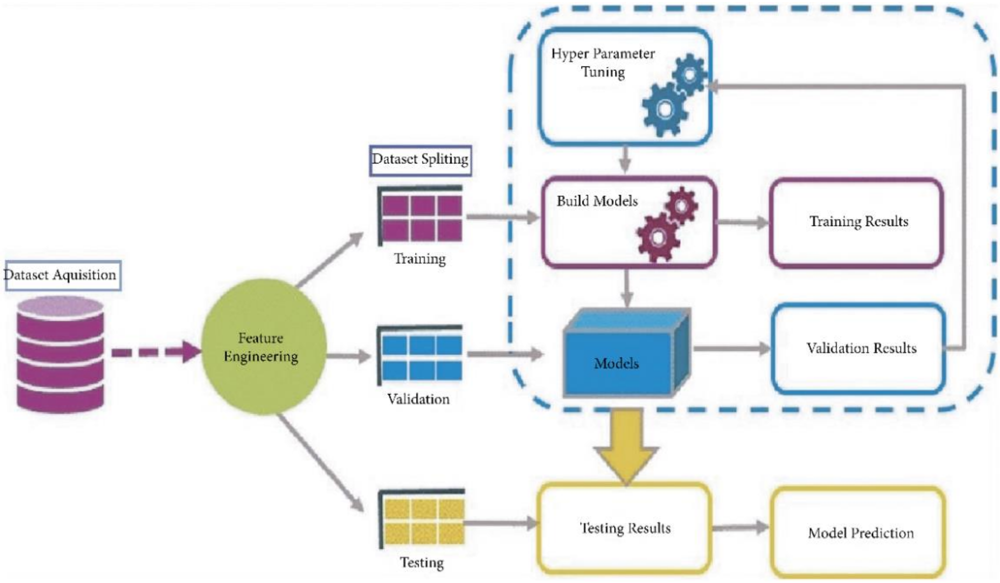

Figure 1. Machine learning key diagram

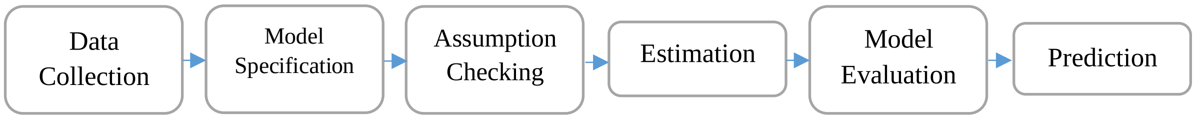

Figure 2. The process of MLR

The basic equation for MLR model is:

$$Y = \beta_0 + \beta_1 x_1 + \beta_1 x_1 + \cdots + \beta_n x_n + \epsilon. \tag{1}$$

Where: Y is the dependent variable, β_0 is the y-intercept (constant term), and $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients of the independent variables $x_1, x_2, \dots, x_n$ respectively.

1.2. Logistic Regression (LR) algorithm

LR is a statistical and machine-learning technique used primarily for binary classification problems. It is a predictive analysis algorithm and a particular case of linear regression models that predict the probability of a binary result given a set of independent variables [13]. The general equation for LR model is:

$$P(Y = 1) = \frac{1}{e^{-(\beta_0 + \beta_1 \times_1 + \beta_1 \times_1 + \cdots + \beta_n \times_n)}}. \tag{2}$$

Where: P(Y=1) is the probability that the dependent variable equals 1 (one of the two classes), e is the base of the natural logarithm, β_1,β_2,…,β_n are the coefficients of the model, and ×_1,×_2,…,×_n are the independent variables.

1.3. Random Forest (RF) algorithm

The RF algorithm is a famous and adaptable ML model utilize for the two classification and regression operations. It is an ensemble learning technique that joins the predictions from considerable machine learning models to make more precise forecasts than any particular model [14].

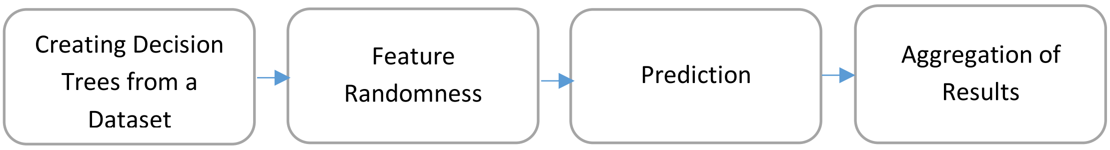

Figure 3. Process of Random Forest Model

Unlike to the previous algorithms, the RF does not rotate around a central equation. Regardless, there are significant concepts and calculations:

- Gini Impurity: The quality of a split in the decision trees needs to be measured. The better split refers to Lower Gini impurity.
- Information Gain: To assess the quality of a split based on the concept of entropy from information theory.

1.4. Support Vector Machine (SVM) algorithm

The SVM is a powerful and universal supervised machine learning algorithm mostly used for classification assignments, but it can also engage in regression. It is mainly known for its effectiveness in high-dimensional spaces and its ability to model complex non-linear decision boundaries [15]. The general equation for SVM model is as follows:

$$\omega \cdot x + b = 0. \tag{3}$$

Where: ω is the weight vector, × represents the feature vectors, and b is the bias.

For non-linear SVMs, the kernel trick is used to transform the input space into a higher-dimensional space where a hyperplane can be used for separation. Commonly used kernel functions include:

- Linear: $k(x, x') = x \cdot x'$,
- Polynomial: $k(x \cdot x') = (\gamma\, x \cdot x' + r)\, d, \gamma > 0$,
- Radial Basis Function (RBF): $k(x \cdot x') = e\,(-\gamma\, II\, x \cdot x'\, II2),\ \gamma > 0$.

1.5. Gradient Tree Boosting (GTB) algorithm

Also known as Gradient Boosting Machines (GBM), it is an assertive machine learning approach used for both classification and regression readings. It is a costume learning method, combining the predictions from multiple models to improve accuracy. Specifically, it builds the model in a stage-wise fashion, like other boosting methods [16]. Figure 4 illustrate the process of the algorithm.

Figure 4. Process of GTB model

The general equation for GTB model is as follows:

$$F_m(x) = F_{m-1}(x) + \rho_m + h_m(x). \tag{4}$$

Where:
$F_m(x)$ is the model at iteration m.
$F_{m-1}(x)$ is the model till the previous iteration.
ρ_m is the learning rate.
$h_m(x)$ is the output of the decision tree at iteration m.
The loss function $L(y, F(x))$ is minimized, where y is the actual value and $F(x)$ is the predicted value. The gradient descent step involves computing:

$$\rho_m = \arg min_\rho \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + \rho h_m(x_i). \tag{5}$$

1.6. Ensemble Voting (EV) algorithm

The EV is a technique related to ML that integrates predictions from multiple models to enhance the overall performance and accuracy of predictions. This method falls under the broader category of ensemble learning, which is based on the principle that association of powerless trainees can come jointly to construct a strong trainee [16]. Below is a principle of the EV algorithm

- Hard Voting:

$$Y_{final} = model(Y_1, Y_2, \dots, Y_n). \tag{6}$$

- Soft Voting:

$$P_{final}(c) = \frac{1}{n}\sum_{i=1}^{n} P_i(c), \tag{7}$$

where $P_{final}(c)$ is the final probability for class c, n is the number of models, and $P_i(c)$ is the probability of class c predicted by the i-th model.

2. Deep Learning

One subgroup of the Machine Learning (ML) and Artificial Intelligence (AI) is Deep Learning (DL) that simulates the functioning of the human brain in creating patterns after processing data to be use in decision-making [17]. It is characterized by its use of artificial neural networks (ANN) with multiple of layers, hence the term "deep." These deep neural networks enable the model to learn complex patterns and representations from large amounts of data, making it particularly effective for assignments related to image processing issues and speech recognition, natural language processing, and sophisticated decision-making [18]. DL computerize much of the feature extraction techniques.

2.1. Deep Feedforward Neural Networks (DFNN)

DFNNs, also known as Feedforward Deep Networks or Multilayer Perceptron's (MLPs), are an essential type of deep learning model. They are outstanding deep learning models, laying the groundwork for multiple advanced neural network architectures [17]. In DFNN, every layer employs a nonlinear transformation on its input to attain its output. The neural network(NN) is supposed to consist of N layers [19].

2.2. Convolutional Neural Networks (CNN)

The CNNs typically comprise progressive convolutional and subsampling layers, at least one secret layer, and a result layer. The initial two kinds of layers consolidate to separate undeniable level element vectors in a single aspect. The completely associated multi-facet perceptron and yield layers subsequently take care of the element vectors. Likewise, an initiation capability is usually applied to the subsequent field following the convolution activity [17].

2.3. Gated Recurrent Units (GRUs)

GRUs are a class of neural network architecture primarily used to process sequential data. They are an evolution of the traditional recurrent neural network (RNN) and are designed to solve some of the challenges associated with RNNs, such as the Vanishing Gradient Problem (VGP) [20].

2.4. Long Short-Term Memory (LSTM)

The LSTM networks are recurrent neural network (RNN) architectures used in deep learning. LSTMs are specifically designed to address the issue of long-term dependencies and vanishing gradient problems that can occur in traditional RNNs. This makes them particularly effective for learning from data sequences such as time series, speech, or text. A very long-time lags in determined issues square measure bridged victimization LSTMs wherever they conjointly restrain noise, distributed models, and continuous values [20]. With LSTMs, there's no ought to maintain a limited type of conditions from earlier PRN within the hidden mathematician model (HMM) [12].

3. Performance Metrics

3.1. Mean Absolute Percentage Error (MAPE)

The Mean Outright Rate Mistake (MAPE) is a factual measure used to assess the precision of a figure model. It communicates the exactness as a rate, and it's ordinarily utilized in different fields, including finance, production network the board, and financial matters [21]. Mathematically the MAPE is represented as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Ai - Fi}{Ai}\right| \times 100\%, \tag{8}$$

where n is the number of observations, Ai is the actual value, and Fi is the forecasted value.

3.2. Mean Absolute Error (MAE)

Mean Outright Mistake (MAE) is a generally involved measurement in measurements, especially in relapse examination, to gauge the precision of a model in foreseeing quantitative information[22]. Mathematically the MAE is represented as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Yi - \hat{Y}i\right|, \tag{9}$$

where n is the number of observations, Yi is the actual value, and $\hat{Y}i$ is the predicted value.

3.3. Mean Squared Error (MSE)

The Mean Squared Mistake (MSE) is a broadly utilized proportion of the nature of an assessor or a model. It is particularly considered normal in relapse examination and sign handling [22]. Mathematically the MSE is represented as follows:

$$MMSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{\theta}i - \theta\, i)^2. \quad (10)$$

Where n is the number of observations, $\hat{\theta}i$ is the predicted value, and θi is the actual value.

3.4. Root Mean Square Error (RMSE)

Root Mean Square Mistake (RMSE) is a habitually utilized proportion of the distinctions between values anticipated by a model or an assessor and the qualities noticed. It is especially considered normal in relapse examination and gauging [22]. Mathematically the MSE is represented as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2}. \quad (11)$$

3.5. Coefficient of Determination

The coefficient of assurance, frequently signified as R2 (R-squared), is a factual measure that addresses the extent of the change for a reliant variable that is made sense of by a free factor or factors in a relapse model. It gives a sign of the decency of spasm of a model [22]. Mathematically it is represented as follows:

$$R^2 = 1 - \frac{\text{Sum of Squares of Residuals (SSR)}}{\text{Total Sum of Squares (SST)}}. \quad (12)$$

4. Technical Indicators Module

The "Specialized Pointers Module" alludes to a part, regularly in a product or monetary examination device, that gives different specialized markers. Technical analysis traders use these indicators, which are mathematical calculations based on a security or contract's price, volume, or open interest. Moving averages, the Relative Strength Index (RSI), Bollinger Bands, MACD (Moving Average Convergence Divergence), and other indicators would be included in the module. Each indicator aids traders in making informed decisions by serving a distinct function, such as determining market strength, momentum, trends, or volatility. The module could permit clients to apply these pointers to authentic information of stocks, forex, items, or other tradable resources for dissect market patterns and examples[23].

Analyzing Machine Learning Approaches

To predict cryptocurrency prices several types of research have been done. Researchers are carried out various models and approaches to achieve prices near the actual prices of cryptocurrencies. They considered machine learning methods when they did their work. The researchers have also considered different cryptocurrencies, such as Bitcoin, Ethereum and Litecoin, etc. Some articles addressed short-term strategy, while others focused on long-term analysis [24]. A systematic review has been done to identify the machine learning algorithms that have been used to inform the future cryptocurrency prices, and related papers are arranged and discussed in Table 1. Some of these papers have been discussed below. Developed models are utilized to inform the affective factors on the prices, combining both quantitative and qualitative approaches. To do so, it was possible to comprehensively understand the factors affecting Bitcoin prices and develop an efficient model for predicting future prices. This review paper contributes valuable understandings into the current knowledge in the research field. It helps identify suitable machine learning algorithms for Bitcoin price prediction using technical indicators from historical price data. Quantitative research methodology involves experimenting to collect empirical data related to predictions made on historical Bitcoin price data [25]. This experience involves building a model using the selected algorithms, training, testing, and evaluating it using the relevant data set and appropriate metrics [26].

Table 1. Summary of recent works in the filed of cryptocurrency price prediction

No.	Reference	Dataset Source	Techniques	Metrics	Accuracy	Findings	Disadvantages	Crypto-currency
1.	(Jaquart et al., 2022) [26]	3 Datasets from Bloomberg, Twitter, and Blockchain.com	RF, LSTM, and GRU	Sharpe ratio, and Sortino ratio	50%	The Validity of results might be restricted because of utilizing accumulated digital currency cost information over numerous trades. It also identifies the most relevant features for prediction, such as technical and blockchain-based features.	One major disadvantage is that while the models predict market movements, they don't necessarily translate into profitable trading strategies, especially after accounting for transaction costs. This limitation is significant in the context of practical financial trading applications	Bitcoin
2.	(Patel et al., 2020) [6]	Investing.com	LSTM and GRU	RMSE	LSTM=2.2986 and GRU=3.2715 respectively	It predicts cryptocurrency prices with greater precision for a variety of prediction windows, demonstrating its potential for use in a variety of cryptocurrency price predictions.	The study limitations in cryptocurrency price prediction models typically include sensitivity to market volatility and reliance on historical data, which may not fully capture future market dynamics.	Litecoin and Monero
3.	(Akyildirim, Cepni, Corbet, & Uddin, 2021) [27]	Chicago Mercantile Exchange (CME)	LR, NB, RF, SVM, kNN, XGBoost	SPR	56%	The typical characterization exactness for five out of six AI calculations (MLAs) was reliably above half, recommending that MLAs beat benchmark models.	The limitations include potential overfitting, the need for extensive computational resources, and the requirement for large and comprehensive datasets to train the models effectively	Bitcoin
4.	(Zoumpekas et al., 2020) [5]	Poloniex platform	CNN, LSTM, and GRU	RMSE, MAE, and MDA	CNN=64%, LSTM=71%, and GRU=71% respectively	The examination demonstrates that specific profound learning models can anticipate Ethereum's end cost with huge precision and benefit continuously.	The study doesn't have a specific policy against outliers in the data. While this approach is common in similar studies.	Ethereum
5.	(Shruthi, Anbarasu, Sabarish, & Sciences, 2023)	Not Mentioned	LSTM and GRU	RMSE and MAPE	RMSE and MAPE values were 0.029 and 0.021, respectively.	The GRU model merges quicker and more consistently than LSTM, with less	The study acknowledges the need for further enhancements to increase the accuracy of these deep learning	Bitcoin, Ethereum, and Litecoin

	[28]				Similarly, for Ethereum, the RMSE was 0.032 and MAPE was 0.023, and for Litecoin, RMSE and MAPE values were 0.027 and 0.016, respectively	variety among genuine and anticipated costs.	models. It suggests that additional parameters should be considered in future models for better prediction capabilities	
6.	(Borges & Neves, 2020) [16]	Binance's API	RF, GTB, EV, and SVM	ROI, MDD, Sharpe ratio, and Sortino ratio,	SVM= 53.7%, LR=54.3% GTB= 55.1%, and EV=56.28%	The researchers directed contextual investigations utilizing time resampling, rate resampling, and sum resampling to survey the effect of these techniques on speculation results	One of the noted disadvantages in the study is related to decision trees, which are a fundamental part of the Random Forest method. Decision trees tend to have high variance and can overfit on training data, leading to poor generalization on unseen data.	Bitcoin, Ethereum, and Cardano
7.	(Lahmiri et al., 2020) [21]	Binance's API	SVR, GPR, RT, KNN, FFNN, BRNN, and RBFNN	RMSE, Hurst's exponent, sample entropy, Lempel–Ziv complexity, and Kolmogorov complexity	84.43	AANs were more adequate than other models due to their ability to simulate human decision-making and process nonlinear input-output relationships in loud environments.	The study notes some limitations. Models like the SVR, GPR, RT, KNN, required more time for parameter optimization. (RBFNN) showed relative underperformance, potentially due to non-optimized kernel width.	Bitcoin
8.	(Andi et al, 2021) [29]	www.chartoasis.com	LR and LSTM	Not Mentioned	LR=50%, LSTM=55% respectively	The study found that integrating logistic regression with LSTM led to more accurate predictions compared to other models. They noticed the large datasets having better accuracy.	The primary challenge is managing large datasets, which can lead to overfitting.	Bitcoin
9.	H.-M. Kim et al., 2021) [15]	daily basis from Etherscan, and DataStream	SVM and ANN	RMSE and MAPE	values are not directly mentioned	They emphasize the differences in Blockchain information between Ethereum and other cryptocurrencies like Bitcoin, and how these contrasts influence expense forecasts.	The research focused only on Ethereum and a limited set of other cryptocurrencies.	Bitcoin, Ethereum, Litecoin, and Dashcoin
10.	(Chowdhury, Rahman, Rahman, Mahdy, & Applications, 2020) [30]	seven-day week from CoinMarketCap.com	XGBoost, FNN, CNN, RNN, kNN, and LSTM	RMSE, AE, and prediction trend accuracy	92.4%	The key finding is that group learning strategies showed the most noteworthy accuracy among all models at foreseeing digital currency costs.	One of the main disadvantages noted in the paper is the less effective performance of the K-NN model in forecasting, particularly due to the presence of noisy random features and extreme volatility in the data.	various cryptocurrencies, including an index called cci30

11.	(Oyedele et al., 2023) [17]	Yahoo Finance, UK Investing, and Bitfinex	CNNs, DFNN, GRU, AdaBoost, GBoost, and XGBoost	NSE, EVS, t-test, and MAPE	96%	The CNNs outflank others by showing the most un-mean typical rate mistake and the most elevated consistency in results. This finding feature CNN's unwavering quality and generalizability in anticipating everyday shutting costs of various cryptographic forms of money	Some of the challenges faced by models include uncontrolled convergence speed and local optima in ANNs, computational complexity issues in Bayesian Neural Networks and SVMs, and high variance across samples in decision trees, making predictions and probabilities unstable for new cases	Bitcoin, Ethereum, Binance Coin, Litecoin, Stellar Lumens, and Dogecoin
12.	(Sahi, Saluja, & Nargotra, 2023) [31]	Investopedia and CoinMarketCap .com	LR, DT, RF, SVM, and LSTM	RMSE and MAPE	For Bitcoin, the RMSE and MAPE values were 0.029 and 0.021, respectively; for Ethereum, they were 0.032 and 0.023; and for Litecoin, 0.027 and 0.016, respectively	Researchers shows the significance of machine learning in predicting cryptocurrency prices. ML techniques yeild the highest accuracy when metrics are nearest to zero.	Limitations include the reliance on historical data, which may not account for future market changes. The study suggests that using more diverse datasets and new algorithms could improve accuracy	Bitcoin, Ethereum, and Litecoin
13.	(Mudassir, Bennbaia, Unal, Hammoudeh, & applications, 2020) [32]	BitInfoCharts	RF, VIF, ANN, SANN, SVM, and LSTM	MAPE RMSE MAE F1-score, AUC, and ROC	65% for next-day forecasts and 62-64% for 7-90-day forecasts	They noticed the performance during three intervals, at the early two intervals (ANNs) demonstrates the most robust performance compared to the late interval (SVM).	The high volatility of Bitcoin prices and the complex nature of cryptocurrency markets may pose challenges to prediction accuracy, especially over longer forecast horizons	Bitcoin
14.	(Chevallier et al., 2021) [22]	synthetic data	PSO and LS-SVM	Type I/II precision, total precision, rate test, RMSE, and Dstat	75%	The review uncovers the prevalence of mixture models over delicate and hard registered models through a horse race examination, exchanging execution, and calibrating of the calculations.	Most statistical models, which are based on the assumption of stationary and linear data, fail to deal effectively with the non-linear patterns in financial trading series, leading to unsatisfactory prediction results	Bitcoin
15.	(Kavitha et al., 2020) [8]	"USD_1-min_data_2012-01-01_to_2019-03-13" from Kaggle	RNN with LSTM and LR	RMSE, MAE, and R^2	Specific accuracy values aren't summarized	DLs are more adequate for predicting cryptocurrency prices compared to logistic regression. A limitation noted is the significant computational requirement for training the models, especially for large datasets.	A significant limitation noted is the substantial computation required for training the models. Additionally, if the dataset size is small, the RNN model may not train effectively, resulting in poor predictions	Bitcoin
16.	(Nikitha et al., 2022) [33]	CoinMarketCap .com	RF, SVM, and RNN with LSTM	Yield, Average Return, Trading and	52.9% and 54.1%	The study claims the proposal is modest compared to other investigations; they underlined the	The paper mentions the challenge of accurately forecasting market prices, acknowledging the difficulty and	Ethereum, Litecoin, and Ripple

				Network Variables, Currency, and Reliability		influence of external factors like government policies and public opinion on cryptocurrency prices.	variability of predictions across different models and cryptocurrencies. It notes a decline in forecast accuracy between test and validation phases, possibly due to divergent price trends in these periods	
17.	(Gadey, Thakur, Charan, Reddy, & Technology, 2020) [34]	Coin Market.com Cap and Blockchain	LSTM	Min-Max Scaling, Mean Normalization, and Z-Score	50-55%	It utilizes historical data to forecast future prices, indicating exceptional performance over different machine learning techniques.	The document acknowledges potential issues like overfitting, especially when dealing with large training sets. It also suggests that traditional methods and algorithms might need reconsideration to reduce these problems	Bitcoin
18.	(Mounika et al., 2021) [35]	Quandl.com	CNN and LSTM	MAE	doesn't specify a numerical accuracy value	The experimental results suggest that the proposed system provides more accurate predictions for Bitcoin prices. The CNN is outperformed.	The paper does not explicitly list disadvantages but implies challenges in predicting cryptocurrency prices due to high volatility and market fluctuations	Bitcoin
19.	(Vaddi, Neelisetty, Vallabhaneni, & Prakash, 2020) [36]	Blockchain.com	LR, and RNN with LSTM	Accuracy	LR= 69.9%, and RNN with LSTM=96.2 %.	DLs outperformed and were highly accurate against linear regression while predicting cryptocurrency prices. Using multiple features leads to enhancing the precession.	Linear Regression models were less accurate due to their inability to handle the non-linear and noisy nature of cryptocurrency data efficiently	Bitcoin, Ethereum and Litecoin
20.	(Chen et al., 2020) [4]	Daily price data and High-frequency from CoinMarketCap .com and Binance respectively	LR, RF, SVM, LSTM XGBoost, LDA, and QDA	Confusion Matrix, Accuracy, Precision Recall, and F1-Score	67.20%	The study indicates the value of considering sample dimension in ML techniques for price prediction. They claim that the statistical models outperform complex MLAs.	A notable limitation of the study is its reliance on specific data sources and features, which may not generalize to other contexts or cryptocurrencies	Bitcoin
21.	(Marne, Churi, Correia, & Gomes, 2020) [37]	"Bitcoin price data" from kaggle	RNN with LSTM	RMSE	33.8%	The examination found that the LSTM model was viable in foreseeing Bitcoin costs with a RMSE. This shows a serious level of precision in the forecasts made by the model.	Specific disadvantages are not explicitly listed, but it can be inferred that challenges may include handling the high volatility and unpredictability of cryptocurrency markets	Bitcoin
22.	(Iqbal, Iqbal, Jaskani, Iqbal, & Hassan, 2021) [38]	"Bitcoin historical data from" Kaggle	ARIMA, FBProphet, and XGBoost	RMSE, MAE, and R^2	RMSE= 32.24 and MAE=22.73	The investigation discovers that the ARIMA model beats FBProphet and XGBoost in anticipating Bitcoin costs while markers having low qualities.	The limitations or disadvantages of the approach aren't explicitly discussed in the document, but generally, the challenges could include the inherent volatility of cryptocurrency markets	Bitcoin

							and the limitations of predictive models in such unpredictable environments	
23.	(Nesarani, Ramar, Pandian, & Innovation, 2020) [39]	IoT monitoring system	LSTM with GRU, RF and LR	MAE, MSE, RMSE, and R^2, Sharpe Ratio, Sortino Ratio, and VaR.	R^2=94.1 and RMSE=62.3913	They noticed the importance of the statistical measures. The average accuracy for all cryptocurrencies was raised for a subset of predictions with the highest model confidence.	The paper does not explicitly list the disadvantages. However, common challenges in similar systems can include the complexity of integrating blockchain and IoT, the need for extensive data for accurate machine learning predictions, and potential security vulnerabilities in the IoT network	Bitcoin and Ethereum
24.	(Erfanian et al., 2022) [40]	data.gov	HARRVJ, NARX, and SVR	Economic Indicators	HARRVJ =93.75%, NARX =98.95%, and SVR 78.76%	SVR beats other machine learning models. Information related to Macroeconomics are significant durable predictors of Bitcoin price.	The document mentions that in terms of data preparation, no feature selection method significantly improved the model, and Variance Inflation Factor (VIF) was found to be the least effective feature selection technique. This suggests a limitation in enhancing model performance through feature selection methods	Bitcoin and Ethereum
25.	(Dimitriadou & Gregoriou, 2023) [41]	Bitcoin data from Coinlore.com, Macroeconomic variables and interest rates from the (FRED), and exchange rates from Yahoo Finance	SVM and RF	Recall, Accuracy, Precision, and F1-Score Accuracy	66%	The proposed algorithm shows the highest accuracy from SVM and RF algorithms.	The paper does not explicitly list disadvantages, but one can infer challenges such as the complexity of accurately predicting cryptocurrency prices due to market volatility and external factors	Bitcoin, Dogecoin, MaidSafeCoin, XRP, Novacoin, Namecoin, Litecoin, GoldCoin, Dash, Deutsche eMark, ArtByte, Dimecoin, Orbitcoin, and Groestlcoin
26.	(G. Kim, Shin, Choi, & Lim, 2022) [42]	Glassnode	LSTM and GRU	MSE, MAE, RMSE and MAPE	MAE = 0.3462, RMSE = 0.5035, MSE = 0.2536, and MAPE = 1.3251	A hybrid technique was used called DL-GuesS. They examine the work of the proposed cryptocurrencies depending on prior prices and views from social media, especially Twitter.	The document does not explicitly list disadvantages. However, potential limitations could include reliance on historical data, which might not always predict future trends accurately, especially in a volatile market like cryptocurrencies	Bitcoin, Ethereum Ripple, Litecoin, and Tether
27.	(Ammer & Aldhyani, 2022)	CoinMarketCap .com	LSTM	RMSE, MAE, NRMSE,	R = 96.73%	They compared the LSTM with current models. They found	While not explicitly detailed in the summary, generally, challenges	AMP, Ethereum,

	[43]			and the Pearson (r)		the high performance of the proposed algorithm against models done by others concerning the used metrics.	with such models could include handling the high volatility and unpredictability of cryptocurrency markets, and the potential for overfitting to past data	EOS, and XRP.
28.	(Shahbazi & Byun, 2022) [44]	digitalcoinprice. com	XGBoost	MAE, RMSE, and MAPE	76.5%	The method enhances the system's performance by utilizing different filters and measures. Moreover, the security of the system, as well as the clarity, has been raised as well.	Specific disadvantages are not explicitly detailed in the document, but generally, the prediction of cryptocurrency rates is challenging due to market volatility and unpredictability	Ether, Litecoin, and Monero
29.	(Basher & Sadorsky, 2022) [45]	Yahoo Finance and the St. Louis Federal Reserve	RF and Bagging	RSI, ADX, MACD, RCO, MFI, and WAD	85%	Suggested techniques were examined to predict cryptocurrency movements. The proposed algorithm noticed that the technical indicators have a crucial rule for price predictions.	While not explicitly stated, potential disadvantages might include the complexity of the models used and the challenges in interpreting the results of machine learning models like random forests compared to more straightforward statistical models	Bitcoin
30.	(Aljadani, 2022) [46]	Yahoo Finance	LSTM and GRU	MAE, MSE, RMSE, and MAPE	Bitcoin RSME=0.01711, Ethereum RSME, 0.02662, and Cardano RSME=0.00852	The paper presents a structure for predicting cryptocurrency prices relying on the DL architectures concentrated on real-time datasets. GRU is beaten for some cryptocurrencies; on the other hand, the other algorithm outperformed the rest.	Specific disadvantages are not directly stated, but the limitations section might provide insights into potential drawbacks or areas of improvement for the framework.	Bitcoin, Ethereum, and Cardano
31.	(Lahmiri & Bekiros, 2021) [47]	65,535 samples	DFFNN	RMSEs	Levenberg-Marquardt (RMSE = 14.406%), Powell-Beale restarts (RMSE = 23.187%), and the resilient (RMSE = 29.715%).	The study found that the proposed algorithm trained with the Levenberg-Marquardt technique outperformed those trained with the Powell-Beale restarts and resilient algorithms.	While not explicitly stated, the disadvantages could be inferred from the varying RMSEs indicating differing levels of prediction accuracy across algorithms. The resilience algorithm, despite being fast, showed the least accuracy	Bitcoin
32.	(Nair, Marie, Abd-Elmegid, & Applications, 2023) [48]	Bitcoin Cryptocurrency dataset from Kaggle	(RNN), (LSTM), (GRU), (Bi-LSTM), and (CONV1D)	RMSE, MAE, MSE, and R2	The best is LSTM model: RMSE = 1978.68268, MAE = 1537.14424, MSE = 3915185.15068, and R2 = 0.94383	The study focused on predicting Bitcoin prices using deep learning techniques. It compared five deep learning approaches, and the LSTM model outperformed the others regarding prediction accuracy.	The models are noted to be vulnerable to overfitting, especially when trained on small datasets. This could lead to suboptimal performance with new data. models might not fully account for the various factors influencing cryptocurrency values,	Ethereum and Litecoin on Bitcoin's

							potentially affecting prediction accuracy	
33.	(Jay et al., 2020) [49]	blockchain network information	MLP and LSTM	MAE, RMSE, and MAPE	LSTM have higher accuracy that MLP. For Bitcoin, the RMSE= 0.08116, y; for Ethereum, RMSE= 0.06610; and for Litecoin, RMSE= 0.07053	The classification models achieved up to sixty-five percent accuracy for next-day forecasts and sixty-two to sixty-four accuracies for forecasts ranging from seven to ninety days, with the lowest error percentage.	Limitations generally relate to the challenges of predicting highly volatile and non-stationary data like prices and relying on historical data, which may only sometimes accurately predict future trends.	Bitcoin, Ethereum, and Litecoin
34.	(Akyildirim, Goncu, & Sensoy, 2021) [50]	“Bitfinex exchange” from the Kaiko digital asset store	LR, SVM, RF, and ANN	Mean, Median, Min, and Max	69%	The study suggests that weak-form efficiency was violated in cryptocurrency markets at daily and various minute levels and trading volume is a valuable input in algorithms for forecasting cryptocurrency returns.	The study focusing only on daily returns and neglecting high-frequency analysis.	Bitcoin, Ethereum, Litecoin, Ripple, Bitcoin Cash, Dash, EOS, Ethereum Classic, Iota, Litecoin, OmiseGO, Monero, and Zcash
35.	(Albariqi & Winarko, 2020) [51]	Bitcoin's blockchain data	MLP and RNN	Accuracy, Precision, and Recall	81.30%	The best learning rate for MLP and RNN was found, with a validation loss.	The accuracy paradox issue is discussed, where models may not generalize well beyond their training data	Bitcoin
36.	(Rafi et al., 2023) [52]	Yahoo Finance	LR and XGBoost	RMSE	LR=64.84% and XGBoost=59.4%	The study focuses on forecasting Bitcoin and Ethereum values over different time intervals, demonstrating significant improvements in forecasting accuracy compared to existing models.	Limitations involve the inherent unpredictability and volatility of cryptocurrency markets and the challenges in generalizing the model for other cryptocurrencies or over different time frames.	Bitcoin, Ethereum, and Cardano

Analyzing the provided dataset highlights significant findings in the field of cryptocurrency price prediction, utilizing a variety of machine learning and deep learning techniques. The models used include Random Forest (RF), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM), among others. These models have been tested across different datasets sourced from reputable platforms like Bloomberg, Twitter, Blockchain.com, and CoinMarketCap. For instance, the study by Jaquart et al. (2022) [13], utilized RF, LSTM, and GRU, achieving a 50% accuracy and emphasizing the identification of relevant features for prediction despite the challenge of transaction costs limiting practical applications.

The findings consistently show that while certain models like LSTM and GRU often outperform traditional methods, the accuracy and practicality of these predictions can be significantly influenced by factors such as market volatility, data quality, and computational resources. For example, Patel et al. (2020) [6] demonstrated that LSTM models could predict cryptocurrency prices with greater precision than GRU for Litecoin and Monero, despite the sensitivity to market volatility. Similarly, Zoumpekas et al. (2020) [5] found CNN and LSTM models to be highly effective in predicting Ethereum's closing prices, achieving accuracies up to 71%. However, these studies also point out limitations, including the potential for overfitting, the requirement for large and comprehensive datasets, and the models' reliance on historical data, which might not fully capture future market dynamics.

Additionally, various studies highlight the necessity for further enhancements to improve prediction accuracy and the importance of integrating additional parameters and diverse datasets. For instance, Shruthi et al. (2023) [28] suggested incorporating more parameters to enhance the deep learning models' accuracy in predicting prices for Bitcoin, Ethereum, and Litecoin. Another significant insight is the impact of external factors such as government policies and public sentiment on cryptocurrency prices, as noted by Nikitha et al. (2022) [33]. These insights underscore the complexity and multifaceted nature of cryptocurrency price prediction, suggesting that while current machine learning models provide a solid foundation, ongoing research and development are crucial for refining these predictive tools and enhancing their applicability in real-world trading scenarios.

Discussion

A critical step in any research process is about identifying gaps and limitations. it's considered as a path to a better for future works. It gives the knowledge and opportunities to the researcher to gain a new insight in an impactful and meaningful manner. The limitation of [13] study's limited sample size, the assumption that it is possible to short-sell cryptocurrencies, and the inability to buy and sell cryptocurrencies at mid-price. [29] recognizes the difficulties of overfitting in enormous datasets and endeavours to address this in its proposed model. [41] examined over one hundred cryptocurrencies. The Table 1 as shown above present a comparison of the existing literature concerning cryptocurrency price prediction. The researchers utilized both machine learning and deep learning models to predict altcoins prices. Various technical indicators are used to improve the accuracy. In contrast different datasets and different types of cryptocurrencies are examined like Ethereum, Litecoin, Ripple, and etc.

Conclusion

People employed various techniques to gain knowledge and derive new insight into the forthcoming trends regarding cryptocurrency. Predicting cryptocurrency prices is essential in financial markets, especially digital ones. To do so, investors utilize machine learning and their methodologies and techniques. A comparison among relevant research papers was conducted. Various algorithms, various metrics, and technical indicators were reviewed, and they examined multiple types of cryptocurrencies in various environments and conditions and showed the best models and findings in performance in predicting altcoin prices, considering various factors affecting the financial market. In addition, we pointed out gaps, limitations, and challenges researchers face while doing their work, which helps them in their future work.

Our contribution is about reviewing the current methods and techniques and providing readers an overview of the current work by focusing on the approaches utilizing the structure of machine learning, deep learning, technical indicators importance, time-series, small dataset, large dataset, various events, and market condition that is affecting the prices, considering how some techniques outperform the others.

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