**Predicting Cryptocurrency Prices based on Machine Learning: Review**

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**Abstract:**

Predicting cryptocurrency prices and market direction has gained wide popularity in the financial community. Cryptocurrencies have time series data of past prices that can be used to create a model capable of predicting future prices and determining the direction of market movement. One of the most critical problems that researchers will face in this field is choosing the algorithm that can be used to create an effective model capable of predicting cryptocurrency prices and determining the direction of market movement. Through the survey we conducted, it became clear that neural network algorithms: LSTM, RNN, CNN, BNN, and GRU are the most suitable for solving time series prediction problems. The two methods, LSTM and GRU, achieved results with an accuracy of more than 90%.

**Keywords:** Cryptocurrency; LSTM; RNN; CNN; BNN; GRU; prediction; neural network.

**1. Introduction**

The Internet of things (IoT), e-commerce, and digital payments are just a few technological advancements that have changed the globe over the last few decades. These developments alter how people interact with the outside world and how they interact and trade money for goods and services. Due to recent technological advancements, banking, transactions, and other e-commerce activities are getting more sophisticated. During the shift from print to virtual money over the past 20 years, a new kind known as cryptocurrency has developed[[1](#_ENREF_1)]. Blockchain technology is used to safeguard it, making it impossible for it to be duplicated, falsified, or double-spent. Bitcoin BTC, the most well-known cryptocurrency, was created in 2009 and remained the only Blockchain-based cryptocurrency for over two years. However, there are currently 5.8 million active users using over 5000 cryptocurrencies. BTC has recently attracted much interest in economics, cryptography, and computer science due to its inherent nature of fusing encryption technology with monetary units[[2](#_ENREF_2)]. Cryptocurrency is currently employed in official economic flows and the exchange of products due to their expansion and popularity.

In particular, ML techniques, and price prediction, a crucial step in financial decision-making linked to asset allocation, risk assessment, and trading, have seen increased appeal in the cryptocurrency market. The cryptocurrency market, however, is highly volatile and intricate. Therefore, the need for models that can reliably predict the cryptocurrency market at a level comparable to the stock market is paramount. Despite being a newcomer to the financial sector, cryptocurrency is seen as a viable substitute for traditional paper money. BTC, Litecoin LTC, Ethereum ETH, and other cryptocurrencies currently garner a lot of investment. Cryptocurrency price prediction is a time series prediction problem that makes predictions on a time series scale using past data[[3](#_ENREF_3), [4](#_ENREF_4)]. In this paper, we review many kinds of research related to solving the problem of predicting cryptocurrency prices using machine learning and deep learning techniques. And compare the results and determine which algorithms are appropriate to solve this problem. The research was divided according to the following structure. Section 2 provides types of cryptocurrencies and what currencies are most popular. Section 3 of previous works presents a summary of the study and its results in a brief form and a table that compares the results of the earlier works. Section 4 is Challenges and limitations, Section 5 is a Maturity evaluation, and Section 6 is the Conclusion.

**2. Popular Cryptocurrencies and typing**

Many cryptocurrencies have been developed, each with unique features and characteristics. Some of the most popular types of cryptocurrencies include:

* BTC: is the original and most well-known cryptocurrency. It was created in 2009 and had the most significant cryptocurrency market capitalization. BTC is based on a decentralized ledger technology called the blockchain, which allows it to operate without a central authority. Transactions made with BTC are recorded on the blockchain and can be verified by anyone, making it a transparent and secure way to transfer value[[2](#_ENREF_2)].
* ETH: is a cryptocurrency that was created in 2015. It is different from BTC because it was designed to be a platform for decentralized applications. ETH has its programming language, which makes it possible for developers to build and run applications on the ETH network. These applications are called smart contracts, and they can automate various processes, such as tracking the ownership of a piece of property or facilitating the exchange of goods and services[[3](#_ENREF_3)].
* Dogecoin DOGE: is a cryptocurrency that was created in 2013 as a parody of BTC. It is named after the Shiba Inu dog breed, featured on the coin's logo. DOGE has become popular as a means of tipping content creators online and has been used to raise funds for charitable causes.

Other popular cryptocurrencies include Binance Coin BNB, Cardano ADA, and Tether USDT. The popularity of a cryptocurrency can vary over time and depend on various factors, such as the level of adoption by merchants and consumers, the level of media attention it receives, and its market performance. BTC is generally considered the leader in the most popular cryptocurrencies. It has the highest market capitalization and is widely accepted as a form of payment by merchants worldwide. ETH is also popular among developers who use its smart contract platform to build decentralized applications[[5](#_ENREF_5)]. DOGE has gained a significant following due to its lighthearted nature and has been used in several charitable fundraising campaigns. Overall, the popularity of a cryptocurrency can vary greatly and is subject to change based on various factors.

figer1 show step to predict cryptocurrency .

**3. Previous works**

In 2019, Valencia et al. [[6](#_ENREF_6)] implemented a machine learning and sentiment analysis to project financial time series in cryptocurrency markets. The aim is to demonstrate machine-learning technologies by investigating the connections between internet variables and cryptocurrency values using elements from Twitter and market data as input features. Three models of machine learning algorithms were applied, and their results were compared. The algorithms are (i) neural network NN based on the Multilayer perceptron's MLPs model, (ii) support vector machine SVM (iii) random forest RF. The findings demonstrate that machine learning and sentiment analysis can be used to forecast cryptocurrency markets. The accuracy of the three algorithms has been tested for four cryptocurrencies, namely BTC, ETH, Ripple XRP, and Litecoin LTC, applied on three types of Data Twitter, Market, and Twitter and Market. The most accurate and precise model for BTC was an MLP model, which achieved scores of 0.72 and 0.74 using both Twitter and market data. Other social media platforms, such as Facebook, were not considered when analyzing communities' sentiments.

In 2019, Alahmari [[7](#_ENREF_7)] used the daily, weekly, and monthly time series in the traditional Autoregressive Integrated Moving Average ARIMA model to predict the prices of the three significant cryptocurrencies BTC, XRP, and ETH, where the data was collected from (http:// www.kaggle.com). The primary goal is to produce indications of price predictions for the three significant cryptocurrencies above. ARIMA Algorithm achieved the best results on the daily currency price forecasts XPR. The MAE, MSE, and RMSE were 0.041, 0.0097, and 0.096, respectively. This procedure makes the researchers think that the algorithm utilized in the study may have had a more significant impact on the outcomes than the variations in the dataset. The results of the ARIMA algorithm were not compared with the results of another algorithm for the same data set

In 2020, Chen and Sun [[8](#_ENREF_8)] created a peer-to-peer electronic payment system known as BTC in 2008 to address the inherent flaw in the trust-based paradigm of transactions. Then, it evolved into an asset, or commodity-as product exchanged in more than 16,000 exchanges worldwide. Forecast the BTC price using machine-learning methods based on two datasets. The first dataset includes the daily average BTC price from CoinMarketCap.com, analyzed by machine learning algorithms linear regression LR and linear discriminant analysis LDA. The second dataset contains real-time 5-minute interval BTC trading price data from Binance.com, analyzed by algorithms RF, XGBoost XGB, quadratic discriminant analysis QDA, SVM, and algorithms-long short-term memory LSTM. The highest model accuracy LR was 66% for the daily BTC price, and LSTM was 67.2% for the 5-minute interval price. However, the accuracy was relatively low.

In 2020, da Silva et al. [[9](#_ENREF_9)] created a cryptocurrency function as a means of exchange and employed powerful encryption to ensure its security. BTC is the most popular cryptocurrency, gaining interest worldwide. Due to the high volatility in BTC prices, forecasting prices ask is challenging. The research aims to create a model for BTC price prediction. That integrates Variational Mode Decomposition VMD and Stacking-ensemble learning STACK with machine learning methods. The machine learning algorithms are k-Nearest Neighbors KNN, Support Vector Regression SVR, Feed-forward Neural Network NNET, and Generalized Linear Model GLM. When compared to alternative options, VMD + STACK showed a noticeable improvement. Due to the principle of ensemble learning, this combination results in a robust model. The outcomes show MAPE was 0.0626 for the VMD-STACK strategy outperforms the approaches used separately. The suggested technique proved the most accurate for all predictions.

In 2020, Derbentsev et al. [[10](#_ENREF_10)] limited the risk while making daily decisions about buying and selling different cryptocurrencies and getting the desired return from investment. Many elements that affect market conditions and produce upward or negative trends must be analyzed. The research explores the challenges of supervised machine learning ML -based on short-term financial time series forecasting. The main objective is to forecast the value of the target variable for the upcoming time using several ML algorithms, SVM, and artificial neural networks ANN, RF, and Gradient Boosting Machine GBM and compare how well they accomplish this task. The result of MAPE was 1.03, and RMSE was 106.5, respectively. For the SVM algorithm, BTC time series price predictions were the best among all the above algorithms. The ML approaches have shown efficiency in predicting financial time series. Future studies should expand by examining the predictive accuracy of the ML techniques presented by incorporating more features.

In 2020, Mudassir et al. [[11](#_ENREF_11)]volatilited decentralized cryptocurrency price as one of the critical issues. The research uses ML algorithms to create a model to predict BTC prices in the medium period of 30 to 90 days and the short-term period from one to 7 days. BTC time series is used with technical indicators of the currency market to process and extract features using the RF method. Then it is transferred to the ML models for classification and regression: artificial neural network ANN, stacked artificial neural network SANN, SVM, and LSTM to predict BTC prices at several levels dataset: end of the day, seven days, 30 days, and 90 days. The collected data was from https://bitinfocharts.com. The performance of the regression models in terms of MAPE was 0.73, 1.88, 0.52, and 0.93. For SVM, ANN, SANN, and LSTM, receptivity at Interval I (April 2013–July 2016). In contrast, the performance of the classification models in terms of accuracy was 55%, 57%, 60%, and 54% for SVM, ANN, SANN, and LSTM, respectively, for the same interval. The performance SANN model outperformed the other models.

In 2020, Poongodi et al. [[1](#_ENREF_1)] achieved financial profits from cryptocurrency trading. They need to predict prices and determine the direction of the markets. The research aims to identify ETH currency and forecast its price based on previous price inflations. The LR and SVM algorithms using in the suggested method for predicting the price of the ETH cryptocurrency. They extracted all data from https://etherchain.org, which contains every ETH transaction that has ever been made up to this point. The data were then saved in the JSON file format following this extraction. Close, date, open, high, low, quotation volume, and the weighted average were only a few variables or factors this dataset contained. A cross-validation method was used throughout the training phase. The SVM method outperforms the LR method in terms of accuracy of 96.06% vs. 85.46%. Additionally, incorporating features into the SVM approach can raise the accuracy score to 99%. The researcher did not address the equations used to calculate the accuracy of the algorithm's results.

In 2020, Kumar and Rath [[3](#_ENREF_3)] examined the role of deep Learning methods like MLP and LSTM in forecasting ETH price movements. The data was collected from the coindesk and coinmarket repositories. The data collection period was from August 2015 to August 2018. In MLP, the data travels from the input to the output layer, and the backpropagation technique uses to train the model. The nonlinearly separable issue is solved using the backpropagation method. Pattern classification, prediction, and approximation can all be made with MLP. The LSTM model was created primarily to address the problem of long-term reliance. Because LSTM has memory cells that transmit information through networks and controls, it can retain data for extended periods. MAPE results revealed that the predicted model error uses to evaluate price prediction difficulties. In addition, three metrics, Mean Squared Error MSE, Root Mean Squared Error RMSE, and Mean Absolute Error MAE—are used to assess various prediction techniques. The authors observed that the LSTM model predicts better than the MLP for daily price trend analysis. The results of MAPE are 3.67 and 32.29 for LSTM and MLP. Deep Learning Models are suitable methods for capturing the price trends of cryptocurrencies for larger datasets. Both MLP and LSTM can predict price trends. However, studies indicate that LSTM is more reliable and accurate for long-term reliance than MLP. The Binary Auto Regressive Tree BART, MLP, and RF models were explored as three different ML algorithms to predict short-term cryptocurrency time series and compare their predictive properties.

In 2020, Derbentsev et al. [[12](#_ENREF_12)] utilized complex systems theory techniques. They showed that it was possible to create indications of critical and crash occurrences in the volatile stock and cryptocurrency markets. Findings demonstrate the high volatility, unusual observations, and complicated dynamics that the cryptocurrency time series exhibit. The research focuses on the challenges of applying machine learning ML to forecast cryptocurrency time series over the short term. The study's primary goal is to examine the predictive capabilities of several ML approaches for the short-term forecast problem of cryptocurrency exchange prices. Applying Binary Auto Regressive Tree BART, ANN, and RF to predict cryptocurrency prices. They collected data on daily price exchanges from finance.yahoo.com for the three cryptocurrencies' most capitalized coins: BTC, ETH, and XRP. The BART and MLP have higher prediction accuracy for all-time series than the RF models. The BART model's average values for the Accuracy measure are 62%, 61% for MLP, and 57% for RF. They use the lag values of the time series under study as their dataset (closing prices). A larger dataset that includes open, maximum, minimum, average prices, trade volume, etc., can improve forecast accuracy.

In 2020, Alonso-Monsalve et al.[[13](#_ENREF_13)] categorized cryptocurrency exchange rates using technical analysis in high frequencies. This study investigated the suitability of neural networks with a convolutional component as an alternative to conventional multilayer perceptrons. It is determined whether six well-known cryptocurrencies, including BTC, Dash, ETH, LTC, XMR, and XRP, appreciate relative to the US dollar over one minute by comparing the performance of four different network architectures: convolutional neural network CNN, hybrid CNN-LSTM network CLSTM, MLP, and radial basis function neural network RBFNN. They collected a set of cryptocurrency price datasets from the platform https://www.cryptocompare.com. The results showed a high accuracy of the CLSTM model at the expense of the rest of the models, as it achieved the following results for the four cryptocurrencies: BTC, Dash, ETH, LTC, XMR, and XRP accuracy was 0.68, 0.74, 0.59, 0.68, 0.80, and 0.67 respectively. From the preceding, we see that it is possible to predict the direction of the movement of cryptocurrencies, and the accuracy can be increased by expanding the data set and using blockchain information.

In 2021, Hamayel and Owda [[2](#_ENREF_2)] designed education models using ML to provide accurate results near the market prices of cryptocurrencies. These models are crucial because they may impact the economy by assisting traders and investors in determining when to buy and sell cryptocurrencies. The authors used three ML algorithms: LSTM, gated recurrent unit GRU, and bidirectional LSTM bi-LSTM.to forecast the prices of three types of cryptocurrencies: ETH, LTC, and BTC. With MAPE percentages of 0.2454%, 0.8267%, and 0.2116% for BTC, ETH, and LTC, respectively, GRU offers the most precise prediction for LTC. The GRU outperformed the LSTM and the bi-LSTM models regarding price prediction for all types of cryptocurrencies. The researchers did not expand the dataset specification for the target cryptocurrency, which may negatively affect the results.

In 2021, Derbentsev et al. [[14](#_ENREF_14)] challenged the supervised ML-based short-term forecasting of cryptocurrency time series is discussed. The primary goal is to investigate the effectiveness of ML ensemble-based techniques, including RF and Stochastic Gradient Boosting Machine SGBM, on short-term BTC price predictions. By calculating the accuracy criteria, MAPE for SGBM and RF algorithms were 0.92 and 1.84 for XPR, respectively. The results were close, and SGBM offers the most precise prediction. This study has demonstrated the effectiveness of ML ensemble-based methods for forecasting cryptocurrency time series. The study did not contain a table showing the used time series parameters.

In 2021, Cocco et al. [[15](#_ENREF_15)] evaluated how Bayesian Neural Networks BNN perform at predicting BTC price and compared those results to those from other types of Neural Networks NNs.Employed two ML frameworks to predict BTC's daily closing prices. The first framework uses the following NN algorithms: BNN, FFNN, and LSTMNN. This algorithm depends on the data of the technical indicators currency markets SAM, EAM, RSI, MOM, and MACD as inputs to analyze them and extract the results. The second framework adds an algorithm (i.e., Support vector regression SVR) to analyze the data of technical indicators and then enter its effects on NN algorithms. It used the k-fold cross-validation method to evaluate the performance of the above frameworks. The MAPE values run obtained by training the selected best architectures using the whole data set to predict BTC price. The best results from Two-stage frameworks were obtained from the BNN algorithm, where the MAPE was 1.74.

In 2021, Akyildirim et al.[[5](#_ENREF_5)] analyzed the predictability of the twelve most liquid cryptocurrencies, the researcher used machine learning classification algorithms, such as SVM, logistic regression LR, ANN, and RF, along with past price data and technical indicators as model features. Instead of focusing on a particular digital currency BTC, they covered a sample of twelve cryptocurrencies. Aids in understanding the market's overall pricing patterns. This work aims to determine the direction of the cryptocurrency market prices, up or down. Therefore, investors in these markets can achieve the maximum benefit. Use Bitfinex exchange and Kaiko digital asset store to collect the dataset from 1 April 2013 to 23 June 2018. SVM regularly performs above 50% fit and is the most effective and reliable model for predicting the next day's return. Adjusting the inputs to the machine learning algorithms contributes significantly to raising the degree of prediction accuracy to approximately 70% or more. The study's benefits are expanding the application of the prediction in twelve cryptocurrencies and entering data of technical indicators for analysis. It is harmful that the results did not exceed the 75% threshold for prediction accuracy.

In 2021, Kim et al. [[16](#_ENREF_16)] aimed to find the relationship between the information on the private ETH blockchain and the price of ETH and the Data on the blockchain of other popular cryptocurrencies and their impact on predicting the price of ETH. This work utilizes publicly accessible Blockchain-related datasets and well-known and widely used ML algorithms (i.e., ANN and SVM). The ANN and SVM were employed to predict ETH prices. They used the RMSE and MAPE to assess the outcomes. The results disclosed that the MAPE of ANN was 0.048, and the accuracy of 95.2% in predicting ETH price movements. The author concluded that the ANN performed better than SVM. However, the techniques and findings of this study can be replicated by academics and industry professionals who want to forecast ETH pricing in the future.

In 2021, Shahbazi and Byun [[17](#_ENREF_17)] proposed an ML method to forecast financial institutions. The suggested system consists of a Blockchain framework for Reinforcement Learning algorithm RL and protected transaction situation examination and forecast of price. Therefore the RL model was created to forecast the variations in cryptocurrency values. The RL predicated two digital coins, Monero XMR and LTC. This procedure addresses the issue of irregular fluctuation in a cryptocurrency price. The performance matrices like MAE, MSE, RMSE, and MAPE were utilized to evaluate the performance of the proposed model. The preceding clearly shows that the proposed model's accuracy is not relatively high. The results illustrated that the MAE of XMR and LTC was 4.3826 and 3.3097 when three days of price prediction were considered.

In 2021, El-Berawi et al. [[18](#_ENREF_18)] classified cryptocurrency price data and the direction of its movement, and a predictive model based on recurrent neural networks was developed. They use dependable external sources with a possibility for predictability and adaptive dynamic feature selection. Due to the extreme fluctuations in cryptocurrency prices, it isn't easy to predict, classify, and determine the direction of its movement. The primary goal is to build a deep learning-based predictive model for forecasting and classifying the price of cryptocurrency and the direction of its movement. Dataset collected for four cryptocurrencies: BTC, ETH, USDT, and BNB from the https://www.investing.com API web services and external sources, gold\_close, oil\_close, NYSE BTC index, Standard and Poor's 500, and Google Trends for the cryptocurrency name keyword. Use the predictive power scoring method PPS as a first-phase filter to eliminate features with little bearing on the target prediction. Then, by normalizing the features, start the preprocessing of the data. Continue the feature selection procedure in the second phase by calculating the linear statistical relationship between the candidate predictor and target variables. In this stage, the Pearson Correlation Coefficient PCC is utilized. And then, deep learning models LSTM, MLP, and GRU use to predict, classify, and determine the direction of its movement cryptocurrency price. Results for BTC had an accuracy rating of 92%. & For regression, the suggested model for BTC data received a score of 2.4 MAPE. The outcomes indicate a considerable impact of applying an adaptive feature selection strategy to enhance classification performance.

In 2021, Livieris et al. [[19](#_ENREF_19)] used deep learning techniques to make time-series predictions over the past few years, emphasizing well-liked real-world application areas like the cryptocurrency market. These models use unique architectural designs based on convolutional and long short-term memory (LSTM) layers and cutting-edge deep learning approaches. Therefore, creating an accurate and trustworthy forecasting model is crucial due to the significant price variations over a short period. The main objective Of this study is to propose a multiple-input deep neural network model for predicting the price and movement of cryptocurrencies. They conducted a thorough experimental analysis to test and assess the effectiveness of the proposed Multi-Input Cryptocurrency Deep Learning MICDL model in predicting the cryptocurrency prices of BTC, ETH, and XRP. All data for cryptocurrencies were collected from the website https://coinmarketcap.com. Two CNN-LSTM models, Model1 and Model2, were used to compare the suggested model. While Model 2 is trained using all three cryptocurrency data and the proposed MICDL model. However, Model 1 is trained using only one cryptocurrency data set (i.e., BTC, ETH, or XRP). The best result of the performance of the evaluated models for all BTC data Accuracy was 55.03%, 53.46%, and 53.04 for Model1, Model2, and MICDL, respectively. The experiments are very positive. Therefore, adding complex preprocessing methods based on moving averages and exponential smoothing to the proposed MICDL model seems promising.

In 2022, Ammer and Aldhyani [[20](#_ENREF_20)] development of deep learning dramatically contributed to the rise in interest in cryptocurrency price predictions. A long short-term memory (LSTM) method that can be used to predict the values of four different types of cryptocurrencies is presented in this paper. The primary goal of the study by analyzing and comparing multiple ML models for simultaneously predicting the market movements of some significant cryptocurrencies. Cryptocurrency data for this study was collected from the website <https://coinmarketcap.com> for four cryptocurrencies: ETH, XRP, EOS, and AMP. The LSTM model showed outstanding performance in the training and testing phases and high accuracy in predicting cryptocurrency prices. The best results for the cryptocurrency were AMP was 0.000745 and 0.042 for MSE and RMSE, respectively. Instead of using the traditional time series methods to estimate the returns of cryptocurrencies, a unique artificial intelligence methodology was applied. We discovered that the classification of returns using this novel strategy produced precise predicting results.

In 2022, Oyedele et al. [[4](#_ENREF_4)] used several studies that boosted tree-based modeling methods for the cryptocurrency industry, either predicting the existence of a single, well-known cryptocurrency platform or using a single data source for developing and testing the models. The choice of Deep learning approaches is made possible by their exceptional success in addressing problems across a wide range of areas and their ability to uncover complex structures in high-dimensional data. Trading tactics and investing choices are heavily impacted by price volatility for cryptocurrencies. Therefore, it is crucial to develop models that can forecast the cryptocurrency market with the same level of accuracy as the stock market. This study examines the effectiveness of a genetic algorithm tailored for Deep Learning and boosted tree-based techniques to forecast the closing values of numerous cryptocurrencies. The study gathered data from Bitfinex, UK Investing, and Yahoo Finance to examine the robustness of prediction models regarding how they react to patterns in various data sources. For the six cryptocurrencies (BTC, ETH, BNB, LTC, XLM, and DOGE), the Yahoo Finance information spans from January 1, 2018, through December 31, 2021. From July 1, 2021, to March 2, 2022, is covered by the UK Investing dataset. The Bitfinex statistics for the six cryptocurrencies also cover the period from January 1 to July 6, 2021. The study applied three models to predict the closing prices of cryptocurrencies: Boosted tree-based technique. The model used algorithms: Adaptive boosting ADAB, GBM, and Extreme gradient boosting XGB, then the deep learning model where the following algorithms used deep feedforward neural network DFNN, GRU, and CNN, then Genetic algorithms GA model. Deep learning models, especially the CNN algorithm, showed the best results compared to the proposed models and algorithms MAPE was 0.07. This study showed that cryptocurrency data does not differ from the different sources of its collection.

In 2022, Hansun et al. [[21](#_ENREF_21)] examined three well-known RNN deep-learning techniques. Even though many studies used those techniques, most of them concentrated on the univariate prediction model, whereas this research will focus on the multivariate prediction model. Additionally, use the top five cryptocurrencies by market capitalization: BTC, ETH, ADA, USDT, and BNB. And because cryptocurrencies are so dynamic and volatile, it isn't easy to forecast their future prices. Three different RNNs and a multivariate prediction technique should be used. And three-layer deep network architecture for the study's regression goal. The cryptocurrency data for this study was collected from finance.yahoo.com. Each cryptocurrency underwent several preprocessing processes, starting with data imputation to manage missing values and ending with data reshaping so that it could be processed by the deep learning techniques used in this work, namely LSTM, Bi-LSTM, and GRU. The best result achieved by the GRU method when measured using Average MAPE was 0.0446512 for the top five cryptocurrencies by market capitalization above. The study showed that the proposed simple model could compete with more complex deep learning models.

In 2022, Shahbazi and Byun [[22](#_ENREF_22)] volatility value of a digital currency was the most significant issue for dealers. Thus, creating a model to determine digital currency's price before an exchange is an important step. To anticipate the price of digital currency, they used the XGBoost machine learning model. The training and test phases are the two critical stages of this process. The classification and feature selection processes are both parts of the XGBoost algorithm. The data collected for the cryptocurrency, namely: ETH, LTC, and XMR from the https://digitalcoinprice.com/ website, is the most excellent method for predicting exchange rates because it provides comprehensive information on price changes and exchange activity based on date and time. The results of the proposed algorithm XGBoost were compared with the machine learning algorithms CNN, Arima, MLP, and LSTM, and the proposed algorithm XGBoost achieved MAPE was 0.005. The results of the LSTM algorithm are better than the results of the proposed model.

In 2022, Kim et al. [[23](#_ENREF_23)] predicted a model to draw statistical conclusions about historical cryptocurrency price data. They used linear and nonlinear error correction models ECM to forecast cryptocurrency log values. The researcher collected data for the study from the crypto2 R package of the fourteen cryptocurrencies: BTC, ETH, ADA, BNB, XRP, BCH, LTC, LINK, ETC, USDT, DOGE, USDC, LUNA, and XLM. Regarding RMSE, MAE, and MAPE, the linear ECM model1 outperforms the autoregressive and neural network models for predicting the BTC R-squared of model 1 was 0.883. To forecast future log-return prices of each cryptocurrency with highly related cryptocurrencies, they can apply linear ECM. The researcher did not discuss work plans for ECM.

In 2022, Oyewola et al. [[24](#_ENREF_24)] extracted several factors that impact cryptocurrencies, including technical development, internal competitiveness, market pressure, economic concerns, security, and political considerations. Due to the lack of a suitable analytical foundation, forecasting cryptocurrency values is a highly challenging undertaking. The main objective is to apply the hybrid walk-forward ensemble optimization technique to predict the daily prices of fifteen cryptocurrencies. The data on cryptocurrencies ADA, BitcoinCash BCH, BNB, BTC, DOGE, Ethereum Classic ETC, Chainlink LINK, LTC, NEO, Tron TRX, USD, NEM XEM, Stellar XLM, XRP, and Tezos XTZ. was collected from yahoofinance.com. Advanced machine learning models, such as combinations of ARIMA, Holt Winter's exponential smoothing HWES, decision tree BAG, stochastic gradient boosting SGB, RF, LSTM, GRU, and RNN, are used as component learners in the proposed ensemble technique. Therefore thorough simulation analysis was done to gauge how well the suggested model performed. Algorithm SGB achieved the best results for ML algorithms, where the value of scale MAE 0.0048 for encrypted currency TRX. We did not find a proposed model workflow diagram showing the details of the model.

In 2022, Alsharef et al. [[25](#_ENREF_25)] adopted forecasting experiments using ML, DL, and AutoML. Modeling time-series data is challenging due to its uncertainty. The main objective entails tackling the forecasting issue by experimenting with more ML and DL models and AutoML frameworks, as well as broadening the experimental knowledge of AutoML. The researcher has collected the datasets for the analysis gathered from Yahoo Finance for cryptocurrency ETH and BTC. This work combined ML models with AutoML frameworks that automatically find and tune optimal ML models to address the issues of forecasting time series and data drift. LSTM, IndRNN, LR, AR, MA, ARIMA, RNN, GRU, and ARMA were some ML models. The AutoML frameworks featured Auto-Keras and EvalML. Since AutoML for time series could not outperform manually created ML and DL models, they discovered that it is still in the development stage and needs further research to be a practical option. The best outcome for the ML model is LSTM, where the scale MAE value for encrypted currency ETH is 11.57.

Table 1. Comparison between previous works on cryptocurrency prices.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Ref./Year** | **Objective** | **Technique**  **/algorithm** | **Cryptocurrency** | **Dataset** | **Accuracy/ Error** |
| [[6](#_ENREF_6)]  /2019 | investigating the connections between internet variables and cryptocurrency values using elements from Twitter and market data | MLPs, SVM, RF | BTC, ETH, XPR, LTC | * cryptocompare.com API * Twitter API | 0.72  (MLP) for BTC |
| [[8](#_ENREF_8)]  /2020 | Forecast the BTC price using machine learning methods based on two datasets | LR , LDA, RF, XGB, QDA, SVM, LSTM, | BTC | * CoinMarketCap.com * Binance.com | * 66% (LR) for BTC * 67.2% (LSTM) |
| [[9](#_ENREF_9)]  /2020 | It aims to create a model for BTC price prediction. | Integrates the VMD and Stacking-ensemble  The ML in stack are :KNN, SVR, NNET, GLM, | BTC | N/A | * MAPE 0.0626 (VMD-STACK ) |
| [[10](#_ENREF_10)]  /2020 | Forecast the value of the target variable for the upcoming time using several ML algorithms | SVM, ANN, RF, GBM | BTC, ETH. | * Nasdaq * SP&500 | * MAPE was 1.03 * RMSE was 106.5   (SVM) for BTC |
| [[11](#_ENREF_11)]  /2020 | Create a model to predict BTC prices in the medium period of 30 to 90 days and the short-term period from one to 7 days | * Technical indicators * Extract features using the RF method * Predicted BTC prices used: ANN, SANN, SVM, LSTM | BTC | * Bitinfocharts.com | * Regression MAPE 0.73, 1.88, 0.52, and 0.93 for (SVM, ANN, SANN, and LSTM) receptivity * Classification models accuracy was 55%, 57%, 60%, and 54% |
| [[1](#_ENREF_1)]  /2020 | Identify ETH currency and forecast its price based on previous price inflations | LR, SVM | ETH | * Etherchain.org | * 96.06%(SVM) * 85.46%(LR) |
| [[3](#_ENREF_3)]  /2020 | Examined the role of deep Learning methods in forecasting ETH price movements | MLP, LSTM | ETH | * Coindesk * Coinmarket | The MAPE is   * 3.67 (LSTM) * 32.29 (MLP) |
| [[12](#_ENREF_12)]  /2020 | examine the predictive capabilities of several ML approaches for the short-term forecast problem of cryptocurrency exchange prices | BART, ANN(MLP), and RF | BTC, ETH, and XRP | * Finance. Yahoo | * 62% (BART) * 61% (MLP) * 57% (RF) |
| [[2](#_ENREF_2)]  /2021 | Models designed by ML to provide accurate results near the market prices of cryptocurrencies. | LSTM, GRU, bi-LSTM | BTC, ETH, LTC | * Marketwatch.com | (GRU) MAPE   * BTC 0.2454 * ETH 0.8267 * LTC 0.2116 |
| [[14](#_ENREF_14)]  /2021 | Investigate the effectiveness of ML ensemble based on short-term BTC price predictions. | RF and SGBM, | BTC, ETH, XRP | * finance.yahoo.com. | MAPE   * 0.92 (SGBM ) * 1.84 (RF) |
| [[15](#_ENREF_15)]  /2021 | evaluated how BNN performs at predicting BTC price and compared those results to those from other types of NNs | * First framework: BNN, FFNN, and LSTMNN. * SVR to analyze the data of technical indicators + First Framewor-k | BTC, ETH | N/A | MAPE   * 1.74(BNN) |
| [[5](#_ENREF_5)]  /2021 | This work aims to determine the direction of the cryptocurrency market prices, up and down | SVM, LR, ANN, and RF | Bitcoin  Cash BCH, BTC, Dash DSH, EOS, Ethereum Classic ETC,  ETH, Iota IOT, LTC, OmiseGO OMG, XMR, XRP, and  Zcash ZEC. | Use Bitfinex exchange and Kaiko digital asset store to collect the dataset | SVM regularly performs above 50% fit |
| [[16](#_ENREF_16)]  /2021 | aimed to find the relationship between the information on the private ETH blockchain and the price of ETH and the Data on the blockchain of other popular cryptocurrencies and their impact on predicting the price of ETH | ANN, SVM | ETH | N/A | * MAPE 0.048 * 95.2%   (ANN) |
| [[17](#_ENREF_17)]  /2021 | This procedure addresses the issue of irregular fluctuation in a cryptocurrency price. | RL | LTC, XMR | N/A | * 4.3826 for XMR * 3.3097 for LTC |
| [[18](#_ENREF_18)]  /2021 | The primary goal is to build a deep learning-based predictive model for forecasting and classifying the price of cryptocurrency and the direction of its movement. | Deep learning LSTM, MLP, GRU | BTC, ETH, USDT, BNB | * www.investing.com API web services * External sources, * Gold * Oil * NYSE BTC index Standard * Poor's 500 * Google Trends for the cryptocurrency name keyword | * 92% * 2.4 MAPE   For BTC (GRU) |
| [[7](#_ENREF_7)]  /2019 | The primary goal is to produce indications of price predictions for the three significant cryptocurrencies | ARIMA | BTC, XRP, and ETH | * www.kaggle.com | * MAE 0.041 * MSE 0.0097 * RMSE 0.096 for XPR |
| [[13](#_ENREF_13)]  /2020 | investigated the suitability of neural networks with a convolutional component as an alternative to conventional multilayer perceptron’s | CNN, CLSTM, MLP, and RBFNN | BTC, Dash, ETH, LTC, XMR, and XRP | * www.cryptocompare.com | (CLSTM) accuracy   * 0.68 for BTC * 0.74 for Dash * 0.59 for ETH * 0.68 for LTC * 0.80 for XMR * 0.67 for XRP |
| [[19](#_ENREF_19)]  /2021 | The main objective Of this study is to propose a multiple-input deep neural network model for predicting the price and movement of cryptocurrencies | Deep learning  MICDL model | BTC, ETH, and XRP | * Coinmarketcap.com. | * 55.03% for Model1 * 53.46% for Model2 * 53.04 for MICDL   For BTC data |
| [[20](#_ENREF_20)]  /2022 | The primary goal of the study by analyzing and comparing multiple ML models for simultaneously predicting the market movements of some significant cryptocurrencies. | LSTM | ETH, XRP, EOS, and AMP | * Coinmarketcap.com | * 0.000745 MSE * 0.042 RMSE (AMP) |
| [[4](#_ENREF_4)]  /2022 | develop models that can forecast the cryptocurrency market with the same level of accuracy as the stock market | ADA, GBM, XGB, GRU, DFNN, and CNN | BTC, ETH, BNB, LTC, XLM, and DOGE | * Bitfinex * UK Investing * Yahoo Finance | * 0.07 (CNN) |
| [[21](#_ENREF_21)]  /2022 | this research will focus on the multivariate prediction model | LSTM, Bi-LSTM, and GRU. | BTC, ETH, ADA, USDT, and BNB. | * Yahoo Finance | (GRU)   * 0.0446512 Average MAPE for the top five   Crypto |
| [[22](#_ENREF_22)]  /2022 | Creating a model to determine digital currency's price before an exchange is an important step. | XGBoost | ETH, LTC, and XMR | * Digitalcoinprice.com | * 0.005   (XGBoost) |
| [[23](#_ENREF_23)]  /2022 | Used linear and nonlinear error correction models ECM to forecast cryptocurrency log values | ECM | BTC, ETH, ADA, BNB, XRP, BCH, LTC, LINK, ETC, USDT, DOGE, USDC, LUNA, and XLM | * Crypto2 R package | * 0.883   For BTC |
| [[24](#_ENREF_24)]  /2022 | The main objective is to apply the hybrid walk-forward ensemble optimization technique to predict the daily prices of fifteen cryptocurrencies. | ARIMA, Holt HWES, BAG, SGB, RF, LSTM, GRU, and RNN | ADA, BCH, BNB, BTC, DOGE, ETC, LINK, LTC, NEO, Tron TRX, USD, NEM XEM, XLM, XRP, and XTZ | * Yahoo Finance | * 0.0048   (SGB) for TRX |
| [[25](#_ENREF_25)]  /2022 | The main objective entails tackling the forecasting issue by experimenting with more ML and DL models and AutoML frameworks, as well as broadening the experimental knowledge of AutoML | LSTM, IndRNN, LR, AR, MA, ARIMA, RNN, GRU, and ARMA. The AutoML framework Auto-Keras and EvalML | ETH,  BTC. | Yahoo Finance | * 11.57 MAE   (LSTM)For ETH |

**4. Challenges and limitations**

By reviewing the above research, we noted that the most critical determinant that accompanies the process of forecasting cryptocurrency prices is determining the time series period. The best results for predicting cryptocurrency prices were for a period of one day. After selecting this period, the price movement can be determined in both directions, ascending or descending, and predicting the daily closing price of cryptocurrencies. However, the biggest challenge remains the extreme fluctuations in cryptocurrency prices, which makes it more difficult to predict daily closing prices[[9](#_ENREF_9)]. We have also noticed that a specific digital currency affects the results of price prediction, depending on the amount of time series data available for the chosen cryptocurrency.All of the above factors can fundamentally affect the performance of machine learning and deep learning algorithms.

**5. Maturity evaluation**

We have compared the results of previous work in Table 1, which shows the best results of the algorithms used in predicting cryptocurrency prices. We have noticed that neural network algorithms: LSTM, RNN, CNN, BNN, and GRU are the best in terms of measuring the error rate and accuracy of predictions. And from the above, we see that neural network algorithms can deal with time series prediction problems. However, we also found that the SVM algorithm achieved good results in its predictions of cryptocurrency prices**.**

**6. Conclusions**

Through our review of previous work in predicting cryptocurrency prices, we found that researchers rely on machine learning technology and deep learning. Where they were able to reach the highest possible accuracy in predictions based on historical data for cryptocurrencies. Through the survey we conducted, it became clear to us that the algorithms of neural networks outperform the rest of the methods of machine learning and deep learning. We have found that most of the methods used and the most accurate in forecasting are LSTM and GRU to predict currency rates and determine the direction of market movement.

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