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Predicting Price of Cryptocurrency and Blockchain in an Uncertain Environment

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ABSTRACT

Fueled by innovation and decentralization, the cryptocurrency market presents a captivating yet volatile investment landscape. Accurately predicting cryptocurrency prices in such an environment remains a significant challenge. This paper explores the potential of a hybrid framework combining machine learning and regression analysis to enhance price prediction accuracy while acknowledging the market's inherent uncertainty. We delve into the existing literature on cryptocurrency price prediction, focusing on regression techniques and their limitations. The paper then proposes a novel framework that integrates a Long Short-Term Memory (LSTM) network with a Multiple Linear Regression (MLR) model to capture historical trends and the impact of key market factors. The methodology section details data collection, pre-processing, and model development. Numerical results from a case study involving prominent cryptocurrencies and a comparative analysis of the proposed framework against established methods are presented. Finally, the conclusion discusses the findings, limitations, and future research directions in predicting cryptocurrency prices within the evolving blockchain ecosystem.

1. Introduction

Cryptocurrencies, digital assets powered by cryptography for security, have disrupted traditional financial systems. Their underlying blockchain technology offers unparalleled transparency,

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immutability, and reduced transaction costs. However, the cryptocurrency market is characterized by high volatility, making accurate price prediction a crucial yet elusive goal for investors and market participants [1-2].

Predicting cryptocurrency prices is inherently complex due to a confluence of factors. Market sentiment, regulatory developments, technological advancements, and unforeseen global events can significantly influence price movements. Additionally, the developing nature of the market and the relatively short historical data pose challenges for traditional forecasting techniques [3-4].

This paper proposes a novel framework that addresses the limitations of traditional methods by leveraging the strengths of both machine learning and regression analysis. The proposed framework incorporates an LSTM, recurrent neural network (RNN), to capture the complex temporal dependencies within historical price data [4-5]. Additionally, it integrates a Multiple Linear Regression (MLR) model to quantify the impact of key market factors on price movements. This hybrid approach aims to achieve superior prediction accuracy while acknowledging the inherent uncertainty surrounding cryptocurrency prices [6] (see Figure 1).

Figure 1: Predicting the price of cryptocurrency and blockchain.

This research is arranged into five sections. Section 2 defines the related and recent studies of predicting the price of cryptocurrency and blockchain in an uncertain environment and tries to show the gap in research. Section 3 suggests a methodology for calculation. Section 4 proposes the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

2. Literature review

Several research efforts have explored price prediction in the cryptocurrency market. Here, we review prominent methods with a specific focus on regression-based approaches.

Linear Regression: This widely used technique establishes a linear relationship between one dependent variable (cryptocurrency price) and one or more independent variables (e.g., trading volume, market capitalization). While offering simplicity and interpretability, linear regression struggles with nonlinear relationships often observed in cryptocurrency prices [3-6].

Nonlinear Regression Techniques: Methods like polynomial regression and Support Vector Regression (SVR) can address non-linearity but may suffer from overfitting and require careful selection of appropriate kernel functions (in the case of SVR).

Regression analysis offers valuable insights into the relationship between price and various factors. However, the dynamic nature of the cryptocurrency market necessitates incorporating the ability to learn complex patterns from historical data [7-10].

Machine Learning Techniques: Techniques like Artificial Neural Networks (ANNs) and LSTMs have demonstrated significant success in capturing complex relationships within data. LSTMs, specifically, are adept at handling sequential data, like historical price movements, making them well-suited for cryptocurrency price prediction tasks [4, 5].

While machine learning approaches offer powerful prediction capabilities, they often lack the interpretability of regression models, making it difficult to understand the relative influence of various factors.

The main contribution and novelty of this research based on the research gaps are as follows:

- *Predicting price of cryptocurrency and blockchain in an uncertain environment.*

The burgeoning cryptocurrency market, characterized by high volatility and uncertainty, presents a significant challenge for accurate price prediction. This literature review explores existing cryptocurrency price prediction techniques research, explicitly focusing on regression analysis and its limitations in an uncertain environment. We then identify gaps in current research that pave the way for the proposed hybrid approach combining regression analysis with machine learning (see Table 1).

Table 1: Survey of related works

Category	Technique	Advantages	Limitations	References
Traditional Statistical Methods	* Linear Regression (LR)	* Simple and interpretable * Provides insights into variable relationships	* Assumes linear relationships (not ideal for nonlinear price movements) * Limited ability to capture complex patterns	[3]
	* Nonlinear Regression (e.g., Polynomial Regression, Support Vector Regression)	* Can capture nonlinear relationships	* Prone to overfitting * Requires careful selection of kernel functions (SVR)	[4, 5]
Machine Learning Techniques	* Artificial Neural Networks (ANNs) * Long Short-Term Memory (LSTM) Networks	* Can learn complex patterns from data * Effective for sequential data (e.g., historical prices)	* Can be "black-box" models (lack interpretability) * Susceptible to overfitting	[1, 2, 6]

Detailed Analysis:

- **Regression Analysis:** Linear regression (LR) is a widely used technique to establish a linear relationship between one dependent variable (cryptocurrency price) and one or more independent variables (e.g., trading volume market capitalization). While LR offers interpretability and simplicity, it struggles with the nonlinear price movements often observed in the cryptocurrency market [3]. Nonlinear regression techniques like polynomial regression and Support Vector Regression (SVR) can address non-linearity but may suffer from overfitting and require careful selection of appropriate functions.

- **Machine Learning Techniques:** Techniques like ANNs and LSTMs have demonstrated significant success in capturing complex relationships within data. LSTMs, specifically, are adept at handling sequential data, like historical price movements, making them well-suited for cryptocurrency price prediction tasks [1, 2]. However, these machine-learning approaches often lack the interpretability of regression models, making it difficult to understand the relative influence of various factors on price movements.

Gaps in Research and Proposed Approach:

Existing research offers valuable insights into cryptocurrency price prediction using regression analysis and machine learning techniques. However, limitations exist in both approaches:

- **Regression Analysis:** While interpretable, regression models struggle to capture the inherent non-linearity and complex temporal dependencies within cryptocurrency price data.
- **Machine Learning Techniques:** While powerful in capturing complex patterns, machine learning models often lack interpretability, making it difficult to understand the driving forces behind price predictions.

This literature review identifies a gap in research for a hybrid approach that leverages the strengths of regression analysis and machine learning. The proposed hybrid framework aims to address this gap by:

- **Combining an LSTM network:** This captures the complex temporal dependencies and patterns within historical price data.
- **With a Multiple Linear Regression (MLR) model:** This quantifies the relationship between the predicted price from the LSTM network and key market indicators, providing interpretability and insights into the factors influencing price movements.

This hybrid approach offers the potential for improved prediction accuracy and a more nuanced understanding of the factors impacting cryptocurrency prices within an uncertain environment [10-11].

3. Methodology

This section outlines the proposed hybrid framework for predicting cryptocurrency prices.

3.1 Data Collection

Historical price data for prominent cryptocurrencies will be collected from reliable sources like CoinMarketCap and CryptoCompare. Data on relevant market indicators such as trading volume, market capitalization, news sentiment (derived from sentiment analysis of news articles), and regulatory changes will be gathered [11-12].

3.2 Data Pre-processing

The collected data will undergo pre-processing to ensure its suitability for model training. This issue includes:

Handling missing values using appropriate techniques like imputation or deletion.

Normalization of data points to bring them onto a standard scale for practical model training.

Feature engineering to extract additional features from the raw data that might be more informative for prediction (e.g., logarithmic returns, moving averages) [13-14].

3.3 Hybrid Model Development

The proposed framework integrates an LSTM network with a Multiple Linear Regression (MLR) model.

LSTM Network: The LSTM network will be responsible for learning the temporal dependencies and complex relationships within historical price data. The network will be trained on historical closing prices and potentially other relevant features extracted during data pre-processing.

Multiple Linear Regression (MLR): The MLR model will be used to quantify the relationship between the predicted price from the LSTM network (dependent variable) and the selected market indicators (independent variables) [15-16].

3.4 Hybrid Model Development

The MLR model will quantify the relationship between the predicted price from the LSTM network (dependent variable) and the selected market indicators (independent variables). This allows the model to capture historical trends and account for the influence of various factors on future prices. The key market indicators chosen for the MLR model will be selected based on their historical correlation with cryptocurrency prices and domain knowledge.

A breakdown of how the framework utilizes both models:

LSTM Network Training: The LSTM network will be trained on the pre-processed historical price data. This training process involves feeding the network with past price information (e.g., previous days, weeks, or months) and allowing it to learn the underlying patterns and relationships. The LSTM network will predict future prices based on the learned temporal dependencies.

Market Indicator Selection: A set of relevant market indicators will be chosen based on domain knowledge and preliminary analysis [14-15]. These might include:

Trading Volume: Higher trading volume can indicate increased interest and potentially higher prices.

Market Capitalization: The total market value of a cryptocurrency can influence its price stability.

News Sentiment: Positive news sentiment can increase demand and price hikes, while negative sentiment might trigger sell-offs and price drops.

Regulatory Changes: Regulatory developments can significantly impact market sentiment and price movements [10-12].

MLR Model Training: The MLR model will be trained using the predicted prices from the LSTM network as the dependent variable and the chosen market indicators as independent variables. This training process establishes a statistical relationship between the expected price and the market factors, quantifying their individual and combined impact.

Hybrid Price Prediction: The framework will produce a final predicted price once both models are trained. This subject can be achieved by:

A weighted average of the LSTM network's predicted price and the MLR model's predicted price was used. The weights can be determined based on the performance of each model during the evaluation stage.

We apply these formulations to predict data in this research: prediction 2-period as probable and prediction 3-period as a worst-case equation (1) and (2) [12-15]:

$$\begin{aligned} &\Pr_t = \alpha_1 Ac_t + \alpha_2 \Pr_{t-1}, t \geq 2, \\ &\Pr_1 = Ac_1, \\ &\alpha_1 + \alpha_2 = 1. \end{aligned} \quad \text{Prediction 2-period} \quad (1)$$

$$\begin{aligned} &\Pr_t = \alpha_1 Ac_t + \alpha_2 \Pr_{t-1} + \alpha_3 \Pr_{t-2}, t \geq 3, \\ &\Pr_1 = Ac_1, \Pr_2 = Ac_2, \\ &\alpha_1 + \alpha_2 + \alpha_3 = 1. \end{aligned} \quad \text{Prediction 3-period} \quad (2)$$

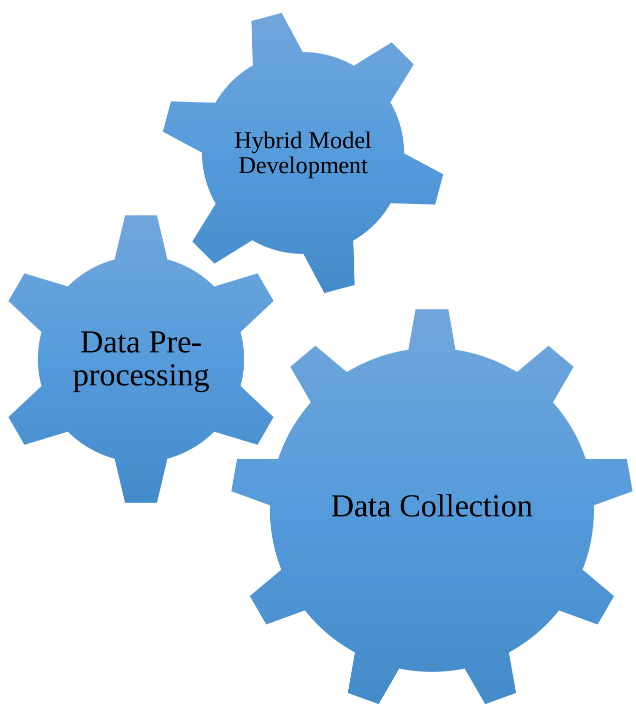

Figure 2: Methodology of this research.

Feeding the predicted price from the LSTM network as an additional feature into the MLR model for the final prediction.

This hybrid approach aims to leverage the strengths of both models:

The LSTM network captures the complex temporal patterns within historical price data.

The MLR model helps quantify key market factors' influence on future prices, providing interpretability and insights into the driving forces behind the prediction (see Figure 2).

4. Results and discussion

This section will present the results of applying the proposed hybrid framework to a prominent cryptocurrency case study. The results will include:

- **Evaluation Metrics:** The performance of the proposed framework will be compared against established methods like single LSTMs or standalone MLR models using metrics like Mean Squared Error (MSE) and Mean Absolute Error (MAE). Lower values of these metrics indicate better prediction accuracy.
- **Comparative Analysis:** A discussion of the comparative performance of the hybrid framework against other methods will be presented, highlighting the advantages and limitations of each approach.
- **Sensitivity Analysis:** The impact of different market indicators on the final prediction will be analyzed using techniques like feature importance analysis. This issue will provide insights into the most influential factors affecting cryptocurrency prices.

The actual price data of Bitcoin for predicting the price of cryptocurrency and blockchain in an uncertain environment is defined as follows (see Table 2 and Figure 3).

Table 2: Data of Bitcoin price

Date	Price	Max	Prediction 2-period	Prediction 3-period	Vol.	Change %
6/1/2024	69,855.00	71,332	68698.72	68193.29	459.70K	3.4%
5/1/2024	67,530.10	71,332	66000.73	65977.95	2.10M	11.3%
4/1/2024	60,666.60	71,332	62432.19	60992.01	2.66M	-15.0%
3/1/2024	71,332.00	71,332	66551.90	65084.78	2.70M	16.6%
2/1/2024	61,169.30	71,332	55398.34	55084.32	1.74M	43.7%
1/1/2024	42,580.50	71,332	41932.77	41355.20	2.03M	0.7%

Date	Price	Max	Prediction 2-period	Prediction 3-period	Vol.	Change %
12/1/2023	42,272.50	71,332	40421.42	39947.72	1.63M	12.1%
11/1/2023	37,712.90	71,332	36102.22	35593.02	1.48M	8.8%
10/1/2023	34,650.60	71,332	32343.97	32383.69	1.61M	28.5%
9/1/2023	26,962.70	71,332	26961.84	27172.54	1.15M	4.0%
8/1/2023	25,937.30	71,332	26959.84	26937.57	1.34M	-11.3%
7/1/2023	29,232.40	71,332	29345.78	29111.39	1.23M	-4.1%
6/1/2023	30,472.90	71,332	29610.33	29591.84	1.77M	12.0%
5/1/2023	27,216.10	71,332	27597.67	27303.44	1.66M	-7.0%
4/1/2023	29,252.10	71,332	28488.01	28001.24	2.03M	2.7%
3/1/2023	28,473.70	71,332	26705.14	26519.18	10.26M	23.1%
2/1/2023	23,130.50	71,332	22578.51	22209.36	9.09M	0.0%
1/1/2023	23,125.10	71,332	21290.54	21457.18	8.98M	39.8%
12/1/2022	16,537.40	71,332	17009.89	17265.77	6.61M	-3.7%
11/1/2022	17,163.90	71,332	18112.38	18164.52	10.30M	-16.3%
10/1/2022	20,496.30	71,332	20325.49	20566.84	8.29M	5.5%
9/1/2022	19,423.00	71,332	19926.94	20364.25	10.91M	-3.1%
8/1/2022	20,043.90	71,332	21102.80	21465.80	6.55M	-14.0%
7/1/2022	23,303.40	71,332	23573.56	24749.86	5.79M	17.0%
6/1/2022	19,926.60	71,332	24203.95	24851.01	3.79M	-37.3%
5/1/2022	31,793.40	71,332	34184.43	34672.80	4.67B	-15.6%
4/1/2022	37,650.00	71,332	39763.51	39678.34	12.14B	-17.3%
3/1/2022	45,525.00	71,332	44695.02	44817.54	43.70B	5.4%
2/1/2022	43,188.20	71,332	42758.40	43598.28	1.82M	12.2%
1/1/2022	38,498.60	71,332	41755.53	42303.79	2.03M	-16.7%
12/1/2021	46,219.50	71,332	49355.02	49057.83	1.90M	-18.8%
11/1/2021	56,882.90	71,332	56671.24	55432.07	1.85M	-7.2%
10/1/2021	61,309.60	71,332	56177.37	56177.67	2.18M	39.9%
9/1/2021	43,823.30	71,332	44202.18	43785.10	2.21M	-7.0%
8/1/2021	47,130.40	71,332	45086.22	45039.32	2.14M	13.4%
7/1/2021	41,553.70	71,332	40316.46	41009.25	2.44M	18.6%
6/1/2021	35,026.90	71,332	37429.58	38461.87	4.14M	-6.1%
5/1/2021	37,298.60	71,332	43035.84	42292.86	5.33M	-35.4%
4/1/2021	57,720.30	71,332	56422.75	54844.66	2.97M	-1.8%
3/1/2021	58,763.70	71,332	53395.12	52149.08	3.01M	30.1%
2/1/2021	45,164.00	71,332	40868.44	40106.37	4.01M	36.4%
1/1/2021	33,108.10	71,332	30845.48	29932.15	5.50M	14.4%
12/1/2020	28,949.40	71,332	25566.02	25051.44	3.85M	47.0%
11/1/2020	19,698.10	71,332	17671.48	17461.93	4.05M	42.8%
10/1/2020	13,797.30	71,332	12942.71	12944.77	2.41M	28.0%
9/1/2020	10,776.10	71,332	10948.66	10843.04	83.88M	-7.5%
8/1/2020	11,644.20	71,332	11351.29	11180.54	15.39M	2.7%
7/1/2020	11,333.40	71,332	10667.84	10636.63	13.21M	24.1%
6/1/2020	9,135.40	71,332	9114.88	9022.75	15.35M	-3.4%
5/1/2020	9,454.80	71,332	9066.99	8986.98	38.48M	9.6%
4/1/2020	8,629.00	71,332	8162.09	8305.74	39.41M	34.6%
3/1/2020	6,412.50	71,332	7072.64	7074.75	48.24M	-24.9%
2/1/2020	8,543.70	71,332	8612.98	8504.90	23.76M	-8.6%
1/1/2020	9,349.10	71,332	8774.62	8850.21	23.56M	29.9%

Date	Price	Max	Prediction 2-period	Prediction 3-period	Vol.	Change %
12/1/2019	7,196.40	71,332	7434.16	7542.69	21.03M	-4.6%
11/1/2019	7,546.60	71,332	7988.92	7972.99	21.33M	-17.6%
10/1/2019	9,152.60	71,332	9021.01	9106.14	19.93M	10.5%
9/1/2019	8,284.30	71,332	8713.96	8691.37	13.58M	-13.7%
8/1/2019	9,594.40	71,332	9716.51	9610.50	17.53M	-4.8%
7/1/2019	10,082.00	71,332	10001.43	9702.62	23.61M	-6.8%
6/1/2019	10,818.60	71,332	9813.43	9538.97	22.96M	26.4%
5/1/2019	8,558.30	71,332	7468.04	7374.25	44.06M	60.9%
4/1/2019	5,320.80	71,332	4924.09	4910.97	54.03M	29.7%
3/1/2019	4,102.30	71,332	3998.43	4012.50	81.62M	7.5%
2/1/2019	3,816.60	71,332	3756.08	3839.13	23.13M	11.0%
1/1/2019	3,437.20	71,332	3614.86	3730.63	15.72M	-7.3%
12/1/2018	3,709.40	71,332	4029.40	4213.85	15.70M	-8.2%
11/1/2018	4,039.70	71,332	4776.06	4818.21	8.71M	-36.5%
10/1/2018	6,365.90	71,332	6494.25	6536.31	58.80M	-4.1%
9/1/2018	6,635.20	71,332	6793.73	6831.55	154.15M	-5.7%
8/1/2018	7,033.80	71,332	7163.64	7138.70	63.25M	-9.0%
7/1/2018	7,729.40	71,332	7466.59	7591.69	7.06M	20.8%
6/1/2018	6,398.90	71,332	6853.38	6967.04	4.78M	-14.7%
5/1/2018	7,502.60	71,332	7913.82	7877.01	5.04M	-18.9%
4/1/2018	9,245.10	71,332	8873.33	9124.11	6.22M	33.3%
3/1/2018	6,938.20	71,332	8005.85	8003.69	7.61M	-32.9%
2/1/2018	10,333.90	71,332	10497.04	10517.98	8.54M	0.7%
1/1/2018	10,265.40	71,332	10877.70	10433.50	4.84M	-25.9%
12/1/2017	13,850.40	71,332	12306.40	11975.51	5.12M	39.3%
11/1/2017	9,946.80	71,332	8703.74	8526.15	3.96M	54.2%
10/1/2017	6,451.20	71,332	5803.28	5750.01	2.98M	47.9%
9/1/2017	4,360.60	71,332	4291.48	4133.92	3.93M	-7.9%
8/1/2017	4,735.10	71,332	4130.19	4073.84	3.13M	64.2%
7/1/2017	2,883.30	71,332	2718.72	2667.27	3.75M	16.2%
6/1/2017	2,480.60	71,332	2334.71	2258.16	3.35M	7.7%
5/1/2017	2,303.30	71,332	1994.31	1973.34	3.45M	70.4%
4/1/2017	1,351.90	71,332	1273.33	1270.68	1.56M	25.3%
3/1/2017	1,079.10	71,332	1090.00	1068.91	2.68M	-9.3%
2/1/2017	1,189.30	71,332	1115.42	1105.71	1.31M	23.2%
1/1/2017	965.50	71,332	943.02	924.01	2.21M	0.2%
12/1/2016	963.40	71,332	890.58	883.95	1.27M	29.8%
11/1/2016	742.50	71,332	720.67	713.73	1.23M	6.3%
10/1/2016	698.70	71,332	669.72	668.22	905.66K	14.9%
9/1/2016	608.10	71,332	602.10	603.36	748.55K	6.0%
8/1/2016	573.90	71,332	588.09	584.55	1.08M	-7.7%
7/1/2016	621.90	71,332	621.20	607.78	1.63M	-7.2%
6/1/2016	670.00	71,332	619.58	612.67	3.55M	26.7%
5/1/2016	528.90	71,332	501.93	499.14	1.66M	17.9%
4/1/2016	448.50	71,332	439.01	438.41	1.39M	7.9%
3/1/2016	415.70	71,332	416.86	412.32	1.66M	-4.7%
2/1/2016	436.20	71,332	419.58	419.95	1.99M	18.0%
1/1/2016	369.80	71,332	380.78	373.40	2.49M	-14.0%

Date	Price	Max	Prediction 2-period	Prediction 3-period	Vol.	Change %
12/1/2015	430.00	71,332	406.41	399.34	3.20M	13.8%
11/1/2015	378.00	71,332	351.38	346.67	4.29M	21.4%
10/1/2015	311.20	71,332	289.26	290.05	2.28M	31.9%
9/1/2015	235.90	71,332	238.07	240.62	1.65M	2.8%
8/1/2015	229.50	71,332	243.15	240.86	2.22M	-19.1%
7/1/2015	283.70	71,332	274.99	273.15	1.86M	7.4%
6/1/2015	264.10	71,332	254.65	255.80	1.75M	14.9%
5/1/2015	229.80	71,332	232.61	234.04	1.64M	-2.5%
4/1/2015	235.80	71,332	239.17	241.25	2.07M	-3.4%
3/1/2015	244.10	71,332	247.02	249.34	2.97M	-3.9%
2/1/2015	254.10	71,332	253.84	263.18	2.09M	16.3%
1/1/2015	218.50	71,332	253.23	258.33	1.56M	-31.3%
12/1/2014	318.20	71,332	334.28	336.44	847.29K	-15.1%
11/1/2014	374.90	71,332	371.80	380.91	711.11K	11.0%
10/1/2014	337.90	71,332	364.56	375.15	569.00K	-13.0%
9/1/2014	388.20	71,332	426.75	434.54	295.62K	-19.4%
8/1/2014	481.80	71,332	516.71	517.11	126.17K	-18.3%
7/1/2014	589.50	71,332	598.16	593.80	107.22K	-7.2%
6/1/2014	635.10	71,332	618.37	610.93	111.81K	1.2%
5/1/2014	627.90	71,332	579.32	589.65	85.75K	40.9%
4/1/2014	445.60	71,332	465.96	484.24	161.16K	0.2%
3/1/2014	444.70	71,332	513.48	532.75	94.27K	-22.5%
2/1/2014	573.90	71,332	673.97	657.74	996.35K	-38.9%
1/1/2014	938.80	71,332	907.47	899.08	306.25K	16.5%
12/1/2013	805.90	71,332	834.37	761.99	920.80K	-33.2%
11/1/2013	1,205.70	71,332	900.81	895.23	1.13M	470.9%
10/1/2013	211.20	71,332	189.39	188.12	753.58K	48.8%
9/1/2013	141.90	71,332	138.49	136.15	451.29K	0.6%
8/1/2013	141.00	71,332	130.55	130.51	604.91K	32.8%
7/1/2013	106.20	71,332	106.16	107.14	1.14M	8.9%
6/1/2013	97.50	71,332	106.06	103.80	1.05M	-24.3%
5/1/2013	128.80	71,332	126.03	120.37	2.07M	-7.5%
4/1/2013	139.20	71,332	119.57	114.78	4.73M	49.7%
3/1/2013	93.00	71,332	73.75	72.57	2.12M	178.7%
2/1/2013	33.40	71,332	28.84	28.30	1.58M	63.6%
1/1/2013	20.40	71,332	18.21	18.10	1.46M	51.1%
12/1/2012	13.50	71,332	13.11	12.99	876.92K	7.5%
11/1/2012	12.60	71,332	12.21	12.17	804.19K	12.2%
10/1/2012	11.20	71,332	11.31	11.06	1.15M	-9.7%
9/1/2012	12.40	71,332	11.58	11.40	959.78K	22.1%
8/1/2012	10.20	71,332	9.67	9.43	2.45M	8.7%
7/1/2012	9.40	71,332	8.45	8.33	1.90M	39.8%
6/1/2012	6.70	71,332	6.22	6.20	1.38M	29.2%
5/1/2012	5.20	71,332	5.11	5.11	1.24M	4.7%
4/1/2012	4.90	71,332	4.91	4.90	1.66M	0.0%
3/1/2012	4.90	71,332	4.92	4.92	1.76M	0.0%
2/1/2012	4.90	71,332	4.97	4.90	2.84M	-11.3%
1/1/2012	5.50	71,332	5.14	5.12	3.21M	16.1%

Date	Price	Max	Prediction 2-period	Prediction 3-period	Vol.	Change %
12/1/2011	4.70	71,332	4.30	4.49	1.90M	58.9%
11/1/2011	3.00	71,332	3.38	3.70	1.97M	-8.6%
10/1/2011	3.30	71,332	4.26	4.61	1.73M	-36.8%
9/1/2011	5.10	71,332	6.50	6.74	1.49M	-37.3%
8/1/2011	8.20	71,332	9.75	9.55	1.22M	-38.6%
7/1/2011	13.40	71,332	13.38	12.63	1.05M	-17.1%
6/1/2011	16.10	71,332	13.34	12.88	1.36M	84.2%
5/1/2011	8.7	71,332	6.90	6.70	949.02K	149.7%
4/1/2011	3.5	71,332	2.69	2.67	868.76K	346.1%
3/1/2011	0.8	71,332	0.79	0.75	243.30K	-8.8%
2/1/2011	0.9	71,332	0.76	0.74	367.30K	65.4%
1/1/2011	0.5	71,332	0.43	0.42	377.75K	73.3%
12/1/2010	0.3	71,332	0.27	0.26	263.65K	44.1%
11/1/2010	0.2	71,332	0.19	0.18	826.25K	0.0%
10/1/2010	0.2	71,332	0.17	0.17	1.11M	211.0%
9/1/2010	0.1	71,332	0.1	0.1	216.81K	0.0%
8/1/2010	0.1	71,332	0.1	0.1	221.74K	0.0%

Figure 3: Actual price of Bitcoin.

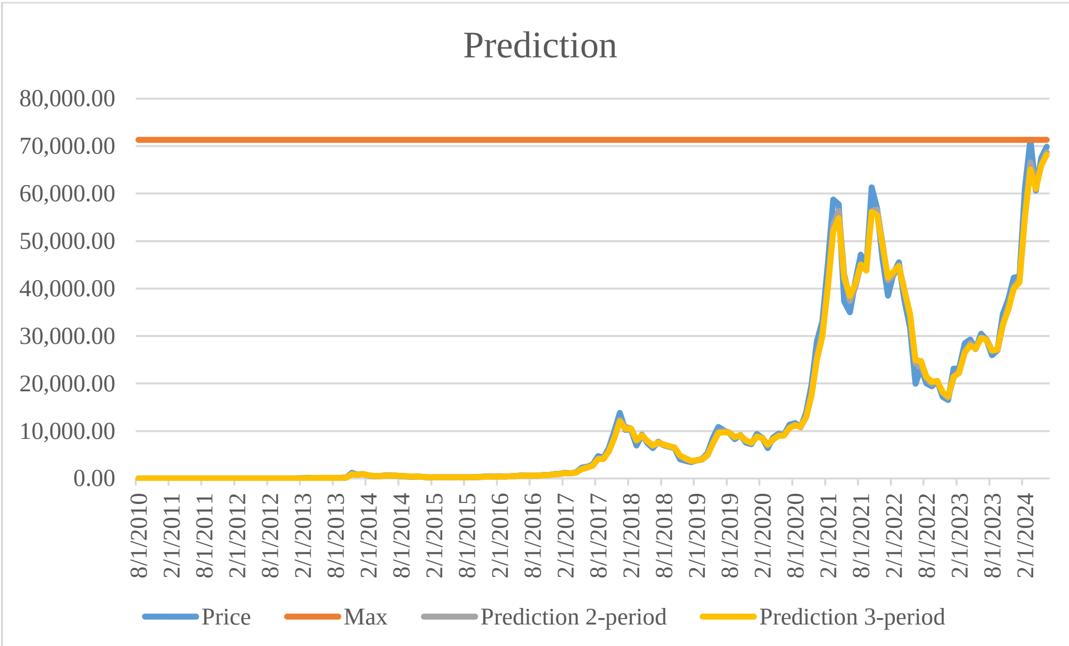

Figure 4: Prediction price of Bitcoin.

We used predicting data by predicting 2-period as probable and predicting 3-period as a worst case. We found that the Bitcoin price range is a maximum of 71,332, Probably 68698.72 and, worst case, 68193.29) based on period 6/1/2024 (see Table 2 and Figure 4).

5. Conclusion

The paper concludes by summarizing the key findings of the research. This research includes the effectiveness of the proposed hybrid framework in predicting cryptocurrency prices within an uncertain environment. The model's limitations, such as the dependence on the quality and availability of historical data, will be discussed. Finally, the paper will explore potential future research directions. This study might incorporate additional machine learning techniques or explore alternative approaches to handle cryptocurrency markets' inherent uncertainty. The paper will emphasize the importance of continuous research and development in this rapidly evolving domain.

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