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Predictive Modeling of Bitcoin Prices using Machine Learning Techniques

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Abstract: This research paper aims to comprehensively examine diverse algorithms employed in forecasting the price dynamics of bitcoin. The study's outcomes have undergone careful analysis, shedding light on emergent trends poised to exert influence on the cryptocurrency market in the proximate horizon. Notable among the algorithms scrutinized are the K-Nearest Neighbors (KNN), Logistic Regression, Linear Regression, and Seasonal Autoregressive Integrated Moving Average (SARIMA). A brief comparison of these algorithms has been done, with the intent of identifying the ideal machine learning-based algorithm for predicting Bitcoin's price. The preeminent criterion for model selection is predicated upon achieving optimal accuracy, culminating in the recognition of Linear Regression as the most adept algorithm for precise Bitcoin price predictions.

Keywords: *Bitcoin Price Prediction, Machine Learning, Linear Regression, Logistic Regression, SARIMA, KNN*

1. Introduction

The rapid evolution of cryptocurrencies has garnered significant attention in recent years, with Bitcoin emerging as the foremost and most widely recognized digital asset. Since its inception in 2009, Bitcoin has exhibited unprecedented price volatility, attracting not only traders and investors but also researchers keen on understanding and predicting its price movements. Precise estimation of Bitcoin prices is crucial for both individual investors looking to maximise their trading tactics and financial institutions and policymakers trying to reduce the risks related to the cryptocurrency space. In order to find insights and predict trends in the constantly shifting world of digital currencies, we apply machine learning algorithms to the domain of Bitcoin price prediction and analysis in this paper.

Because cryptocurrency is a unique asset class, predicting its price is a dynamic and inherently complex problem. Numerous variables, including market sentiment, macroeconomic events, regulatory changes, and technological advancements, have an impact on the price dynamics of bitcoin. With the help of recent developments in machine learning, researchers can now better understand these complex relationships by utilising big data. Promising results have been obtained when applying recurrent neural networks (RNNs) and deep learning to the modelling of Bitcoin price movements, as demonstrated by studies like [1] and [2]. Furthermore, studies like [3] have demonstrated how crucial sentiment analysis from news and social media platforms is for forecasting Bitcoin prices, emphasising the connection between market dynamics and online conversation.

Even though these developments represent a significant advancement, it is still difficult to predict the price of bitcoin. Forecasting in the cryptocurrency market is a difficult task because of its high volatility and vulnerability to abrupt price spikes or crashes. Prediction models are further complicated by the existence of anomalies and irregularities in the market. Inspired by recent studies such as [4], which support hybrid models, this paper addresses these issues by putting forth a thorough framework that combines conventional time series analysis with cutting-edge machine learning methods. Our goal is to provide a comprehensive and reliable approach to Bitcoin price prediction by utilising historical price data, market indicators, and sentiment analysis. This will help us better understand the behaviour of this digital asset and its implications for individual investors as well as the larger financial ecosystem.

Due to its extreme volatility, there is a requirement for accurate predictions to form the foundation for investment choices. Machine learning algorithms have found extensive use in various domains, such as product manufacturing [5], [6], [7], [8] and finance [9], [10], to yield precise predictions. By incorporating historical data, these algorithms facilitate the creation of predictive models rooted in past occurrence patterns. Even in the realm of

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cryptocurrency, like the Bitcoin market, where heightened liquidity and volatility are prevalent due to T+0 trading regulations, similar machine-learning approaches can be adopted for prediction purposes.

While prior research has harnessed machine learning to enhance the precision of Bitcoin price forecasting, limited attention has been given to assessing the applicability of diverse modeling methods to data samples featuring varying structures and dimensional attributes. Our objective is to forecast Bitcoin prices at different intervals, starting with daily and high-frequency prices. In this study, we aim to achieve precise predictions of Bitcoin prices by accounting for a range of influential factors that impact its value. Leveraging the accessible dataset, we endeavor to attain the utmost accuracy in predicting price direction changes. We have compared 4 algorithms-Linear Regression, Logistic Regression, SARIMA, and KNN and analyzed their results to determine which one of the above gives the most accurate results, while being easy to implement.

2. Literature Review

The cryptocurrency market, led by Bitcoin, has witnessed exponential growth in recent years, attracting both institutional and retail investors. The high volatility and speculative nature of cryptocurrencies have made them a fascinating subject for researchers seeking to understand their price dynamics and explore avenues for prediction. This section highlights recent research that have significantly advanced the field and gives a thorough overview of the major advancements in machine learning-based algorithms for predicting Bitcoin prices.

Zheshi Chen et al. [11] originally divided Bitcoin prices into two categories: high-frequency prices and daily prices, in order to forecast Bitcoin prices using machine learning techniques at different time intervals. To accomplish the prediction of Bitcoin's daily prices, a comprehensive set of high-dimensional features encompassing aspects such as trading and market indicators, property and network data, attention metrics, and gold spot prices were employed. In contrast, the 5-minute interval price prediction relied on fundamental trading features obtained from a cryptocurrency exchange. To predict Bitcoin's daily prices, statistical approaches, notably Linear Discriminant Analysis, and Logistic Regression were employed with the high-dimensional feature set, achieving an impressive accuracy rate of 66%. Remarkably, these simpler statistical methods outperformed more intricate machine learning-based algorithms. For the prediction of Bitcoin's 5-minute interval prices, a range of machine learning models, including XGBoost, Random Forest, Support Vector Machine Quadratic, Discriminant Analysis, and Long Short-term Memory, were employed. These machine learning models proved superior to statistical approaches, achieving an impressive accuracy rate of 67.2%

J.B Awotunde et al. [12] employed machine learning-based models for creating a predictive model for cryptocurrency prices. This study focused on the adaptation of the Long Short-Term Memory (LSTM) technique to create a model designed for forecasting cryptocurrency prices. The primary variables considered in this endeavor included available price, high price, closing price, low price, market capitalization, and trading volume. Additionally, the model considered the complex interdependencies among various cryptocurrencies, emphasizing the measurement of critical factors influencing trading volatility to enhance the prediction process's effectiveness. The findings from this analysis demonstrated that machine learning-based models outperform other methods in forecasting cryptocurrency prices. Notably, the LSTM model exhibited superior performance compared to alternative models when applied to Bitcoin, Ether, and Litecoin cryptocurrencies.

In the study suggested by Suryoday Basak et al. [13], the problem of stock price prediction is approached as a directional prediction task, where the aim is set to forecast whether there will be gains or losses. To tackle this classification problem, the authors have devised an experimental framework to predict whether stock prices will rise or fall concerning their values n days earlier. To make these predictions, the authors have employed two models, namely gradient-boosted decision trees, utilizing the XGBoost method, which leverages ensembles of decision trees, and random forests. An important feature of this suggested research is the choice of technical indicators and their application as attributes, with a specific focus on enhancing accuracy in forecasting stock price movements over medium to long periods.

Mohammad J. Hamayel et al. [14] applied three distinct machine learning-based models to predict the prices of three different cryptocurrencies—BTC, ETH, and LTC. The outcomes of the study reveal that the GRU model outperformed the other algorithms, achieving a Mean Absolute Percentage Error (MAPE) of 0.2454% for BTC, 0.8267% for ETH, and 0.2116% for LTC, respectively. However, in comparison to both GRU and LSTM models, the bi-LSTM model demonstrated diminished accuracy, revealing significant differences between the real and forecasted cryptocurrency prices, especially for BTC and ETH. These empirical results highlight the AI algorithm's trustworthiness and suitability for cryptocurrency price forecasting.

In a study conducted by Ciaian et al. [15], time-series analysis methods are employed on daily Bitcoin data to investigate the value drivers of Bitcoin within the framework of Barro's model (1979). Their results suggested that the price of Bitcoin is notably influenced by economic dynamics and its attractiveness to investors. Similarly, Bukovina et al. [16] observed that the explanatory capacity of sentiment is positively associated with Bitcoin's volatility. A. Greaves et al. [17], suggested employing transaction graph data to make predictions about Bitcoin's prices. This research collects Bitcoin transaction data and utilizes various modeling techniques, including Logistic Regression, Linear Regression, SVM, and Neural Networks, to predict price trends. However, the achieved accuracy is limited to 55% because the study does not incorporate the exchange behavior, which has a direct impact on prices, into the transaction data. Consequently, the research advises incorporating exchange behavior data into the transaction data to enhance prediction accuracy.

There is an ongoing debate regarding whether it is more appropriate to employ simpler models or traditional statistical methods for precise Bitcoin price prediction. In practical terms, high-dimensional models with a significant Vapnik–Chervonenkis dimension are often considered the most straightforward solution for most prediction-related challenges, as highlighted by McNally et al. [18]. In such a context, two common paradigms emerge: statistical approaches with a multitude of features and complex models with a limited number of features. In line with the Occam's razor principle, this study utilizes uncomplicated statistical models to forecast Bitcoin's daily price, even when dealing with a multitude of features, while resorting to more intricate machine learning models for predicting Bitcoin's 5-minute interval prices, as discussed by Chen et al. [19]. Dennys C.A. Mallqui et al. [20] utilized daily-updated data on Bitcoin to forecast its minimum, maximum, and closing prices. The author employed various machine learning algorithms, including Recurrent Neural Networks, a tree classifier, and SVM. Among these, SVM yielded the most accurate results in predicting Bitcoin exchange rates.

3. Methodology

The aim of this study is to predict Bitcoin prices through the utilization of machine learning algorithms. To achieve this goal, the proposed work begins by collecting dataset from Kaggle [21], pre-processing it, performing feature selection and data splitting on dataset comprising daily Bitcoin prices as well as prices at 1-minute intervals. The different machine learning algorithms selected for model training include: Linear Regression, Logistic Regression, KNN, and SARIMA. The proposed workflow is shown in figure 1.

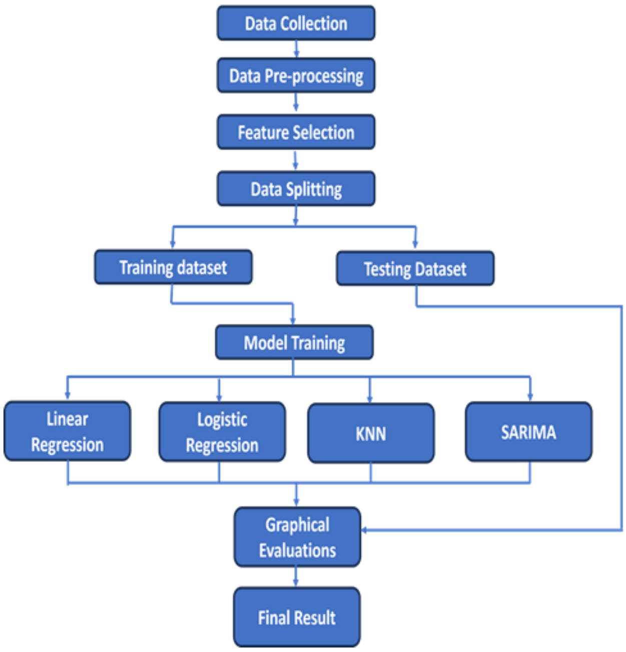

Fig. 1. Proposed workflow

3.1. Data Collection and Pre-processing

We obtained the dataset [21] from Kaggle with the aim of selecting the most suitable machine learning-based algorithm for predicting the price of Bitcoin. During the process of data set selection, we encountered an issue where numerous data sets had undergone modifications. As a result, we opted for historical Bitcoin price data sets that had undergone the least alterations, covering the period from January 2012 to March 2021. The dataset's CSV files provide minute-by-minute updates on various metrics, including OHLC (Open, Low, High, Close) prices, trading volume in BTC, currency information, and the weighted Bitcoin price. Timestamps within these files are represented in Unix time format. In instances where there were no trades or activity during a particular timestamp, the corresponding data fields are populated with NaNs (indicate missing/null values).

The chosen dataset underwent preprocessing procedures to remove null values, abbreviations, punctuation, and similar artifacts. Furthermore, we converted the timestamps within the data into more easily understandable and commonly used time formats. Additionally, normalization was performed using a Min-Max scalar to scale the values within the range of 0 to 1.

3.2. Feature Selection and Data Splitting

Table 1 presented below outlines the dataset's characteristics. This research employed Python's scikit-learn library to build models exclusively using the features - Close, Open, High, and Low - in the prediction of the Weighted price. Initially, we converted trading exchange data collected at 1-minute intervals, which comprised 3,161,057 rows, into a dataset with 2,195 rows representing trading exchange data at 1-day intervals. Following this transformation, we divided the dataset into a training set and a test set, maintaining a 75:25 ratio, resulting in a training set of 1,646 samples and a test set of 548 samples. Subsequently, we calculated the correlation coefficient for all the features and illustrated the corresponding graph in Figure 2, revealing a strong degree of correlation among all the features.

Table 1. Features of the dataset

Features	***Definition***
Open	opening trade
Close	latest trade
Low	lowest trade during day
High	highest trade during day
Weighted price	mean Bitcoin price
Volume_(BTC)	total trade volume of day in BTC
Volume_(Currency)	total trade volume of day in USD
Timestamp	data recorded time

Fig. 2. Correlation coefficient values for each feature parameter represented in a heatmap

3.3 Model Training

The different machine learning algorithms used in the proposed methodology for Bitcoin price prediction are- Linear Regression, Logistic Regression, KNN, and SARIMA.

3.3.1 Linear Regression

Linear regression analysis is a technique used to forecast one variable's value based on the values of another variable, with the dependent variable being the one under prediction, and the independent variable serving as the predictor. Linear regression models are known for their straightforward interpretability and applicability across diverse scientific and business domains [22]. In this project, we employed linear regression to predict Bitcoin prices for the upcoming 30 days, leveraging graphical analysis to discern price trends. The corresponding equation is as follows:

$$Y_i = f(X_i, \beta) + e_i \quad (1)$$

where, Y_i= Price in Dollars

X_i= time in days, months and years

β= Unknown parameters affecting the output

$e_{i=}$ error terms

3.3.2 Logistic regression

Logistic regression analysis is a statistical approach used to anticipate a specific outcome by considering observations within a dataset. It assesses how different independent variables relate to and forecast a dependent outcome. The primary objective of logistic regression analysis is to streamline the computations associated with numerous variables, resulting in models that can help gauge the comparative efficacy of various interventions. The logistic regression equation is as follows:

$$g(E(y)) = \alpha + \beta x1 + \gamma x2 \quad (2)$$

where, E(y) is the expectation of the target variable and $\alpha + \beta x1 + \gamma x2$ is the linear predictor. In the proposed work, while implementing logistic regression, we have considered class 1 for ascending prices and class 0 for descending prices.

3.3.3 K-Nearest Neighbors

The K-nearest neighbors (KNN) algorithm represents a non-parametric framework employed for predicting the classification of a new sample point. It distinguishes itself from other methods by abstaining from making assumptions regarding the nature of the data under examination. KNN is recognized as a "lazy" algorithm, indicating that it refrains from utilizing the data points collected during training to formulate generalizations. Consequently, there is a low requirement for explicit information in the training phase, which ensures a rapid execution of the training phase, and KNN retains the complete training dataset because it is essential for the subsequent testing phase. In the proposed work, the KNN algorithm directly furnishes Bitcoin price values for the data within the test dataset, and its operation is rooted in the utilization of the distance formula:

$$\sqrt{((x2-x1)2 + (y2-y1)2)} \quad (3)$$

3.3.4 SARIMA

SARIMA, also known as Seasonal Autoregressive Integrated Moving Average or Seasonal ARIMA, is an extended version of ARIMA tailored to address univariate time series data featuring a seasonal pattern. In our project, we implemented SARIMA due to its notable advantages, including its simplicity and interpretability, as well as the advantage of having fewer variables and hyperparameters, which simplifies the maintenance of configuration files during model deployment in production. The equation for the SARIMA model is:

$$(1-B12)xt = xt - xt-12 \quad (4)$$

where, xt the current outcomes will be predicted using xt-12 which is the last season's outcome (1 season=12 months).

4. Results

In this section, we present the outcomes derived from applying linear regression, logistic regression, KNN, and SARIMA algorithms to forecast the price of the leading cryptocurrency, Bitcoin. The below graph (Figure 3) displays the dataset [21] to be utilized for prediction, depicting the fluctuation in Bitcoin's price over time.

4.1 Linear Regression

Figure 3 displays the graph of the dataset utilized for prediction, depicting Bitcoin's price fluctuations over time. Below in Figure 4, we can observe the linear regression algorithm's best-fit line for the input data points. Additionally, Table 2 presents both the recorded and forecasted prices for the specified dates.

The graph presented in Figure 5 illustrates the predicted trend for Bitcoin prices over the next thirty days. The red-colored extended forecast for the subsequent thirty days is illustrated in the graph below (Figure 6).

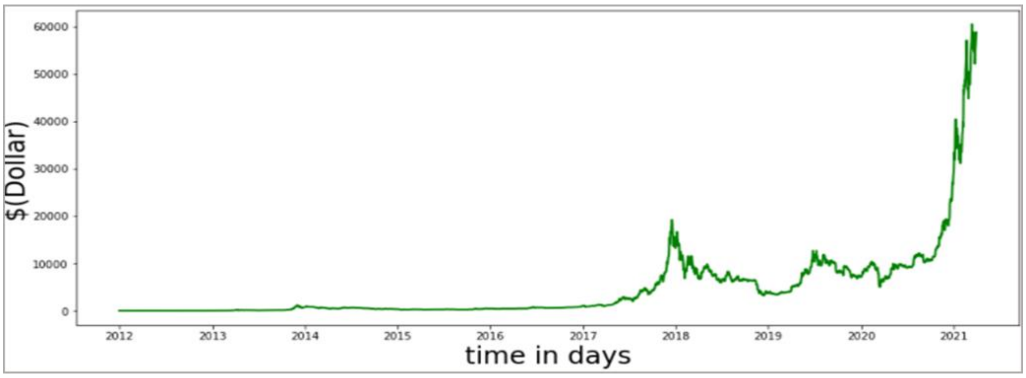

Fig. 3. Fluctuations in Bitcoin's price over time

Table 2. Close and predicted prices for the mentioned dates

Date	*Close*	*Predicted Price*
2011-12-31	4.471603	6.835000
2012-01-01	4.806667	6.386000
2012-01-02	5.000000	6.485000
2012-01-03	5.252500	6.407500
2012-01-04	5.208159	6.495556

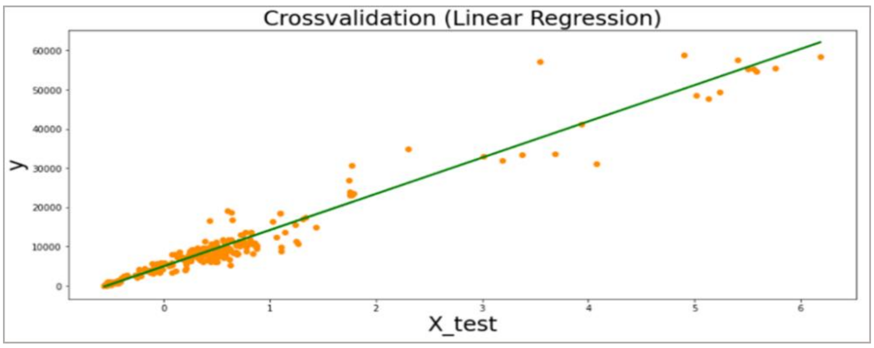

Fig. 4. Linear Regression algorithm's best-fit line for the input data points

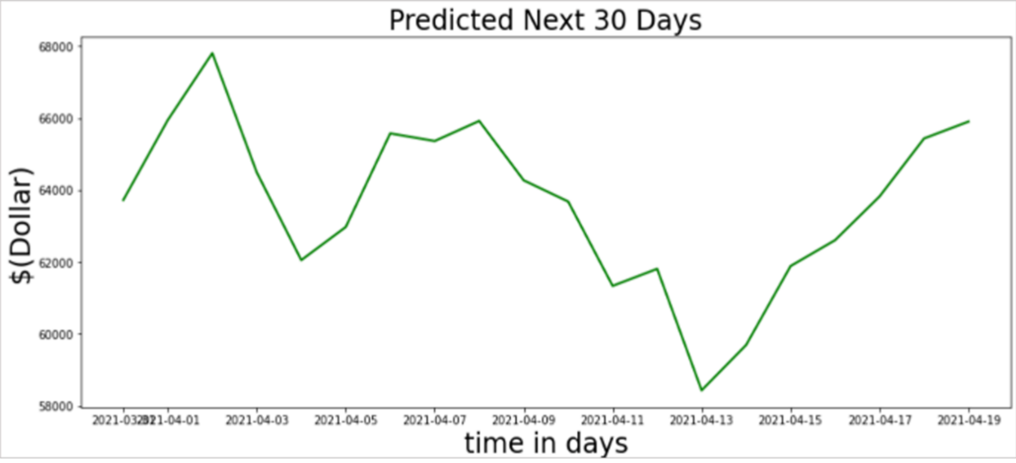

Fig. 5. Predicted trend for the Bitcoin prices over the next thirty days

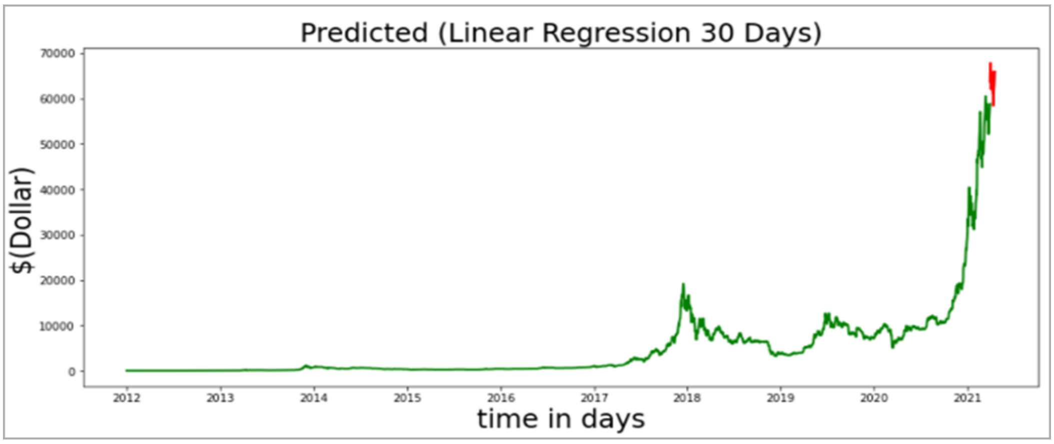

Fig. 6. Extended forecast (red color) for the Bitcoin price prediction for the subsequent thirty days

4.2 Logistic Regression

In logistic regression, we define two classes: "Class 1" represents an increase in the price, while "Class 0" signifies a decrease in the price. After analyzing the data, we obtained the following results. Figure 7 provides a visual representation of the confusion matrix, which includes counts for false positives, true positives, true negatives, and false negatives. Table 3 below displays the predicted ascent or descent in the prices of bitcoin in the test data.

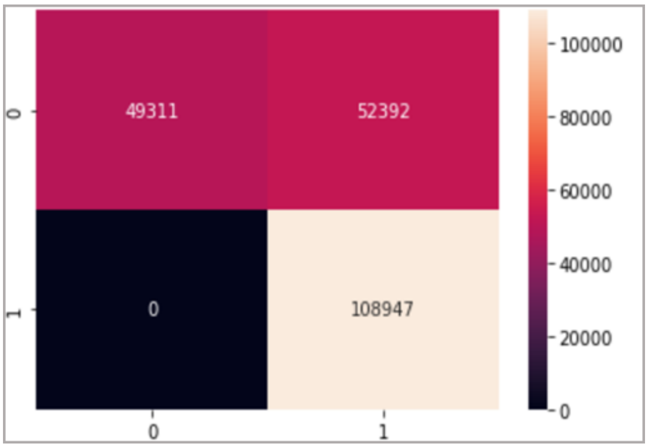

Fig. 7. Confusion Matrix for Logistic Regression

Table 3. Prediction of ascent or descent in the prices of bitcoin in the test data using Logistic Regression

Data row id	*Predicted Class*
387636	0
250677	0
114245	1
569158	1
52617	1
161665	0
332295	0
168325	1
664786	1
445534	1

4.3 K-Nearest Neighbors (KNN)

KNN algorithm's ability to make predictions is grounded in its capacity to adapt to changing market conditions, providing a flexible and dynamic approach in forecasting

Bitcoin prices based on the most analogous historical data points. The predicted prices in Table 4 serve as a valuable reference for understanding the potential trajectory of Bitcoin's value in response to these identified historical patterns and similarities.

Table 4. Bitcoin Price Prediction using KNN

Sr No.	***Predicted market prices of bitcoin***
0	6847.675483
1	6847.675483
2	6718.123972
3	6847.675483
4	6814.338560
5	6814.338560
6	6814.338560
7	6847.675483
8	6847.675483
9	6685.206245
10	6685.206245
11	6718.123972

4.4 SARIMA

In our study, we leveraged the SARIMA algorithm, an extension of the well-established ARIMA (Auto Regressive Integrated Moving Average) model. Our application of SARIMA yielded significant results, which we present below. In Figure 9, we provide a visual representation of the general, seasonal, and residual trends observed in the dataset. This figure offers valuable insights into the underlying patterns that SARIMA has captured. Furthermore, in Figure 10, we present a comparative analysis of the predicted trends generated by SARIMA alongside the actual trends observed in the test data. These visualizations serve to illustrate the model's efficacy in forecasting Bitcoin prices, highlighting its potential for real-world applications.

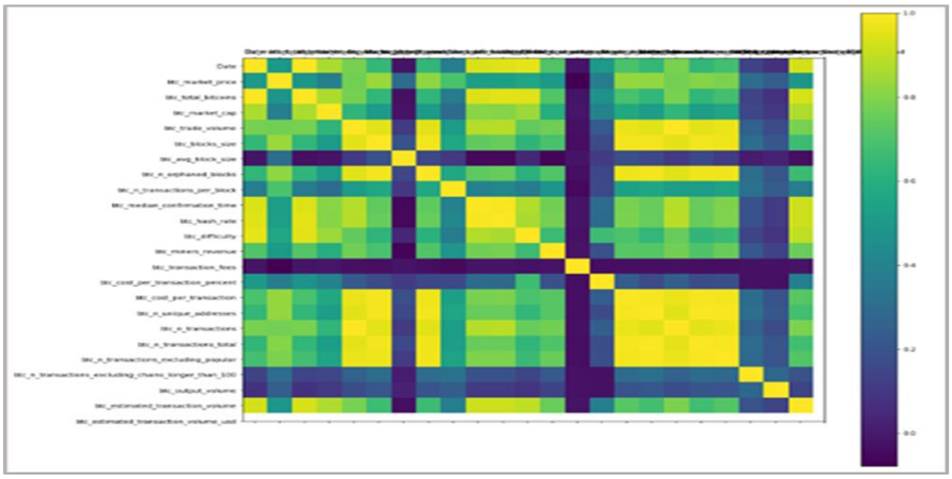

Fig. 8. The graph generated by the KNN algorithm for correlated data

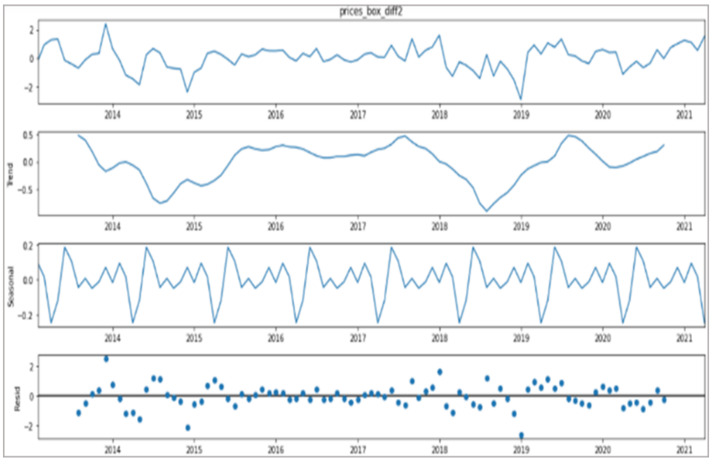

Fig. 9. General, seasonal and residual trends in the data

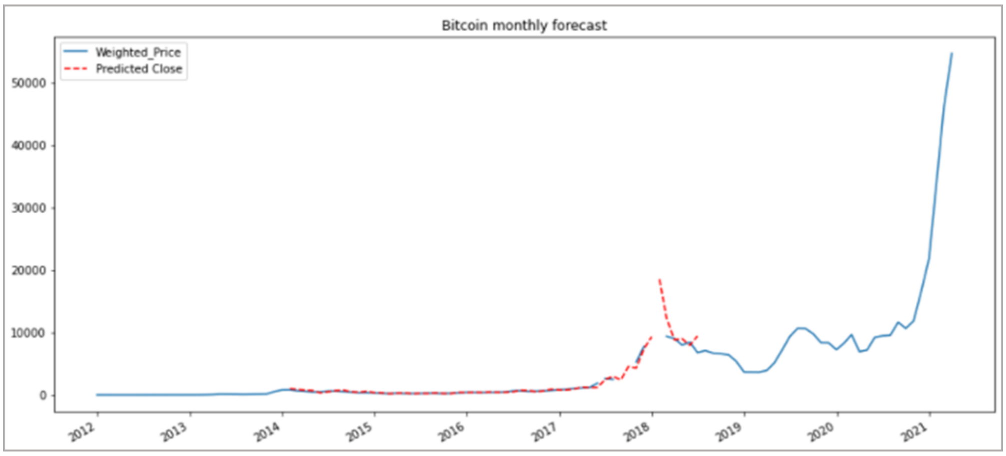

Fig. 10. Predicted and actual trends in the test data using SARINA

Table 5. The accuracy percentages of the various algorithms

Algorithm	*Accuracy Percentages*
Linear Regression	96%
Logistic Regression	72%
KNN	98%
SARIMA	84%

5. Conclusion and Future Work

In our proposed work, we sourced a dataset from Kaggle to forecast Bitcoin prices across various trends. It was observed that, although KNN yielded the highest accuracy, it provided direct price predictions without graphical trends, which did not align with our project's objective of analyzing price trends. The accuracy offered by logistic regression alone was insufficient as it only indicated price ascension or descension without forecasting trends or specific prices. However, when coupled with another algorithm, logistic regression proved effective for trend prediction. SARIMA, on the other hand, offered graphical trend insights but fell short in terms of accuracy and price prediction.

Linear regression, while providing commendable accuracy, supplied both numerical and graphical data. Its ease of implementation and interpretation made it a preferred choice for our project. Consequently, we employed various algorithms to assess and anticipate Bitcoin price trends over time. Such forecasting and prediction hold significant importance for cryptocurrency investors, enabling them to identify investment opportunities and mitigate potential future losses effectively. As the prices of bitcoin are volatile, in the future, we aim to predict the future prices and trends in bitcoin using real-time data.

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