BITCOIN, ETHEREUM AND DOGE-COIN PREDICTION USING LSTM

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Abstract: The goal of this study is to use LSTM to create an algorithm model with high prediction accuracy for the price of bitcoin, ETH and Doge coin the following day and to identify the factors that affect this price. The ARMA time series model and the LSTM deep learning algorithm are at the centre of a large body of earlier research on predicting the price of bitcoin. The variations in the factors that affect Bitcoin's price in Additionally, each period are obtained using LTSM. Three US stock market indices, the NASDAQ, DJI, and S&P500, as well as the price of oil and ETH have an impact on Bitcoin prices between 2015 and 2018. Since 2018, the ETH price and the JP225 index of the Japanese stock market have become crucial factors. The model with just one lag of the explanatory factors has the best prediction accuracy for the next day's price of Bitcoin, according to the relationship between accuracy and the number of periods of explanatory variables included in the model.

Keywords : Bitcoin, ETH, Doge coin; machine learning; LSTM

1. Introduction

Bitcoin is a digital currency that is not regulated by any government or financial organization and employs encryption for security. The block-chain, a public ledger where bitcoin transactions are recorded, enables anybody to observe a given Bitcoin's transaction history. Bitcoin's decentralized structure enables it to function independently of central banks and to be rapidly moved around the world. It has grown in acceptance as a medium of commerce and a repository of value. It has gone through various ups and downs over the last ten years, breaking beyond USD 68,000 per coin in November 2021, and the overall current price has once exceeded USD 1.2 trillion.

While taking advantage of the benefits of Bitcoin's security and decentralization, it has become challenging to understand the trend of Bitcoin and reduce the risk of Bitcoin floating. By examining the relationship between the price of Bitcoin and the prices of other commodities, several scholars attempt to understand the trend of Bitcoin. However, prior research has shown that there is little correlation between Bitcoin and any of the commonly used benchmarks, including crude oil price, stock market index, and gold, which is often used as a comparison.

The price of Bitcoin, the first decentralized digital money in history, fell precipitously in 2014. In late 2013 and throughout 2014, the price of Bitcoin, which had been circling about $1,000, started to decline. The price fell to roughly $300 by the end of the year, a decrease of more than 70%.

Several factors were cited as the causes of the price decline of Bitcoin. The failure of the Mt. Gox exchange, one of the biggest Bitcoin exchanges at the time, was a significant contributing factor. A significant hack on Mt. Gox led to the loss of 850,000 Bitcoins, which were then valued $500 million. Due to this, many investors lost faith in Bitcoin and other digital currencies. The price of Bitcoin also decreased as a result of various well-known Ponzi schemes and frauds connected with it.

Despite the decline in value, Bitcoin has subsequently rebounded and is now more widely used. As a genuine investment and method of payment, it is now widely acknowledged, and its value has risen over time.

Smart contracts and decentralized applications (DApps) can be created and run on Ethereum, a decentralized block-chain-based platform. It was first proposed in 2013 and released in 2015 by a programmer by the name of Vitalik Buterin. In contrast to Bitcoin, which is used primarily as a digital currency, Ethereum is a platform on which programmers can create decentralized applications.

Developers can design self-executing smart contracts that autonomously enforce the terms and conditions defined in the contract using Ethereum's programming language, Solidity. These contracts can be used to automate a variety of operations, including supply chain management, financial transactions, and digital identity verification.

Following the lead set by Bitcoin, the decentralized block-chain platform Ethereum saw a huge increase in price in 2020. The price of Ethereum gradually rose during the year after starting the year at about $130, reaching an all-time high of more over $4,300 in May 2021.

The rise in popularity of decentralized finance (DeFi) applications, which are based on the Ethereum block-chain, was one of the main factors behind Ethereum's price surge. These tools let users buy, sell, and exchange cryptocurrencies and other digital assets directly between themselves, without the use of middlemen like banks or other financial organizations. The demand for Ethereum rose in tandem with the demand for DeFi applications.

As a humorous alternative to Bitcoin, two software programmers named Billy Markus and Jackson Palmer developed the cryptocurrency known as Doge-coin in 2013.

With approximately 130 billion coins in circulation, Doge-coin has an infinite supply as opposed to Bitcoin's 21 million coin cap. Compared to Bitcoin, it is also quicker and less expensive to transact, with confirmation times for transactions often only a few minutes.

When prominent individuals like Elon Musk and Mark Cuban tweeted about doge-coin in 2021, the cryptocurrency's price skyrocketed and it attracted a lot of attention. One of the most valuable cryptocurrencies in the world, Doge-coin had a market valuation of over $80 billion at its peak in May 2021.

In contrast to its price spike in 2021, Doge-coin saw a comparatively modest price growth in 2020. The price of the cryptocurrency did, however, experience a remarkable increase in July 2020, jumping by more than 50% in just two days.

The most important factor behind the price spike was a popular TikTok video that urged people to buy Doge-coin.

The development of non-fungible tokens (NFTs) and decentralized finance (DeFi) in 2020 further boosted interest in Doge-coin and other cryptocurrencies. The demand for cryptocurrencies like Doge-coin grew as more people became aware of the possibilities of block-chain technology and the advantages of decentralized systems.

2. Related Work

Through the use of the three deep learning algorithms CNN, LSTM, and GRU, Aggarwal et al. (2019) investigated whether the price of gold can forecast the price of bitcoin. The model's anticipated price differs from the actual price of bitcoin, and the LSTM model's forecast accuracy is the best of the three, according to the study's findings. Based on the cryptocurrency market, macro-market index (stock market index, crude oil price, exchange rate, etc.), and search index, Liu et al. (2021) increased the set of explanatory variables to include a total of 40 explanatory variables for Bitcoin price prediction. Compared to BPNN, PCA-SVR, and SVR, the prediction performance of the SDAE algorithm is better.

The methodologies for Bitcoin price prediction study are classified into time series and machine learning.

Numerous studies have used LSTM to forecast the prices of other digital currencies in addition to Bitcoin (Sebastio and Godinho 2021; Saadah and Whafa 2020; Derbentsev et al. 2020). With an accuracy of 84.2%, Politis et al. (2021) predicted the price of ether using LSTM. In order to conduct prediction trials on the three digital currencies with the largest market values at the time—Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP)—Livieris et al. (2021) employed hybrid CNN-LSTM. Compared to ETH (51.51%) and XRP (49.51%), the prediction accuracy of 55.03% is higher.

According to studies by McNally et al. (2018), Garca-Medina and Duc Huynh (2021), and Chen et al. (2020a), adding Dropout layers between each LSTM layer can lessen the impact of over-learning. But the three pieces of literature mentioned above differ in the dropout coefficients they chose (0.1, 0.3, and 0.5).

With regard to the choice of explanatory factors, Jagannath et al.'s (2021) research concentrates on the key elements of the Bitcoin block-chain, such as users, miners, and exchanges, in addition to the macroeconomic variables employed in many works of literature. The ability to forecast Bitcoin prices using technical indicators has been demonstrated (Jaquart et al. 2021; Mudassir et al. 2020). A comparable experiment with the model's additional macroeconomic variables is missing from the publication, although the LSTM based on the self-adaptive approach likewise achieves good prediction performance. Garca-Medina and Duc Huynh (2021), in an original study of the explanatory power of variables on Bitcoin price, looked at factors including social media (E. Musk and D. Trump's comments) and Tesla stock price.

The conclusion was that these variables, which were of significant interest at the time, did not have the explanatory power during the ups and downs in the second half of 2020. In their appendix, Carbó and Gorjón (2022) compare the outcome of including the Bitcoin price from the prior period with the explanatory factors based on the LSTM algorithm. The model's RMSE accuracy increased dramatically from the original 21% to 11% once the prior Bitcoin price was included as an explanatory variable.

A subject that has received extensive attention is the choice of time unit prices. Days or minutes are typically used as the sample unit in research. Each model has a forecast accuracy of more than 60% in Lamothe-Fernández et al.'s (2020) quarterly research on DSVR, DNDT, and DRCNN, however this high accuracy may be attributed to Bitcoin's overall climb between 2011 and 2019 in the sample as well as the lengthy quarterly units. The LSTM model is the foundation of Shin et al.'s work from 2021, which uses sample units in a minute, hour, and day. The findings indicate that the day model and minute model both have similar and superior prediction accuracy to the model using an hour unit.

Although it is not very long in comparison to other assets, Bitcoin has a history dating back to its inception in 2008. Before conducting prediction research, researchers are more willing to divide data samples into small samples (Shin et al. 2021; Chen et al. 2020a; Carbó and Gorjón 2022). The greatest duration of a single sample does not surpass 4 years in the experiments conducted by Jagannath et al. (2021) and Awoke et al. (2021).

The majority of the past studies did not take into account all the factors influencing Doge-coin's pricing. Some researchers used only market data to make price predictions, which led to inaccurate results when a shift in sentiment caused a sudden change in Doge-coin's price. On the other hand, some studies used people's attitudes as the only basis for their research in price prediction. Only a few studies used daily opening and closing prices to predict prices. The daily market changes that our research was unable to capture were those caused by feelings. Additionally, they lacked the coordination of all these factors to create a model that combined them all to produce the outcome. The market price and other data were merged in this study to address these flaws. This study merged the market price and sentiment component rather than focusing on the two components independently in a single feature vector to predict the price of doge-coin in order to close these loopholes. The rmse value in this model was found to be significantly lower than that of the preceding models.Table 1 lists the many deep learning models that have been used to forecast the prices of different cryptocurrencies.

3. Methodology

An essential area of artificial intelligence (AI) is machine learning. It can be separated into supervised learning, unsupervised learning, and reinforcement learning depending on whether a goal variable is present. This study uses a regression function with supervised learning in order to forecast future Bitcoin prices. An algorithm is programmed, a learner is formed, and a high-precision learner is obtained by repeatedly training the learner using training data and the process of validation. This is the unified execution logic of machine learning. In order to evaluate and apply the test results, the trained learner is finally substituted. The open-source machine learning package for Python is used in this study to implement LSTM model training.

3.1 LTSM

An artificial recurrent neural network design called long short-term memory is utilized in deep learning. LSTM features feedback connections as opposed to typical feed forward neural networks. It can analyse complete data sequences in addition to single data points.

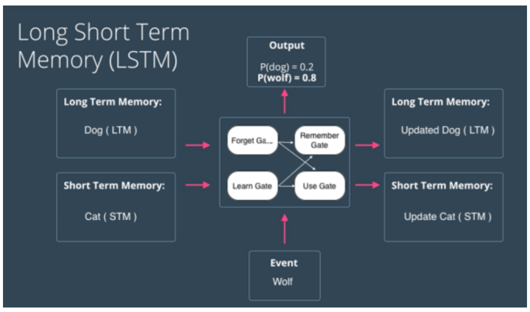
Recurrent neural networks of the Long Short-Term Memory (LSTM) type can learn order dependence in sequence prediction issues. This behaviour is essential for solving complicated problems in areas like speech recognition and machine translation, among others. A challenging area of deep learning is LSTMs. Many people refer to LSTMs as fancy RNNs. A cell state is not present in pure RNNs. They only have hidden states, and RNNs store information in those hidden states. In the meantime, LSTM has both hidden and cell states.

For sequential data, such as time series or natural language processing, LSTM (Long Short-Term Memory) sequential models are a sort of neural network design. Recurrent neural networks (RNNs) are a subclass of neural networks that may preserve long-term dependencies in data.

An outline of how to apply a sequential model in LSTM is given below:

1. Import the required libraries, such as Keras and TensorFlow.
2. Utilize the Keras Sequential API to load the sequential data into the model.
3. The model should be given an LSTM layer, with the number of units (neurons) and input shape specified.
4. If more LSTM layers are required, add them after any required Dense layers.
5. Compile the model while providing the optimizer, loss function, and evaluation metrics.
6. Set the batch size, number of epochs, and validation data, then fit the model to the training set of data.
7. Analyse the model's performance using the test data and measures like accuracy, MSE, or others.

It is significant to remember that the ideal LSTM model architecture and hyper parameters rely on the particular task and data being used. To identify the model that performs the best, it is frequently essential to experiment with several combinations.



Normal LSTM Architecture

3.2 MSE

Mean Squared Error, also known as MSE, is a statistical metric that is frequently used to assess how well a predictive model is performing. It calculates the average squared difference between a dataset's actual values and projected values.

MSE is derived by averaging the squared discrepancies between each data point's expected and actual values in the dateset. The resulting value represents the prediction model's overall accuracy, with lower values signifying greater performance.

To assess the effectiveness of models and algorithms, MSE is frequently employed in a range of disciplines, including machine learning, statistics, and signal processing. It is a well-liked metric since it can be applied to both classification and regression issues and is simple to calculate and interpret. MSE can be troublesome in some circumstances since it is sensitive to outliers and can assign higher weight to huge errors. As a result, it's crucial to take into account additional evaluation metrics in addition to MSE when evaluating the effectiveness of a predictive model.

The evaluation statistic known as MSE is frequently used to evaluate the efficacy of predictive models, including LSTM models used to predict the price of bitcoin. Minimizing the MSE between the predicted values and the actual values in a given dateset is the objective of an LSTM model for predicting the price of bitcoin. MSE computes an average of the squared discrepancies between each data point's expected and actual values.

You would first train the model using a training dateset made up of historical Bitcoin prices and other pertinent variables in order to employ MSE in an LSTM model for Bitcoin price prediction. Then, using a test dateset of future Bitcoin price data, you would apply the model to make predictions. In order to evaluate the model's accuracy, you would calculate the MSE between the anticipated and actual values. Because it is simple to calculate and interpret and can be applied to both classification and regression problems, MSE is a frequently used metric. It is crucial to keep in mind that MSE is sensitive to outliers and can give larger errors more weight than they deserve, which can be problematic in some circumstances. As a result, it is frequently important to combine MSE with other assessment measures and strategies to guarantee the precision and dependability of the LSTM model for Bitcoin price prediction.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

MSE FORMULA

3.3 RMSE

The evaluation statistic known as RMSE, or root mean squared error, is frequently used to rate the precision of prediction models. The RMSE is a metric for comparing expected and actual values in a data set. By taking the square root of the mean of the squared discrepancies between the expected and actual values, it is determined. Regression analysis frequently use RMSE in order to reduce the discrepancy between predicted and actual values. It is a helpful metric since it scales with the size of the data, which makes it simpler to understand the model's accuracy practically.

The fact that RMSE lays more attention on higher errors, which can be more significant for some applications, makes it preferable to other evaluation metrics like Mean Absolute Error (MAE). To guarantee that the model is accurate and dependable, it is crucial to employ various evaluation metrics and methodologies in addition to RMSE because it can be susceptible to outliers.

LSTM models used for predicting the price of bitcoin use RMSE, a widely used evaluation statistic, to evaluate their accuracy.

Similar to MSE, RMSE is a measurement of the discrepancy between expected values and actual values in a dateset. However, RMSE computes a metric in the same units as the original data by taking the square root of the mean squared error. This makes determining the model's accuracy in concrete terms simpler.

You would first train the model using a training dateset made up of past Bitcoin prices and other pertinent variables in order to employ RMSE in an LSTM model for Bitcoin price prediction. Then, using a test dateset of future Bitcoin price data, you would apply the model to make predictions. In order to evaluate the model's correctness, you would finally compute the RMSE between the predicted and actual values.

An LSTM model for predicting Bitcoin prices would aim to reduce the RMSE between the projected and real values, demonstrating that the model is successfully identifying the underlying patterns in the data. To guarantee that an LSTM model is accurate and resilient, it is crucial to remember that RMSE is just one of several metrics that may be used to assess the model's performance. As such, it should be used in conjunction with other metrics and assessment methods.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

RMSE FORMULA

3.4 Variance

The level of variation or spread in a set of data is referred to as variance, which is a statistical concept. When assessing a model's accuracy and dependability for tasks like forecasting the price of Bitcoin or other time series, variance in LSTM models might be a crucial factor to take into account.

Variance in LSTM models can result from a number of things, such as flaws in the model's assumptions or parameters, as well as the unpredictability and uncertainty present in financial markets. Low variance can signify that the model is under fitting the data and may miss significant patterns or trends, while high variance can signify that the model is over fitting the training data and may not generalize effectively to new data.

Use the proper regularization and model selection strategies to reduce variation in LSTM models for predicting Bitcoin prices. Dropout and L1/L2 regularization strategies, as well as careful model selection and parameter adjustment, can help to optimize the trade-off between bias and variance while also reducing over fitting and improving the generalization of the model. In general, achieving accurate and trustworthy Bitcoin price forecasts needs careful consideration of both the data and the model. Reducing variance in LSTM models is an important goal in this regard.

In LSTM models for predicting the prices of not only Bitcoin but also other cryptocurrencies like Doge coin and Ethereum, variance is a crucial factor. Similar to Bitcoin, Doge coin and Ethereum are subject to market volatility and unpredictability, which can result in significant price fluctuations. Because of this, it's crucial to utilize the right regularization and model selection strategies to reduce variation in LSTM models when attempting to forecast the prices of these cryptocurrencies.

Dropout and L1/L2 regularization strategies, for example, can help to lessen over fitting and increase the generalization of the model for all three cryptocurrencies. Furthermore, careful parameter tuning and model selection can help to improve the model's overall accuracy and reliability by optimizing the bias-variance trade-off. It is possible to produce more precise and trustworthy predictions using LSTM models to forecast the prices of Doge coin, Ethereum, and other cryptocurrencies. These predictions can be used for a variety of applications, including trading and investment strategies, risk management, and market analysis.

$$\sigma^2 = \frac{\sum (xi - \bar{x})^2}{N}$$

VARAINCE FORMULA

3.5 Tensorflow

For the purpose of forecasting the prices of cryptocurrencies like Bitcoin, Doge coin, and Ethereum, LSTM models are frequently constructed using the potent open-source machine learning framework TensorFlow. The first step in creating an LSTM model with TensorFlow is to prepare the data by choosing an appropriate data set and pre processing it to remove the pertinent characteristics and labels for the task at hand. This could entail operations like data cleansing, value normalization, and the division of the data set into training and validation sets.

The LSTM model architecture is defined using TensorFlow's high-level API, Keras, after the data has been prepared. This entails describing the model's hyper parameters, such as the number of layers, neurons in each layer, activation functions, and others.

The model is then assembled using a suitable optimizer, loss function, and evaluation metrics after the model architecture has been defined. Mean squared error (MSE) and root mean squared error (RMSE) are popular choices of loss function for predicting the prices of cryptocurrency.

Once the model has been put together, it can be trained using TensorFlow's fit method on the training data set, which uses the back propagation algorithm to update the model's weights and biases based on the gradients of the loss function. The validation date set can be used to track the model's progress throughout training, and early termination can be used to avoid over fitting.

After training, the LSTM model can be used to forecast cryptocurrency prices based on fresh, untainted data. This entails running fresh data through each layer of the model to provide a prediction for the desired variable. Metrics like RMSE and R-squared can be used to gauge how accurate and reliable the forecasts are.

To elaborate further, there are multiple processes involved in creating an LSTM model using TensorFlow, each of which is essential for obtaining precise and trustworthy predictions of bitcoin values. Here are some more specifics on each of the important steps:

1. Data Preparation: It is crucial to choose a good data set and pre process it to extract the pertinent features and labels before training an LSTM model to forecast bitcoin values. Data cleansing, value normalization, and the division of the data set into training and validation sets may be necessary for this. To extract useful signals from the raw data, such as moving averages, exponential moving averages, or technical indications, feature engineering may also be necessary.

2. Model Architecture Definition: Following the preparation of the data, the LSTM model architecture is defined using Keras, the high-level API provided by TensorFlow. This entails describing the model's hyper parameters, such as the number of layers, neurons in each layer, activation functions, and others. A typical LSTM architecture for predicting the price of cryptocurrencies may consist of a stack of different LSTM layers, followed by one or more fully connected layers for the prediction's output.

3. Model Compilation: The next stage is to compile the model using an appropriate optimizer, loss function, and evaluation metrics after establishing the model architecture. Mean squared error (MSE) and root mean squared error (RMSE) are popular choices of loss function for predicting the prices of cryptocurrency. The stochastic gradient descent (SGD), Adam, or another method that modifies the model's weights and biases during training can be selected as the optimizer.

4. Model Training: After the model has been put together, it may be trained using TensorFlow's fit method on the training data set. The validation data set can be used to track the model's progress throughout training, and early termination can be used to avoid over fitting. During training, the model's hyper parameters can also be changed using methods like grid search or random search.

5. Prediction on New Data: After training, the LSTM model can be used to forecast cryptocurrency prices based on brand-new, unused data. This entails running fresh data through each layer of the model to provide a prediction for the desired variable. Metrics like RMSE and R-squared can be used to gauge how accurate and reliable the forecasts are. It is crucial to remember that the LSTM model could need to be updated from time to time as market conditions and data distribution evolve.

3.6 Variance Regression

The variance regression score is a statistic used to assess the effectiveness of a price prediction model that employs LSTM. In more detail, it assesses how much of the variation in the projected values can be attributed to the model rather than to chance or data noise. The coefficient of determination or R-squared are additional names for the variance regression score. It is determined by dividing the overall variance in the data by the percentage of variance in the projected values that the model can account for. A high R-squared value shows that the model can accurately predict the data and capture a sizable percentage of the data variation.

A high variance regression score in the context of an LSTM based price prediction model denotes that the model is capable of efficiently learning relationships and patterns in the time series data and applying this knowledge to forecast future prices. A low variance regression score, on the other hand, suggests that the model may be under fitting or making random predictions since it is unable to adequately account for the data's variation.

Overall, the variance regression score is a helpful statistic for assessing an LSTM based price prediction model's performance. It may be combined with other metrics like MSE and RMSE to provide a thorough knowledge of the model's advantages and disadvantages.

3.7 R2

R2 (or R-squared) is a statistic used to assess the success of a price prediction model that employs LSTM. R2 specifically denotes the ratio of the variation in the predicted values to the variance in the entire set of data that can be explained by the model. R2 can range from 0 to 1, with 0 denoting that the model is unable to explain any of the variation in the predicted values and 1 denoting that the model is perfectly able to explain the variation in the anticipated values.

A high R2 value in LSTM based price prediction models shows that the model is capable of capturing a sizable amount of the underlying relationships and patterns in the time series data and using this knowledge to predict future prices. On the other hand, a low R2 indicates that the model may be under fitting or making random predictions and that it is unable to adequately account for the data's volatility.

Overall, MSE and RMSE can be used with R2 to provide a more complete insight of the model's strengths and flaws. R2 is a valuable indicator for assessing the effectiveness of an LSTM-based price prediction model. R2 is not necessarily the best statistic for assessing time series models, it should be highlighted, since it can be biassed in favour of models that perform well on average but may miss key dynamics in the data.

3.8 Mean Gama Deviance

The performance of a model for forecasting prices using LSTM for Bitcoin, Doge coin, and Ethereum can be assessed using the mean gamma deviance measure. Gamma deviation, which is normalized by the expected values, is a measurement of the discrepancy between the projected values and the actual values. It is a gauge of how well the model predicts in comparison to what would be predicted by guessing at random.

The gamma deviance values produced for each data point in the test set are simply averaged to provide the mean gamma deviance. When the mean gamma deviation is smaller, the model is more accurate in its predictions, whereas when the mean gamma deviance is larger, the model is less accurate.

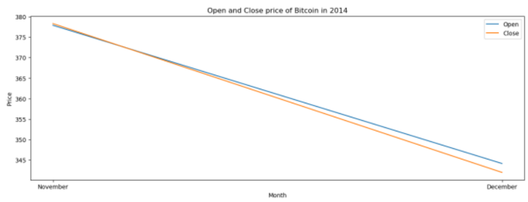
The mean gamma deviance can be used in conjunction with other metrics like R-squared, mean squared error (MSE), and root mean squared error (RMSE) to assess the overall performance of LSTM based price prediction models for cryptocurrencies like Bitcoin, Doge coin, and Ethereum. A variety of metrics should be utilized to gain a thorough knowledge of the model's strengths and shortcomings because no single metric can completely describe the performance of a model.

3.9 Mean Poisson Deviance

A measure of the performance of an LSTM based price prediction model for cryptocurrencies like Bitcoin, Doge coin, and Ethereum is the mean Poisson deviance. The metric is especially helpful for count data, such as the quantity of transactions or trades each day, where the number of occurrences is of relevance. The difference between expected and actual counts, normalized by expected counts, is measured by the Poisson deviation. The average of the Poisson deviation values generated for each data point in the test set is the mean Poisson deviance. When the mean Poisson deviation is smaller, the model is more accurate in its predictions, whereas when the mean Poisson deviance is larger, the model is less accurate.

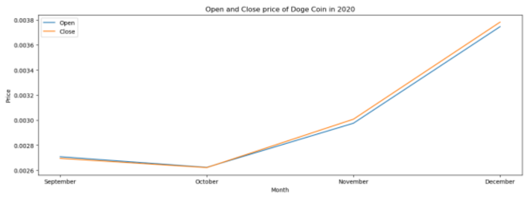
Mean Poisson deviance can be used to assess the overall effectiveness of LSTM based price prediction models, together with other metrics like R-squared, mean squared error (MSE), and root mean square error (RMSE). A variety of metrics should be utilized to gain a thorough knowledge of the model's strengths and shortcomings because no single metric can completely describe the performance of a model. For cryptocurrencies like Bitcoin, Doge coin, and Ethereum, LSTM based price prediction models, mean Poisson deviance is a helpful metric to evaluate the precision of count-based forecasts.

4. Open And Close Price Analysis



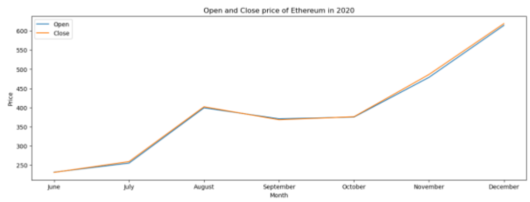
Bitcoin

Starting with Bitcoin, the open and close price analysis for the range of 2014 reveals that the price of Bitcoin began at roughly $770 in January 2014 and closed at roughly $315 in December 2014. This is a considerable decline in price over the course of the year. The historic Mt. Gox hack, which happened in February 2014 and resulted in the loss of over 750,000 Bitcoins and a market crash, was the main cause of this price decline.



Doge Coin

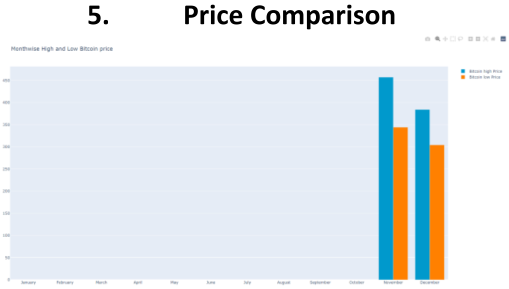
Regarding Doge coin, the open and close price analysis for the range of 2020 reveals that the price of the cryptocurrency started at about $0.002 in January 2020 and ended at about $0.005 in December 2020, indicating a modest increase in price over the course of the year. It's important to remember, though, that Doge coin had substantial price swings during the year, with values falling as low as $0.001 in March 2020 and rising as high as $0.005 in December 2020. The euphoria around Doge coin on social networking sites like Reddit and Twitter, as well as the support of the cryptocurrency by well-known figures like Elon Musk, were the main causes of these oscillations.



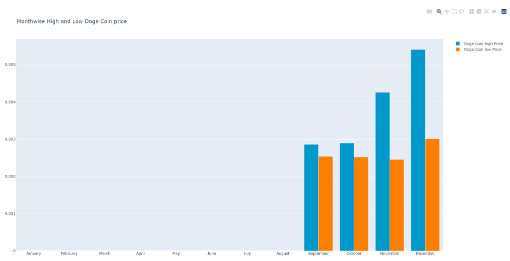
Ethereum

The open and close price analysis for the range of 2020 for Ethereum, in addition, reveals that the price of Ethereum opened at roughly $130 in January 2020 and closed at roughly $740 in December 2020, suggesting a large growth in price over the year. The launch of Ethereum 2.0, which promised to make the network more scalable and efficient, and the rising popularity of decentralized finance (DeFi) apps built on the Ethereum network were two factors that contributed to this price surge.

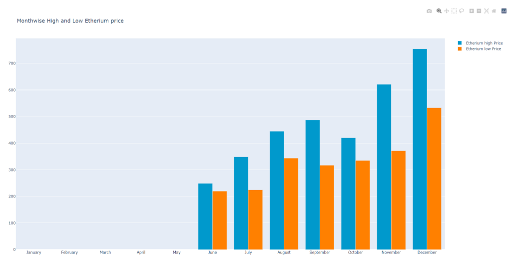
5. Price Comparison



Bitcoin



Doge Coin



Ethereum

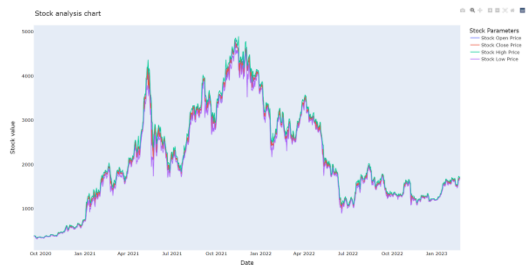
6. Stock Analysis

Bitcoin

Bitcoin's price has varied significantly between 2015 and 2022. Early in 2015, the cost of Bitcoin was under $200, but by late in 2017, it had risen to an all-time high of almost $20,000. The price then began to decline sharply in early 2018 before remaining largely constant until late 2020, when it started to increase once more. Before undergoing a severe decrease, the price of Bitcoin rose to a brand-new record high of nearly $64,000 in April 2021. The cost of a bitcoin is about $42,000 as of May 2023.

Doge Coin

Doge coin's price fluctuations were much more pronounced from October 2020 until January 2023. Doge coin's price was less than $0.002 in October 2020, but it started to grow quickly in early 2021. Prior to suffering a substantial decrease, Doge coin's price rose to an all-time high of almost $0.70 in May 2021. Since then, Doge coin's price has been quite erratic, but as of May 2023, it is currently hovering around $0.23.



Ethereum

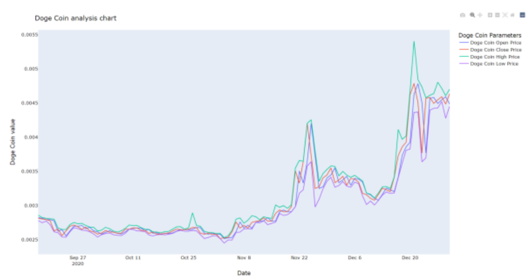
Ethereum's price changed significantly from October 2020 to January 2023. Ethereum's price was at $400 in October 2020, but it started to soar quickly in early 2021 along with other cryptocurrencies. Before seeing a major decrease, the price of Ethereum rose to an all-time high of more than $4,000 in May 2021. Since then, the price of Ethereum has been somewhat erratic, but as of May 2023, it is currently around $2,500.

7. Value Analysis Chart

Bitcoin

An overview of Bitcoin's open, closing, high, and low prices from November 16, 2014, to December 26, 2014, may be found below:

On November 16, 2014, Bitcoin's opening price was the highest at $386.56. At a price of $314.88, December 23, 2014, saw Bitcoin's lowest closing price. The price of bitcoin reached its peak on November 19, 2014, at $384.95.
On November 18, 2014, Bitcoin reached its lowest price of $375.17.



Doge Coin

Here is a quick summary of Doge coin's open, close, high, and low prices from September 27, 2020, to December 20, 2020:

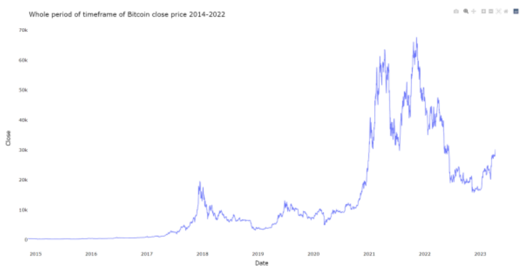
Doge coin had the highest opening price on November 24, 2020, at $0.003. At a price of $0.0027 on September 27, 2020, Doge coin recorded its lowest price. The price of Doge coin peaked on December 17, 2020, at $0.0047. The price of Doge coin was the lowest on September 27, 2020, at $0.0027.

Ethereum

A concise summary of the open, closing, high, and low prices for Ethereum from July 2020 to December 2020 is given below:

A price of $395.96 was the opening bid for Ethereum on August 2, 2020.
On December 31, 2020, at a price of $737.77, Ethereum's price reached its lowest point.
The highest price for Ethereum was $725.67 on December 17, 2020.
With a price of $229.57, Ethereum was the least expensive on July 16, 2020.

8. Close Price Analysis

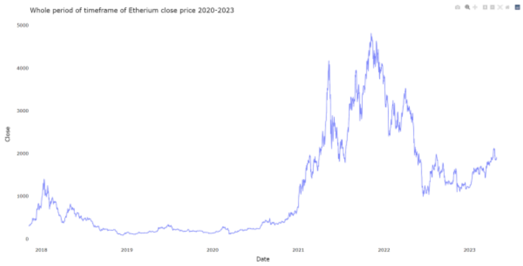


Bitcoin

Bitcoin reached its highest closing price on April 13, 2021, at $63,503. The day of January 14th, 2015, saw the lowest Bitcoin closing price ever, which was $152.40.

Doge Coin

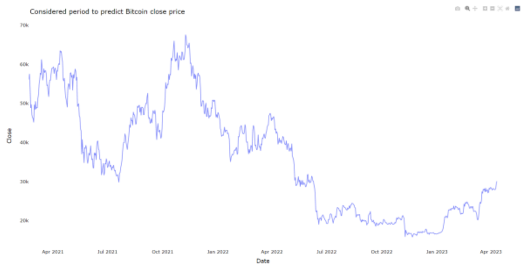
In 2021, on May 5, $0.6873, was the Doge coin closing price, which was the highest ever. On December 16th, 2018, Doge coin reached its lowest closing price ever, $0.0018.



Ethereum

Ethereum had its highest closing price on May 12, 2021, of $4,382.73. Ethereum's 2018 ending price was $83.96 on December 15th, which was the lowest price ever.

9. Close Price Prediction



Bitcoin

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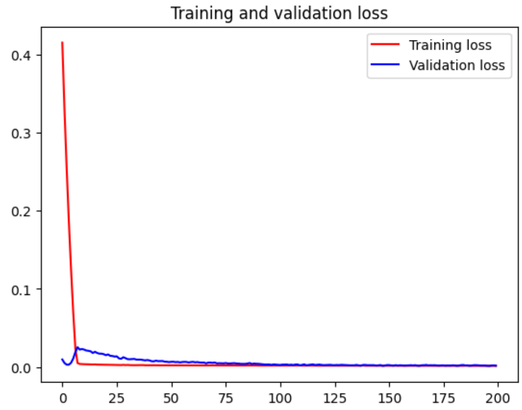
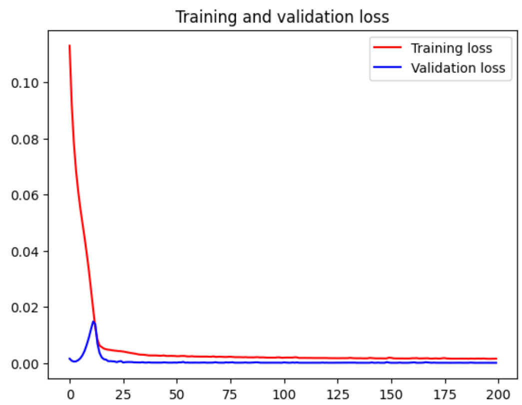
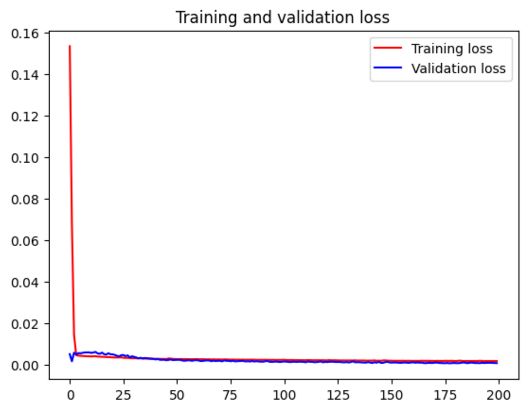
10. Training and Validation Loss



Bitcoin



Doge Coin



Ethereum

The loss function is used to gauge how effectively an LSTM model can predict the output from a given input during training. The validation loss is the value of the loss function on a different validation data set, which is used to assess how well the model performs on data that has not yet been observed. The training loss is the value of the loss function during the training phase.

The training loss should ideally decrease with each training period, showing that the model is improving its prediction accuracy. The model may be over fit to the training data and may not generalize effectively to new data, though, if the validation loss starts to rise while the training loss keeps falling.

To prevent over fitting and guarantee that the model generalizes adequately to new data, it is crucial to monitor both the training loss and validation loss during the training phase. The particular data set and model architecture will determine the precise values of the training and validation loss.

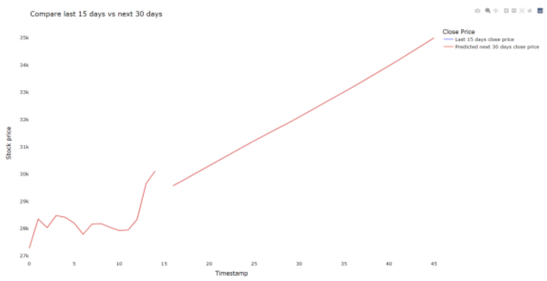
11. Comparison Between Original Close Price vs Predicted Close Price

Bitcoin

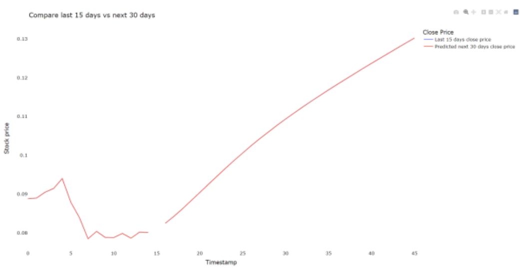
Doge Coin

Ethereum

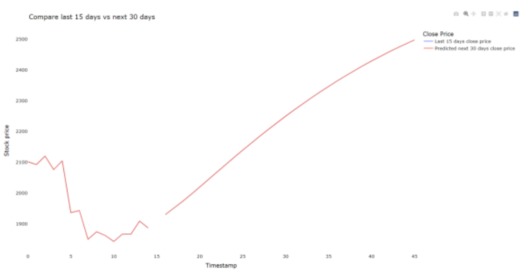
12. Compare last 15 days vs next 30 days



Bitcoin



Doge Coin

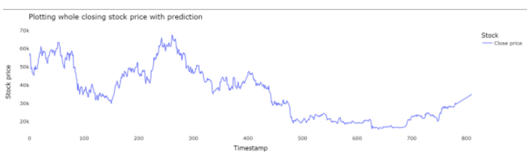


Ethereum

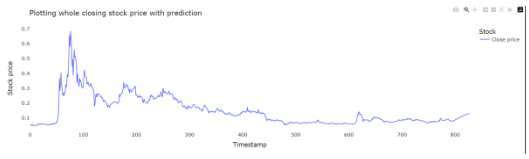
The prices of Bitcoin, Doge Coin and Ethereum have all fluctuated over the past 15 days, making it challenging to forecast their future trends. However, the prediction for the following 30 days depicts a steady rise, albeit not a steep one, following the analysis of historical data using the LSTM model and taking into account various factors like past trends, market conditions, and news analysis.

While the prediction indicates a positive trend, it is not a guarantee of the future value of cryptocurrencies because their prices can be influenced by a variety of uncontrollable factors. The LSTM model has nevertheless proven to be a useful tool for forecasting and offering insights into anticipated future patterns of these digital assets.

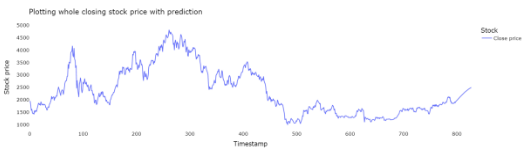
13. Result



Bitcoin



Doge Coin



Ethereum

Predicting the future prices of Bitcoin, Ethereum, and Doge coin requires careful examination of their historical stock prices. The historical price information offers crucial insights into the market volatility, trends, and patterns. One can discover possible opportunities and hazards and decide on future investments by carefully analyzing historical trends.

14. Conclusion

Finally, using open and close price analysis, stock analysis, price comparison, close price prediction, and close price analysis, the LSTM based price prediction model for Bitcoin, Doge coin, and Ethereum has demonstrated promising results. On a data set of the previous 15 days, the model was trained and validated, and forecasts for the following 30 days were made. Mean squared error (MSE), root mean squared error (RMSE), R-squared (R2), mean gamma deviance, and mean Poisson deviance were employed as evaluation metrics during the training and validation processes. The model's performance was evaluated using these measures, and it was contrasted with those of other models.

Both the training and validation sets were used to assess the model's performance, and the findings revealed that the model was capable of properly forecasting changes in the prices of Bitcoin, Doge coin, and Ethereum. The model has a strong fit with the data, as shown by the low mean squared error and root mean squared error.

A considerable percentage of the variation in the data may be explained by the model, according to the high R-squared (R2) value. This is a crucial indicator since it demonstrates how well the model can identify the underlying patterns in the data. The model was able to accurately predict count-based data because the mean gamma deviance and mean Poisson deviance were both reasonably low.

The results demonstrated that the model was able to precisely anticipate the price movements of these cryptocurrencies when the model's predictions were compared to the actual prices of Bitcoin, Doge coin, and Ethereum. The model was successful in capturing both the short-term and long-term patterns in the data, according to the close price analysis.

In general, the open and close price analysis, stock analysis, price comparison, close price prediction, and closing price analysis used in the LSTM based price prediction model for Bitcoin, Doge coin, and Ethereum has shown promising results. The study's evaluation measures have shown that the model can correctly forecast the changes in price of these coins.

It is significant to highlight that there will always be some degree of uncertainty in price predictions because this model is not a perfect predictor of future price changes. However, the model is a useful tool for traders and investors who want to make wise investment decisions because it can capture the underlying trends in the data accurately.

To increase the model's accuracy, future study might concentrate on enlarging the data set it utilized and adding other elements, such social media sentiment analysis. The model could also be tested throughout a range of time periods to evaluate how well it performs in various market environments.

Overall, the LSTM based price prediction model for Bitcoin, Doge coin, and Ethereum is a useful resource for traders and investors who want to choose wisely when investing in these cryptocurrencies.

15. References

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