EAI Endorsed Transactions
on Scalable Information Systems

Research Article EAI.EU

Bitcoin Price Prediction Using N-BEATs ML Technique

G. Asmat[1] and K. M. Maiyama[1,*]

[1]School of Engineering and Physical Sciences, University of Lincoln, Brayford Pool, Lincoln, LN6 7TS, England, United Kingdom

Abstract

Bitcoin is a decentralised digital currency that has been in existence for some time now. Its value has been volatile, with most of its prices fluctuating significantly, making it difficult to predict its prices when investing. This paper employed a Neural Basis Expansion Analysis Time Serie (N-BEATS) deep learning architecture to predict Bitcoin prices. The model was chosen because of its proven capabilities of modelling intricate patterns in time series data. An hourly Bitcoin price data of 729 days collected from Yahoo Finance extensively assesses the N-BEATS model's performance while comparing it with other machine learning models like the Linear Regression and the long-short-term-memory (LSTM) networks. Mean Absolute Error (MAE) and R-squared (R^2) were utilised as performance evaluation metrics. N-BEATS surpassed the others by providing an R^2 score of 0.00240 and an MAE score of 0.9998. These findings are significant and shed light on how deep learning models can be used for financial forecasting. The result shows that the N-BEATS model is more accurate and reliable for predicting cryptocurrencies' prices, which may be very useful for investors in making decisions and managing risks.

Keywords: Bitcoin, Price Prediction, Machine Learning, Time Series Data, N-BEATS

Received on 30 August 2024, accepted on 01 November 2024, published on 01 April 2025

doi: 10.4108/eetsis.9006

1. Introduction

Bitcoin, developed by an unknown person under the name Satoshi Nakamoto in 2008, is the first decentralised digital currency that allows users to make transactions directly without the help of third parties like banks or governments [1]. It is based on Blockchain technology, a distributed and shared ledger database that records and tracks every transaction in a business. The limited number of Bitcoins available in circulation, up to 21 million, has made the currency described as 'digital gold' with value determined by market forces, innovation and macroeconomics. This high variability indicates great volatility, which exhibits high price fluctuations, hence the need for accurate price forecasting, which is advantageous and disadvantageous to investors.

Many traditional financial time-series forecasting methods are based on conventional econometric techniques such as Autoregressive Integrated Moving Average (ARIMA). However, these methods fail to capture the nonlinear and volatile characteristics of Bitcoin [2]. Recent technologies like deep learning and machine learning, especially the long-short-term-memory (LSTM) networks and Temporal Convolutional Networks (TCNs), have been proven to overcome some challenges by learning from past data and identifying temporal patterns. However, problems like overfitting, shortage of data, and interpretability of the results keep posing a threat to these models.

Machine Learning has been integrated into the financial markets since it can work through large amounts of data, identify complex patterns, and make more precise predictions. One of the most popular and suitable methods in finance is time series forecasting, which consists of predicting future values based on past observations [3]. The fact that

*Corresponding author. Email: kmaiyama@lincoln.ac.uk

financial time series data is intrinsically noise-sensitive, that is, depends on factors such as market mood, economic data, political events, and so on, makes prediction tasks even more challenging. Such variables cause Bitcoin's price to vary significantly; therefore, the process is highly nonlinear and stochastic.

Neural Networks (NN) based deep learning architectures have been widely used in financial forecasting because of their ability to capture multi-variable data patterns. Among such NNs are Recurrent Neural Networks (RNNs), and, in particular, LSTM networks have shown their effectiveness in learning dependencies over time. That makes them suitable for Bitcoin price analysis and prediction. However, it has also been revealed that LSTM is likely to be overfit. It requires large training data for better performance, which is not always possible in real-world financial markets due to shortcomings in the available historical data [4].

To address the challenges mentioned above, this study examined using the Neural Basis Expansion Analysis Time Series (N-BEATS), a state-of-the-art deep learning model for time series forecasting. Compared with conventional methods, fully connected layers are combined with residual connections in N-BEATS for learning long-term and short-term dependencies in time series data. The model's architecture is very distinct in that the model is organised in blocks, and each block is designed to predict a segment of the time series, such as the trend or the seasonality [5]. This decomposition helps interpret the model's predictions, which is crucial in financial forecasting.

The first reason is the capability of the N-BEATS model to perform without domain-specific feature engineering, and the second reason is the model's versatility for univariate and multivariate time series. Since the model is based on the market's volatility and trends, it is possible to achieve better results when it comes to forecasting and decision-making, which is crucial for investors aiming to minimise risks and generate maximum profit from their operations. This study shows the better performance of the present model over LSTM and Linear Regression and its potential to be used in real-life applications in the context of cryptocurrency trading and other financial activities.

Accurately forecasting the Bitcoin price lies in its theoretical value for academicians and its practical value for investors, financial analysts, and policymakers. The use of accurate forecasts helps enhance investment decisions, trading, and risk management strategies, thus increasing the chances of making the correct decisions at the right time. Also, they help to decrease the level of risk and uncertainty together with speculation movements inherent to the crypto market.

This paper investigates Bitcoin price prediction using the N-BEATS model using 729 days of hourly Bitcoin price data. The evaluation compares the performance of N-BEATS with other popular models, including LSTM and Linear Regression, regarding accuracy and adjustment of fit measures in terms of MAE and R^2. These findings indicate that N-BEATS is a much superior model to these models and generates better and more accurate predictions. These results suggest that N-BEATS has much potential for further use in financial prediction, especially in the uncertainty and instability of contemporary crypto-currencies.

2. Review of Related Literature

The foundational work by Nakamoto in [1] introduces the idea of a new decentralised digital currency named Bitcoin. It describes how it works with the help of a blockchain. It underlines the capability of making direct transactions devoid of intermediaries, therefore highlighting Bitcoin's versatility as a financial instrument. This paper provides a conceptual base for analysing the technological and economic opportunities of the Bitcoin network. It provides a basis for further studies concerning the volatility of Bitcoin cryptocurrency prices and casting.

Machine learning (ML), a subset of Artificial intelligence (AI), has been at the forefront of this century's evolution, shaping our lives in various forms. Its main types were supervised, unsupervised and reinforcement learning [6]. This classification helps explain various approaches to time series forecasting, thus highlighting the importance of machine learning in eradicating time-consuming tasks like financial forecasting and analysis, especially considering volatile markets like cryptocurrencies.

Authors in [7] devoted their study to the significant energy demand of mining bitcoins and concerns about its environmental impact. Dev does an excellent job of contrasting the decentralisation of security in Bitcoin with the high resource consumption in the proof of work. This remains significant in the larger conversation about Bitcoin's sustainability. It bears implications for literature focusing on financial forecasting, especially given that energy costs impact Bitcoin's market prices.

Hara [8] explored how Bitcoin was positioned as the 'digital gold' that investors hold because of its scarcity, which makes it a tool for fighting inflation. This analogy further supports the discussions regarding Bitcoin's nature as a valuable, actually useful, means of storing wealth and a valuable financial instrument. Thus, the paper offers an understanding of the role and impact of market sentiment and macroeconomic factors as potential exogenous factors affecting Bitcoin prices in a way that impacts the existing forecasting models.

Shumway's work in [2] explores the basics of classical time series models, including the seasonal ARIMA, which is widely applied in finance. Shumway and Stoffer also point out that these models are restricted to modelling complicated nonlinear time series data like Bitcoins. This offers theoretical justification for using advanced machine learning for time series forecasting.

Research by [5] presented another work on the N-BEATS model, a deep-learning architecture for time series forecasting. It explains how the model's various unique features, such as the fully connected layers and residual connections, make it easy for the model to give good predictions without the need to implement specialised features from the domain. The paper is critical in demonstrating N-BEATS' superior performance over traditional models like ARIMA in handling volatile financial data.

In this context, deep learning is pointed out by Gamboa [3] as comprising Recurrent Neural Networks (RNNs) as well as the LSTM networks for the analysis of time-dependent patterns. The paper under consideration also notes their suitability in the financial markets because of their capability to capture temporal dependencies. At the same time, the paper describes potential issues, such as overfitting and higher computational complexity in the context of cryptocurrencies' fluctuation.

Sunny Maswood [9] works on modelling cryptocurrency price prediction using machine learning algorithms, including SVM and random forests. It shows that machine learning can substantially enhance forecasting precision compared with the econometrics approach, and that is why it is highly suitable for uncertain and fairly abundant information such as Bitcoin trading.

Another review of the field and theoretical background of blockchain technology, along with its relation to cryptocurrencies such as bitcoin, is given by Yuan and Wang [10]. They talk about blockchain preconditions as the foundation of secure and decentralised environments. This work is crucial in deciphering the 'technology behind Bitcoin prices' that is core to investigating the ledgers for forecasting financial markets.

Golosova and Romanovs assessed the issues related to blockchain technology concerning energy consumption and integration costs [11]. They underlined the calls for addressing these barriers as they underpin Bitcoin's extensibility and sustainability, which define price predictability and market behaviours, among other things.

ElBahrawy and his team, in their work in [12], chose to examine the dynamic market growth in the cryptocurrency market, specifically the rising number of digital currencies and the decreasing market share of Bitcoin. They discuss the need for versatile forecasting models that suit the volatile and competitive nature of the cryptocurrency market.

Lee analysed cryptocurrency as an investment asset and, more specifically, as a diversification asset. Based on their work, they further explained that the use of Bitcoin and other cryptocurrencies contributed to the diversification process, similar to gold [13]. This research highlights how uncertainty and managing the risks and rewards of a cryptocurrency investment go hand in hand with the ability to forecast.

The work by [14] compares the cryptocurrency market's maturity by analysing its statistical features with those of the traditional financial market. It reveals that its return is high volatility and multifractal, especially in Bitcoin and other well-established cryptocurrencies. These findings further indicate an urgency to borrow efficient models like N-BEATS to capture underlying patterns.

Transmission of volatility across several cryptocurrencies and traditional financial markets is a subject Liu and Serletis take [15]. Their study evidenced considerable volatility spillovers and proved how integrated financial systems are, and for better forecasting of BTC prices, these features should not be overlooked.

Trump et al. in [16] focus on governance questions regarding cryptocurrencies or, more specifically, problems related to decentralised consensus. They investigate the possibility of changes to Bitcoin's protocol, known as hard forks, that can potentially disrupt the market and contribute to price determination. In doing so, this paper examines how and why governance factors play a part in shaping Bitcoin's price movements and fluctuations.

Another work by [17] also focuses on using gradient-boosted trees, neural networks, and ensemble learning that help predict cryptocurrency prices. Their research found that machine learning is conducted very well by enhancing prediction accuracy, contrary to traditional methods, primarily when investing in volatile markets such as Bitcoin. This paper is central to raising awareness of the possibility of better predictive models for cryptocurrencies.

Among the studies covered by [18] is an analysis of Random Forest and LSTM methods for predicting cryptocurrency volatility. By showing that the use of machine learning models produces superior results to the GARCH, Wang et al. also confirm that the cryptocurrency markets' complexity is well addressed in the case of machine learning. Their work also reveals that deep learning models have benefits when predicting unpredictable assets like Bitcoin.

Kim developed an on-chain data-based combined model for Bitcoin's price prediction employing machine learning [19]. Their approach uses self-attention and LSTM networks to identify Intraday and Multi-Day movements. The paper emphasises that the enhanced accuracy of the model in predicting volatile cryptocurrency prices makes a valuable paper for financial analysts and traders.

Shaikh used the N-BEATS model for the short-term energy consumption prediction, which the author demonstrates can be used for time series data in any domain [20]. Their results prove that it can handle unpredictable data, making it suitable for predicting Bitcoin prices using N-BEATS.

Zhang et al. [21] implemented a study on using the N-BEATS model to identify and differentiate anomalies in sewage treatment processes. Although their study was applied to another field, it shows how flexible the model is in a time series context and its capability to recognise patterns in time series, which is valuable for time series data such as cryptocurrency price predictions.

To the best of our knowledge, none of these studies provides insight into a robust Bitcoin price prediction using a medium-sized dataset, hence the motive for conducting this research.

3. Problem Statement

The high degree of nonlinearity and uncertainty in Bitcoin's price remains a source of significant difficulties regarding accurate prediction. Famous models, such as ARIMA and econometric models, fail to consider the complexity and stochastic movement of the price of cryptocurrencies. Although current approaches like LSTM have increased the levels of prediction, aspects such as overfitting, to mention some, pose some challenges, requiring ample training data. Although some literature on financial time series forecasting has employed machine learning in the past decade, especially for time series, there is still a lack of methods and approaches that extend the high predictive accuracy of machine learning-based models while simultaneously providing interpretability. Specifically, the current models of LSTM and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) fail to capture the complex interdependencies between the movements present in Bitcoin's price data. Accompanied by the need for a more robust model to capture both short and long-run dynamics in Bitcoin data and make a suitable model interpretable enough and free from overfitting, this research solely applies the N-BEATS model.

4. Proposed Methodology

In this study, we proposed a model that uses N-BEATS architecture to forecast Bitcoin prices since this model is effective in analysing time series data. The given model was used to forecast the variation of the value of Bitcoin during the next hour by considering the data obtained during the past three hours to examine the short-timescale oscillations and long-term movements. This approach helped us deal with Bitcoins' inherent variability and generate more accurate forecasts.

The training set included the model's hourly estimates of Bitcoin price received from Yahoo Finance for 729 days. These features of the current day were included in this dataset; they consisted of the opening price, the high price, the low price, the closing price, the adjacent closing price and trading volume. These features were important when tracking the Bitcoin market and the movement of the prices. In this study, analysis was done using a two-year data set with a high-frequency interval of one hour to ensure the model was trained to detect both short-term price fluctuations and long-term trends required in effective financial forecasting.

The validity of the proposed model was checked by dividing the data set into training and testing sets, where 80% of the data was aimed at training and the rest 20% for testing. This split made it possible to check the model's performance on data not used during exercise, which is useful when testing the model in real-life situations. The proposed model methodology is depicted in Figure 1 below.

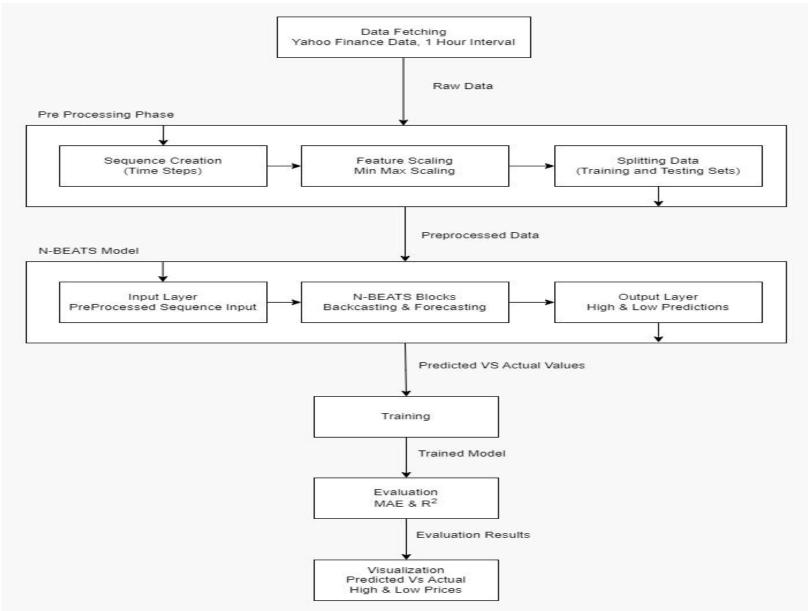

Figure 1: Proposed Methodology Workflow

4.1 N-BEATS

Unlike many other existing architectures, the Neural Basis Expansion Analysis for Time Series (N-BEATS) model is a deep learning architecture tailored for time series forecasting [5]. It is constructed with fully connected layers grouped into blocks comprising the backcast and forecast. The key focus of the backcast module is the backcast component of the time series, while forecasting is pursued in the forecast module. The main advantage of the model under consideration is that it can work without explicit feature engineering based on domain knowledge.

Like most neural networks, N-BEATS model uses residual connections, which help the network capture short-time schlock and long-time trends. This has made it ideal for analysing the cryptocurrency market, which is very volatile, since it can break down the forecast into its components, thereby aiding our understanding of trends and seasonality. The adaptability and interpretability of the model, coupled with high accuracy in solving a myriad of time series problems, have set the N-BEATS as a potent instrument for financial forecasting. N-BEATS architecture, as per [5] is Figure 2 below

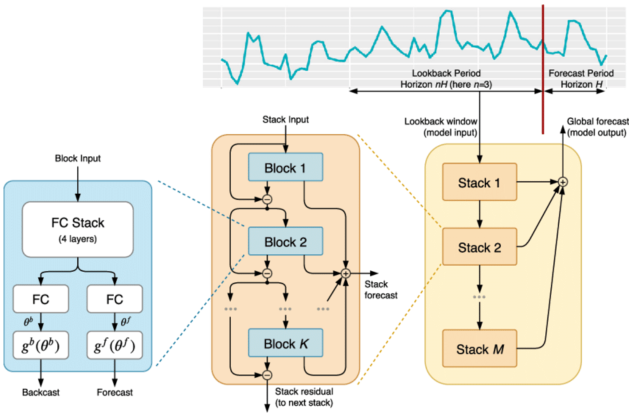

Figure 2. N-BEATS Architecture

5. Implementation

5.1 Data Acquisition and Its Nature

The daily historical Bitcoin price data was gathered from Yahoo Finance [22], and for the 729 days, it covered hourly data. This offered a rich dataset in line with prices' fluctuating nature, a characteristic of cryptocurrency markets. The data included six key features: open, close, high, low, adj close, and volume. These features were crucial for identifying the broad market trends and the temporal patterns evident within an hour in the Bitcoin domain.

5.2 Selection of Hourly Data

Due to the extensive variability of Bitcoin prices, we have chosen hourly data, which may fluctuate drastically in a short period. The model also captured significant and rapid fluctuations in the values by choosing one-hour intervals, and forecasting was more accurate than other time intervals. The dataset was spread over two years, giving enough information for the model to predict both short-term price behaviours and long-term trends. Hourly information also allows real-time market conditions' results to be incorporated into the model.

5.3 Data Preprocessing

Data preprocessing was necessary for cleaning up and steps for preparing the raw data that were fed to the program. We followed several steps to ensure the data was ready for the N-BEATS model as follows:

a. Time Step Creation

We used three-hour time steps so that the model could use the data from the previous three hours to forecast the next hour's high and low prices. This perspective was useful in capturing the dynamics in the dataset in the different time steps.

b. Data Standardisation

There could be some drawbacks when the features are of different ranges; thus, Min-Max scaling was used to make all features scale appropriately. This normalisation technique effectively scaled all features into a range of 0 to 1, helping avoid a given feature that overly influenced the model.

c. Data Splitting

The data was then split into training and testing data, in which 80 per cent of the data was used for training the data while 20 per cent was used for testing. This split enabled us to estimate the model's performance on unseen data, thus, the model's ability to perform well in new market conditions.

d. Data Reshaping

To fit the data into the structure used in the N-BEATS model, we transformed the data into a 3D structure. The input data was in the form of time steps with several features, making it easier for the model to process the historical sequences and learn from them.

5.4. Hyperparameter Tuning

Adjusting these hyperparameters was crucial, especially when obtaining a better-performing model. For some of the parameters, we tried different values. For the final configuration, we picked the parameters shown in Table 1. below.

Table 1: Hyperparameters Tuning

Hyperparameters	Values
Sequence Length	3 hours
Number of blocks	3
Units per block	128
Forecast dimension	2
Batch size	64
Epochs	50
Optimizer	Adam

These values were selected to include in the model to meet an acceptable complexity level that would allow generalisation to unseen data while simultaneously providing stable training and convergence.

5.5 Performance Metrics

In order to assess the performance of the proposed model, we employed two performance measures.

a. Mean Absolute Error (MAE).

Mean Absolute Error quantifies the mean of the absolute differences between the test results and the predictions, providing an easy method for determining the degree of accuracy of the prediction [23]. The N-BEATS model achieved an MAE of 0.00240, indicating minimal deviation from the true values.

b. R-squared (R^2).

This metric defines the percentage of total variation described by the model. R^2 score that is as close to 1 as possible means that the model tested is highly accurate [24]. In our case, the model produced the R^2 of 0.9998, which indicates how well the model was able to capture the basic tendencies in the Bitcoin price fluctuations with great accuracy.

6. Results

The performance of the proposed N-BEATS model for predicting Bitcoin's high and low prices was evaluated using key performance metrics, MAE and R-squared. The analysis shows that the model was able to capture the dynamic structures of Bitcoin's price patterns. The accuracy was trained over 50 epochs during the training, and the Adam Optimiser, with a learning rate of 0.001, provided stable convergence. The model was also assessed on a test set containing 20 per cent of the entire data, as the model's output was checked on data it had not seen before.

The n-BEATS model delivers a very low MAE of less than 0.00240, showing little deviation from the actual performance value. This low error proves that the model was precise and could predict the future high and low prices of Bitcoin. Also, the model provided an R^2 score of 0.9998, meaning it got a capture rate of 99 per cent. This high R^2 value showcased that the model could forecast such complexity and volatile prices that effectively occur in cryptocurrencies, guaranteeing that it could perform well for unseen data rather than fit only for the dataset used for the training.

To further validate the N-BEATS model's performance, we plotted the actual Bitcoin prices against the predicted values on the 500 initial test data points, as shown in Figure 3. This comparison gives more detailed information on how accurate the model has been over the years, besides establishing a clear indication of how close the model has been in predicting Bitcoin price fluctuations. The predicted values mirror actual price movements, thus suggesting that the model is susceptible to short-term fluctuations and long-term trends.

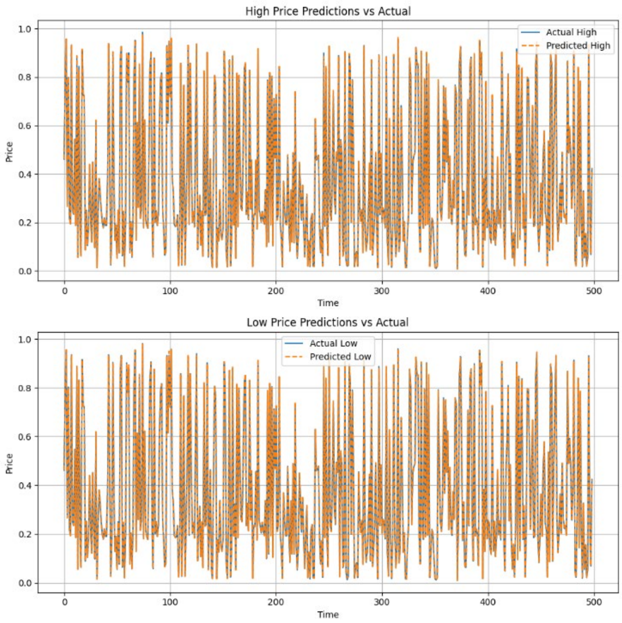

Figure 3. Actual vs Predicted prices for the first 500 data points

6.1 Comparison with Other Models

To further validate the robustness of the N-BEATS model, its performance was compared with two commonly used models for time series forecasting: LSTM and Linear Regression. Finally, both models were evaluated using the same set of performance metrics, namely MAE and R^2, and both were trained on the same dataset.

With the help of performance metrics, the N-BEATS model demonstrated higher efficiency, accuracy, and predictability than the LSTM and linear regression models. The N-BEATS model obtained an MAE of 0.00240. LSTM's MAE was found to be slightly higher, 0.04753. The linear regression model has an even higher MAE, 0.008994. This means these models had larger prediction errors compared to the N-BEATS model.

R^2 was nearly perfect with a value of 0.9998 for the N-BEATS model, and LSTM got 0.9263, whereas Linear Regression got an R^2 of 0.9645. These results again validated that NBEATS capture both short-term fluctuations and long-term trends in the Bitcoin price data more effectively. The reason is the architecture of N-BEATS, which presents the capacity to manage complex temporal dependencies and volatility in the Bitcoin price data, unlike the LSTM and Linear Regression models that failed to manage the cryptocurrency market's nonlinear and highly dynamic character. Table 2 below reveals that N-BEATS has many benefits for the time series forecasting financial market data and the volatile asset of Bitcoin, specifically over LSTM and Linear Regression.

Table 2: Models Performance Comparison Table

Model	Mean Absolute Error (MAE)	R-squared (R^2)
N-BEATS	0.00240	0.9998
Linear Regression	0.008994	0.9645
LSTM	0.04753	0.9263

Higher accuracy of N-BEATS for both high and low prices indicates its capability to capture complex price dynamics as compared to the traditional and advanced models such as Linear Regression and LSTM. This confirms that the use of deep learning architectures like the N-BEATS when it comes to making financial forecasts that require high accuracy in decision-making and risk control is vital. Figure 4 below shows the visualisation of all three models' performance comparisons using a bar chart.

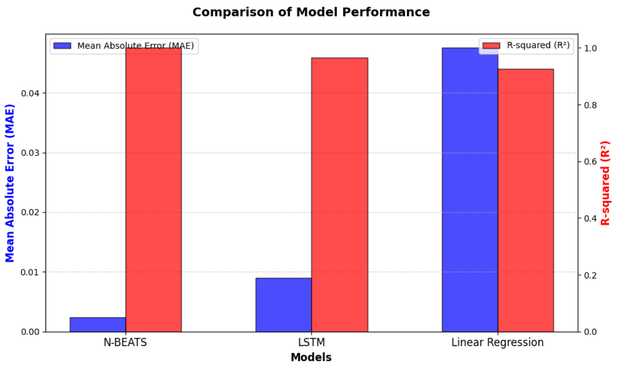

Figure 4. Models Performance Comparison

7. Conclusion & Future Work

This work demonstrated that the N-BEATS model can accurately predict Bitcoin's high and low values. Due to the specifics of the architecture, the constructed model is superior to the classic models, including LSTM and Linear Regression with the MAE of 0.00240 and R^2 score of 0.9998. As demonstrated in the above results, N-BEATS effectively models the underlying characteristics of Bitcoin prices and their volatility with high accuracy. The instant work corroborates the possibility of developing sophisticated deep learning models for time series forecasting of financial markets, particularly those in cryptocurrencies, which require accurate models for informed decisions and risk management.

Further work could be done to extend the model by incorporating more external variables like the macroeconomic index, social media, and regulatory announcements, which also affect Bitcoin prices. However, conducting other tests on the model on other cryptocurrencies or other financial assets might be additional confirmation of the model's efficiency. Lastly, it would be possible to improve the model's accuracy by using more complex methods of model optimisation, including ensemble learning or hybrid models. This would provide additional and more valuable information for investors and financial analysts.

Acknowledgements.

The authors wish to thank the reviewers whose suggestions helped in improving the quality of this paper.

References

[1] Nakamoto, S.: Bitcoin: A peer-to-peer electronic cash system. (2008).
[2] Shumway, R.H., Stoffer, D.S.: ARIMA Models. In: Time Series Analysis and Its Applications. pp. 75–163. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-52452-8_3.
[3] Gamboa, J.C.B.: Deep Learning for Time-Series Analysis, http://arxiv.org/abs/1701.01887, (2017).
[4] Andi, H.K.: An accurate bitcoin price prediction using logistic regression with LSTM machine learning model. Journal of Soft Computing Paradigm. 3, 205–217 (2021).
[5] Oreshkin, B.N., Carpov, D., Chapados, N., Bengio, Y.: N-BEATS: Neural basis expansion analysis for interpretable time series forecasting, http://arxiv.org/abs/1905.10437, (2020).
[6] Ayodele, TO: Machine learning overview. New Advances in Machine Learning. 2, 16 (2010).
[7] Dev, J.A.: Bitcoin mining acceleration and performance quantification. In: 2014 IEEE 27th Canadian conference on electrical and computer engineering (CCECE). pp. 1–6. IEEE (2014).
[8] John, K., O'Hara, M., Saleh, F.: Bitcoin and Beyond. Annu. Rev. Financ. Econ. 14, 95–115 (2022). https://doi.org/10.1146/annurev-financial-111620-011240.
[9] Sunny, M.A.I., Maswood, M.M.S., Alharbi, A.G.: Deep learning-based stock price prediction using LSTM and bi-directional LSTM model. In: 2020 2nd novel intelligent and leading emerging sciences conference (NILES). pp. 87–92. IEEE (2020).
[10] Yuan, Y., Wang, F.-Y.: Blockchain and cryptocurrencies: Model, techniques, and applications. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 48, 1421–1428 (2018).
[11] Golosova, J., Romanovs, A.: The advantages and disadvantages of the blockchain technology. In: 2018 IEEE 6th workshop on advances in information, electronic and electrical engineering (AIEEE). pp. 1–6. IEEE (2018).
[12] ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., Baronchelli, A.: Evolutionary dynamics of the cryptocurrency market. R. Soc. open sci. 4, 170623 (2017). https://doi.org/10.1098/rsos.170623.
[13] Lee, D.K.C., Guo, L., Wang, Y.: Cryptocurrency: A new investment opportunity? Journal of Alternative Investments. 20, 16 (2018).
[14] Drożdż, S., Kwapień, J., Wątorek, M.: What is mature and what is still emerging in the cryptocurrency market? Entropy. 25, 772 (2023).

[15] Liu, J., Serletis, A.: Volatility in the Cryptocurrency Market. Open Econ Rev. 30, 779–811 (2019). https://doi.org/10.1007/s11079-019-09547-5.
[16] Trump, B.D., Wells, E., Trump, J., Linkov, I.: Cryptocurrency: governance for what was meant to be ungovernable. Environ Syst Decis. 38, 426–430 (2018). https://doi.org/10.1007/s10669-018-9703-8.
[17] Chowdhury, R., Rahman, M.A., Rahman, M.S., Mahdy, M.R.C.: An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. Physica A: Statistical Mechanics and its Applications. 551, 124569 (2020).
[18] Wang, Y., Andreeva, G., Martin-Barragan, B.: Machine learning approaches to forecasting cryptocurrency volatility: Considering internal and external determinants. International Review of Financial Analysis. 90, 102914 (2023).
[19] Kim, G., Shin, D.-H., Choi, J.G., Lim, S.: A deep learning-based cryptocurrency price prediction model that uses on-chain data. IEEE Access. 10, 56232–56248 (2022).
[20] Shaikh, A.K., Nazir, A., Khan, I., Shah, A.S.: Short term energy consumption forecasting using neural basis expansion analysis for interpretable time series. Scientific reports. 12, 22562 (2022).
[21] Zhang, Y., Suzuki, G., Shioya, H.: Prediction and Detection of Sewage Treatment Process Using N-BEATS Autoencoder Network. IEEE Access. 10, 112594–112608 (2022).
[22] Yahoo Finance - Stock Market Live, Quotes, Business & Finance News, https://finance.yahoo.com/, last accessed 2024/08/20.
[23] Error, MA: Mean absolute error. Retrieved September. 19, 2016 (2016).
[24] Chicco, D., Warrens, M.J., Jurman, G.: The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. Peerj computer science. 7, e623 (2021).