A combined recurrent neural network model for cryptocurrency time series forecasting

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ABSTRACT
Forecasting cryptocurrency time series presents a difficult challenge, primarily attributable to their inherent non-linearity and chaotic behavior. While traditional statistical methodologies have yielded notable efficacy in specific domains, such as directional market prediction and individual equity price forecasting, the advent of neural networks and recurrent neural networks has catalyzed the exploration of novel paradigms in financial time series prediction. Furthermore, contemporary research posits that the synergistic integration of statistical and machine learning techniques can yield enhanced predictive accuracy relative to their isolated application. This study, therefore, proposes a combined framework that integrates statistical features derived from financial time series with a recurrent neural networks architecture for temporal forecasting. The efficacy of this methodology was evaluated through the prediction of Bitcoin (BTC) closing prices, utilizing a suite of performance metrics. Empirical results demonstrate the superiority of our model compared to univariate statistical and machine learning models.

KEYWORDS
Forecasting; BTC; Time series; RNN; GRU

1. Introduction

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> Scraping historical crypto data
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> Processing historical crypto data
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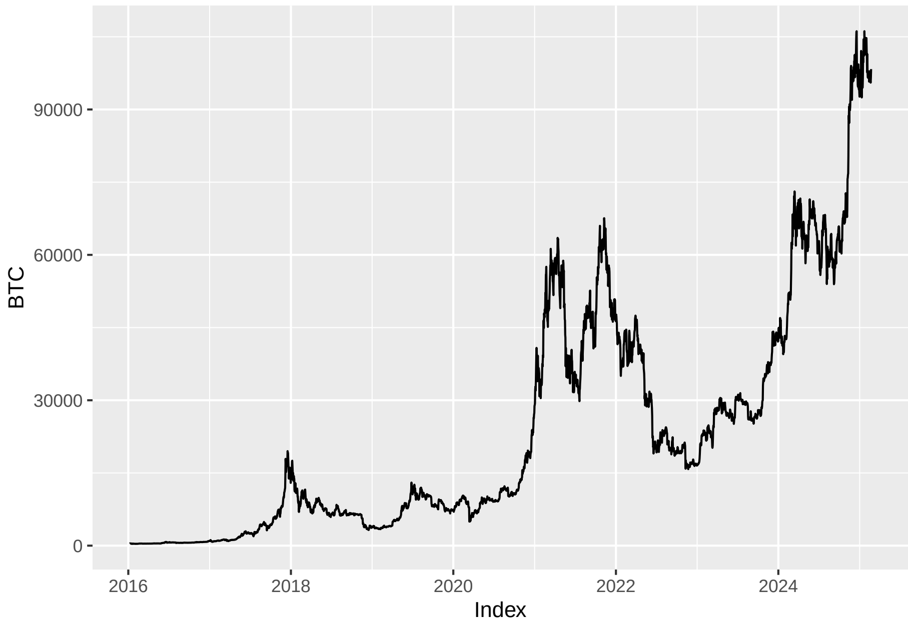

2. Introduction

The rapid growth of cryptocurrencies over the past decade has transformed them into a significant component of the global financial system. However, the volatile and non-linear nature of cryptocurrency prices presents unique challenges for accurate forecasting. Traditional statistical methods often fall short in capturing the intricate temporal dependencies and high volatility of cryptocurrency time series. As a result, researchers have increasingly turned to deep learning models, particularly Recurrent Neural Networks (RNNs), to address these challenges (Nasirtafreshi 2022; Kumar T et al. 2023; Seabe, Moutsinga, and Pindza 2023) .

Recurrent Neural Networks (RNNs) are well-suited for time series forecasting due to their ability to model sequential data and capture temporal dependencies. Variants of RNNs, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have been widely adopted for cryptocurrency forecasting. These models are particularly effective in handling long-term dependencies and mitigating the vanishing gradient problem, which is common in traditional RNNs. For instance, Nasirtafreshi (2022) proposed an RNN-LSTM model to predict cryptocurrency prices, demonstrating its ability to outperform traditional methods in terms of accuracy.

To further enhance the predictive performance of RNNs, researchers have explored hybrid models that combine RNNs with other techniques. For example, Guo et al. (2021) developed a hybrid method that integrates a multiscale residual block with an LSTM network to forecast Bitcoin prices. This approach leverages the strengths of both components: the residual block captures multi-scale features, while the LSTM network models temporal dependencies.

Similarly, other studies have proposed combining RNNs with convolutional layers or graph-based methods to improve the model's ability to capture spatial and temporal patterns in cryptocurrency data. The combined RNN models offer several advantages over standalone RNNs or traditional methods. By integrating complementary techniques, these models can better handle the non-stationarity and noise inherent in cryptocurrency time series. For instance, hybrid models that incorporate wavelet transforms or attention mechanisms have been shown to improve feature extraction and focus on relevant patterns in the data. Additionally, ensemble approaches that aggregate predictions from multiple RNN-based models have demonstrated enhanced robustness and accuracy in cryptocurrency forecasting.

3. Related works

Machine Learning is an artificial intelligence device that uses beyond information to predict the future. In simple words, we can expect the future price movements of cryptocurrencies to some extent by training a machine learning model using their past price data. Some recent studies have shown that machine learning based methods have many advantages of using traditional forecasting models, such as the ability to produce results that are approximately equal or identical to the actual outcome, while also improving the precision of the outcome (Hitam et al. 2021). Decision trees, support vector machine, and neural networks are some of the different machine learning methods that can be used for this purpose. As evidenced by the authors in (Andrianto and Diputra 2017), the inclusion of cryptocurrencies in multi-asset portfolios significantly improves portfolios in several ways. To start, it will enhance the portfolio's minimal variance and furthermore transfers the green frontier to a higher location.

Several research studies in the literature that using machine learning algorithms in BTC price forecasting achieve encouraging results. According to a study (Hitam et al. 2021), machine learning algorithms were applied to perform the price prediction of many currencies including BTC, ETH, LTC, XRP, and Stellar. According to the researchers, the SVM model was able to beat other machine learning models in terms of predicted values as well as accuracy. (Saad et al. 2019) used a variety of variables, carefully choosing the most accurate predictors using correlation analysis. The results showed that linear regression performed better than the other approaches when SVM, linear regression, and random forest (RF) were used to these selected features. The authors also tried predicting the prices of BTC and ETH using LSTM, a specific kind of deep learning, and discovered that LSTM had the lowest prediction error for BTC. To predict the prices of nine different cryptocurrencies, (Chowdhury et al. 2020) studied the application of machine learning-based ensemble methods, namely ANN, KNN, Gradient Boosted Trees and an ensemble model made up of multiple methods. The ensemble learning model had the the lowest error in the predictions. (Derbentsev et al. 2021) studies the difficulties faced when forecasting short-term cryptocurrency time series using supervised machine learning (ML). The ensemble methods were then applied to the daily closing prices of Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) using historical prices and technical indicators such as moving averages as features: Random Forest (RF) and Stochastic Gradient Boosting Machine (SGBM). The results showed that ML ensemble methods held promise, with SGBM and RF yielding good accuracy on short-term predictions.

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Disclosure statement

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Nomenclature/Notation

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Notes

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4. References

4.1. *References cited in the text*

4.2. *The list of references*

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5. Appendices

Any appendices should be placed after the list of references, beginning with the command `\appendix` followed by the command `\section` for each appendix title, e.g.

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\appendix
\section{This is the title of the first appendix}
\section{This is the title of the second appendix}
```

produces:

Appendix A. This is the title of the first appendix

Appendix B. This is the title of the second appendix

Subsections, equations, figures, tables, etc. within appendices will then be automatically numbered as appropriate. Some theorem-like environments may need to have their counters reset manually (e.g. if they are not numbered within sections in the main text). You can achieve this by using `\numberwithin{remark}{section}` (for example) just after the `\appendix` command.

Please note that if the `endfloat` package is used on a document containing appendices, the `\processdelayedfloats` command must be included immediately before the `\appendix` command in order to ensure that the floats in the main body of the text are numbered as such.

Appendix A. Troubleshooting

Authors may occasionally encounter problems with the preparation of a manuscript using LaTeX. The appropriate action to take will depend on the nature of the problem:

(i) If the problem is with LaTeX itself, rather than with the actual macros, please consult an appropriate LaTeX 2_ε manual for initial advice. If the solution cannot be found, or if you suspect that the problem does lie with the macros, then please contact Taylor & Francis for assistance (`latex.helpdesk@tandf.co.uk`).

(ii) Problems with page make-up (e.g. occasional overlong lines of text; figures or tables appearing out of order): please do not try to fix these using 'hard' page make-up commands – the typesetter will deal with such problems. (You may, if you wish, draw attention to particular problems when submitting the final version of your manuscript.)
(iii) If a required font is not available on your system, allow TEX to substitute the font and specify which font is required in a covering letter accompanying your files.

Appendix B. Obtaining the template and class file

B.1. *Via the Taylor & Francis website*

This article template and the `interact` class file may be obtained via the 'Instructions for Authors' pages of selected Taylor & Francis journals.

Please note that the class file calls up the open-source LATEX packages booktabs.sty, epsfig.sty and rotating.sty, which will, for convenience, unpack with the downloaded template and class file. The template calls for natbib.sty and subfigure.sty, which are also supplied for convenience.

B.2. *Via e-mail*

This article template, the `interact` class file and the associated open-source LATEX packages are also available via e-mail. Requests should be addressed to `latex.helpdesk@tandf.co.uk`, clearly stating for which journal you require the template and class file.