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Improving cryptocurrency price prediction through advanced LSTM-based deep learning techniques

Rihab Qasim Abdulkadhim *
Hasanen S. Abdullah †
Mustafa Jasim Hadi §
Department of Computer Science
University of Technology
Baghdad
Iraq

Abstract

One In the evolving financial market landscape, cryptocurrencies have seen a notable surge in investments. This study delves into the advancements in cryptocurrency price predictions using LSTM (Long Short-Term Memory) neural networks. One of the integral components of our neural architecture is the "dense layer", which plays a pivotal role in finalizing the output from the LSTM layers, making the predictions more compact and refined, by focusing on four major cryptocurrencies: We used LSTM networks to improve the precision of forecasting for USDT, BTC, ETH, and BNB. One important aspect of this study is that it includes the "LeakyReLU" function which helps to solve the issue of vanishing gradients, thus enhancing the predictive power of LSTM networks. This integration is really accurate in making predictions, it sets a new standard. We also put in a lot of effort to analyze the optimum value for the "lookback" parameter, to determine how it can impact the efficiency of the model. This highlights how crucial it is to carefully adjust the settings to improve the accuracy of the predictions. In terms of performance metrics, the best MAPE outcomes were achieved for USDT with a 'lookback' of 5 (MAPE = 0.000256%), BTC with a 'lookback' of 10 (MAPE = 0.030105%), ETH with a 'lookback' of 30 (MAPE = 0.038678%), and BNB with a 'lookback' of 30 (MAPE = 0.030903%). These reports will provide the investors with the legitimate and trustable level of understanding related to cryptocurrencies.

Subject Classification: *Primary 93A30, Secondary 49K15.*

Keywords: *LeakyReLU, Price prediction, Deep learning, LSTM, Cryptocurrency.*

* *E-mail:* `Cs.21.13@grad.uotechnology.edu.iq (Corresponding Author)`
† *E-mail:* `Hasanen.S.Abdullah@uotechnology.edu.iq`
§ *E-mail:* `110077@uotechnology.edu.iq`

1. Introduction

The world of finance has seen a significant development, specifically brought about by the emergence of cryptocurrencies. [1]. The very foundation of these cryptocurrencies is intricately tied to cryptography and the underlying principles of the blockchain, offering a robustness that's truly transformative [2]. These days, with the development of technology, there are a lot of digital currencies available, and Bitcoin (BTC) stands out because it is decentralized, private, and non-inflatable, making it a new way for people to own things [3].

Bitcoin started in 2009 and it has become very famous in the market of cryptocurrency. It is worth is now over $5 billion [4]. these markets face unique challenges related to cybersecurity and legal regulation [5], which adds a layer of uncertainty about their stability and acceptance. Global. Extreme price volatility stands out as a major challenge [6]. The unpredictability of crypto market is very interesting and attracts a lot of researchers to study its trends and behavior. Researchers, investors and other insiders are eager to know what the future holds for crypto market [7].

It is very difficult to understand the small changes in the price of cryptocurrency and it requires advanced methods to analyze it. explain the deep learning technique known as LSTM [8] [9]. LSTMs [10] are very good at detecting long term dependencies in sequential data and they are the best option for forecasting tasks [12] [13]. By incorporating the Dense architecture, DL [14] models become more sophisticated, enabling them to accurately predict the price of cryptocurrencies. [15-17]. Our research underscores:

- Innovative Model Architecture: The paper presents an intelligent model that joins LSTM-Dense for predicting cryptocurrency market trends.
- Strategic Function Integration: By incorporating "LeakyReLU" function, we could solve the problem of disappearing gradients, thus improving our network's capacity to learn.
- Parametric Exploration: A thorough study and careful adjustment of the 'lookback' parameter, which helps improve the accuracy of the predictions.

The discussion is organized step by step. The "Related Works" section of Section II provides a summary of all the research work done in the field of cryptocurrency forecasting. The proposed methodology section in part III discusses the method we will use for research. The "Result Analysis" in Section IV gives a detailed explanation of our discovered facts and the comprehension we gained from them. In my opinion, the last part of the report should summarize all the important findings and give an overview of the possible future research directions

2. Review of Related Work

There has been a lot of research done on predicting the price of cryptocurrency. Through the use of multiple complex models and techniques, these studies have broadened our knowledge about the movements in the cryptocurrency market. Below is a systematically arranged chronology of seminal studies in this field:

Z. Munim, et al. [15], investigated Bitcoin price prediction using ARIMA and NNAR models. ARIMA consistently outperformed NNAR. For May 2013-Oct 2018, ARIMA reported a mean error of 0.037 compared to NNAR's 0.048. During Jun 2017-Oct 2018, ARIMA's RMSE was 0.042 versus NNAR's 0.093. The study concluded ARIMA as superior in forecasting Bitcoin prices.

Mudassir et al. [16] utilized SVM and random forest for short and medium-term Bitcoin price predictions. Data was sourced from bitinfocharts.com. Results showed up to 65% accuracy for next-day predictions and 1.44% error rate for daily forecasts.

Chen and Sun [18] investigated various ML techniques for BTC price prediction. They evaluated different time intervals. Logistic Regression and Linear Discriminant Analysis achieved 66% accuracy for daily predictions, while models like Random Forest, XGBoost, and others reached 67.2% for 5-minute intervals. The study emphasized the role of sample dimension engineering in diverse prediction contexts.

G. Kim, et al. [19] suggest a framework for Bitcoin price prediction using change point detection and on-chain data. Their SAM-LSTM model, combining LSTM and attention mechanism, showed high accuracy. Tested on real BTC data, the metrics were MAE 0.3462, RMSE 0.5035, and MAPE 1.3251, indicating the model's reliability.

Yuan, Q, et al. [20] introduced the 1DCNN-GRU hybrid model for cryptocurrency price prediction, merging a 1D convolutional neural network (CNN) with gated recurrent units. Evaluating BTC, Ethereum, and Ripple from January 2012 to March 2021, they achieved low RMSEs:

43.933 (Bitcoin), 3.511 (Ethereum), and 0.00128 (Ripple), signaling a potential shift in cryptocurrency forecasting methods.

N. Latif, J. Durai Selvam, and V. Mahajan [21] compared ARIMA and LSTM for short-term Bitcoin price prediction, using data from 12/21/2020 to 12/21/2021. Over nearly 20 hours of testing, with 10-minute interval predictions, LSTM outperformed ARIMA, registering an MAE of 126.97, MAPE of 0.27%, and RMSE of 151.95, against ARIMA's significantly higher error metrics.

These landmark studies synergistically propel our comprehension of cryptocurrency market nuances. While these efforts have undeniably elevated the research paradigm, the quest for refinement and enhanced predictive accuracy in cryptocurrency forecasting persists.

3. Proposed Methodology

In this section, we delve into the comprehensive methodology employed, essential for accurately predicting Bitcoin prices. We begin by acquiring data from reputable sources. This data then undergoes a rigorous preparation process to ensure its readiness for analysis. Subsequently, the data is partitioned into training and testing sets. With these datasets in hand, we proceed to build our model using cutting-edge DL techniques. Once the model is developed, it's deployed for predictions. The resulting predictions are then assessed for accuracy and effectiveness. Figure 1 explain the overall diagram for Methodology of Cryptocurrency Price Prediction: From Data Collection to Evaluation.

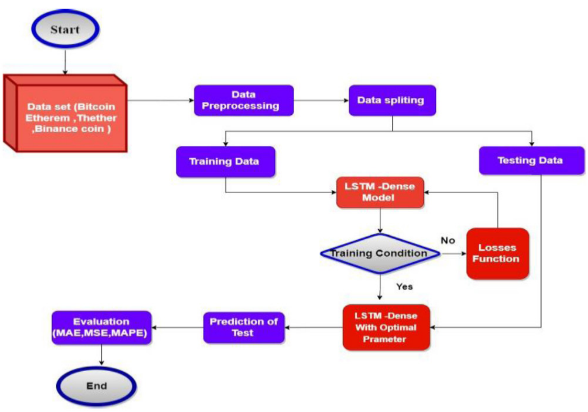

Figure 1

Methodology of Cryptocurrency Price Prediction

3.1 *Dataset Description*

The dataset from Cryptocurrency Prices Dataset, Kaggle [22], covering the period from November 9, 2017, to November 9, 2022, and consisting of 1,828 records, offers insights into four key cryptocurrencies that are Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB) and Tether (USDT). The dataset focuses on closing prices, a critical metric that encapsulates the market's consensus on value at the end of each trading period, serving as a key indicator for trend analysis and predictive modeling.

3.2 *Dataset preprocessing*

The preprocessing is very important and is often considered as the first and foremost stage when it comes to the efficiency of DL's generalization based on the meaning of data [23]. In the context of LSTM neural network applications for cryptocurrency price forecasting, scaling data attributes is crucial. Normalization plays a central role in this process, as it standardizes the influence of all input features, improving training efficiency and forecast accuracy. We used Min–Max Normalization, often called scaling, is a fundamental technique used to boost the performance of predictive models [24].

3.3 *Dataset splitting*

The Partitioning data into training and testing sets is a fundamental step in model validation. This division ensures that models are robust and not just tailored to a specific subset of data. It also allows for measuring and comparing the accuracy of different model predictions without concern over overfitting to the training data. While the 80:20 split, influenced by the Pareto principle, is common [25] [26], our methodology employs a 70:30 ratio.

3.4 *Architecting a Prediction Model with LSTM -Dense Layers*

In the sophisticated realm of cryptocurrency predictions, understanding multifaceted temporal patterns is essential. Our model, leveraging state-of-the-art DL methodologies, integrates LSTM, DENSE, and LeakyReLU layers, showcasing an intricate blend of these techniques. Before delving into detailed specifications, it's beneficial to gain an overarching perspective of our model's architectural composition in Figure 2.

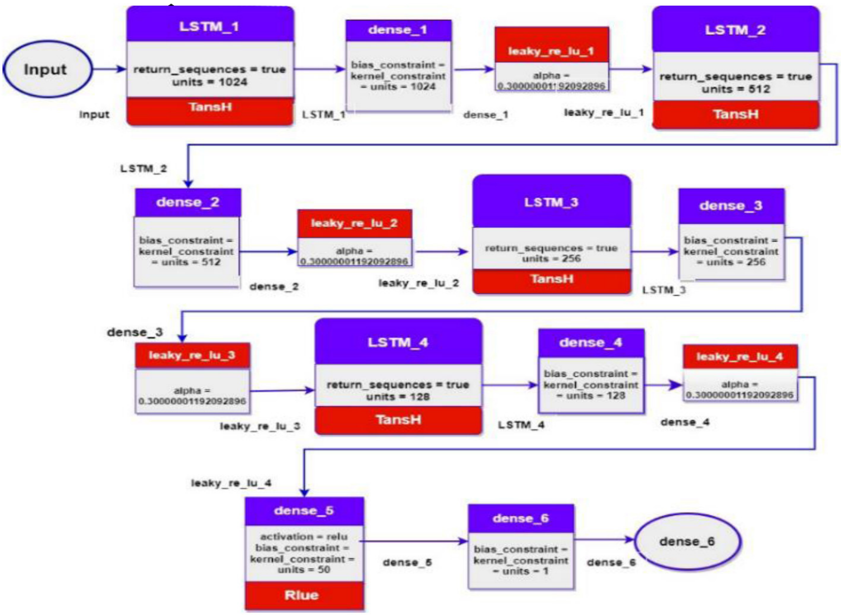

Figure 2

Visual Representation of the DL (LSTM –Dense layer)

A. *The proposed LSTM-Dense model design*

The articulated LSTM-Dense-LeakyReLU model encompasses 14 distinct layers, the model's depth is further highlighted by its 9,854,693 trainable parameters, indicating a balance between complexity and precision, to train our LSTM model, we set the max epochs at 1000 and a batch size of 64 we used the Adam optimizer, known for its efficiency in updating the model's weights and helping it learn faster. Table 1 explains these layers in some detail.

Table 1

Layer Types and Their Functional Descriptions in The Dl Model

Layer Type	Number of Units	Activation Function	Description and Function
LSTM	1024	Tanh	LSTM layer that takes input of size (1, look_back) and outputs a sequence to the next layers.

Contd...

Dense	1024	ReLU	Fully connected Dense layer that receives data from the previous layer and contains 1024 units.
LeakyReLU	-	Leaky ReLU (α=0.3)	LeakyReLU activation function with a leakage parameter of 0.3, adding a simple non-linearity.
LSTM	512	Tanh	Another LSTM layer that receives a sequence from the previous layer and outputs another sequence.
Dense	512	ReLU	Fully connected Dense layer that receives data from the previous layer and contains 512 units.
LeakyReLU	-	Leaky ReLU (α=0.3)	LeakyReLU activation function with a leakage parameter of 0.3.
LSTM	256	Tanh	Another LSTM layer that receives a sequence from the previous layer and outputs another sequence.
Dense	256	ReLU	Fully connected Dense layer that receives data from the previous layer and contains 256 units.
LeakyReLU	-	Leaky ReLU (α=0.3)	LeakyReLU activation function with a leakage parameter of 0.3.
LSTM	128	Tanh	Another LSTM layer that receives a sequence from the previous layer and outputs another sequence.
Dense	128	ReLU	Fully connected Dense layer that receives data from the previous layer and contains 128 units.
LeakyReLU	-	Leaky ReLU (α=0.3)	LeakyReLU activation function with a leakage parameter of 0.3.
Dense	50	ReLU	Fully connected Dense layer using the ReLU activation function with 50 units.
Dense	1	Linear	Fully connected Dense layer for output using the linear activation function.

The proposed model amalgamates the prowess of LSTM layers in processing sequential data and the enhancements brought about by fully connected (Dense) layers. With this composition, the model is anticipated to deliver reliable and efficient results in complex tasks.

4. Result

This study ventures into the realm of predicting cryptocurrency trends using DL techniques. The model's performance has been rigorously assessed using key evaluation metrics. A detailed Table 2 will follow, presenting in-depth findings that include data on epochs, execution time, values of the metrics, and specifics of the cryptocurrencies under analysis.

Evaluation metrics are crucial in DL as they offer a quantitative way to assess model performance, there are using three types of metrics:

- **Mean Absolute Error (MAE) Test**: The mean difference among the expected and actual numbers can be used to assess prediction accuracy.
- **Mean Squared Error (MSE) Test:** The measures the average squared differences among predictions and actual values.
- **Mean Absolute Percentage Error (MAPE: (**The average percentage difference between expected and actual values, as compared to the actual mean. It provides a percentage-based error rate.

4.1 *Lookback*

The 'look back' parameter is essential in time series forecasting, setting the amount of historical data, like 30 days, used by the model to predict future events. The correct selection of this window, whether short or long, is crucial for the model's accuracy.

Table 2

Cryptocurrency Analysis: Key Performance Results

Currency	Lookback	Epoch	Loss Validation	Time (sec)	MAE Test	MSE Test	MAPE
USDT	5	405	0.00002051	1453.15	0.00000256	0.00000401	0.00000256
USDT	10	581	0.000014617	2134.80	0.00000373	0.00000492	0.00000373
USDT	30	237	0.000028278	947.83	0.00000370	0.00000540	0.00000370
BTC	10	147	0.00061413	607.63	11.6386	15.9421	0.00030105
BTC	30	203	0.00068333	700.69	12.2877	16.8163	0.00032841
BTC	50	274	0.00099072	1376.04	15.4331	20.2484	0.00039867

Contd...

ETH	10	156	0.0019	595.61	1.5937	2.0465	0.00063015
ETH	30	198	0.00072253	986.29	0.9699	1.2708	0.00038678
ETH	50	274	0.00099072	357.10	3.1801	3.6664	0.00132241
BNB	10	221	0.00092024	1057.65	0.1522	0.2055	0.00039306
BNB	30	370	0.00062090	1642.98	0.1138	0.1572	0.00030903
BNB	50	225	0.00080459	806.99	0.1388	0.1912	0.00038647

Table 2 contains our LSTM model analysis of four important cryptocurrencies. An epoch is a very important term in the field of neural networks, referring to a complete pass through our dataset. During the epoch, the model undergoes several iterations to optimize the error rate. This is an examination of the effects of history on the future of cryptocurrencies, and how these impacts are measured and evaluated through metrics.

4.2 Analyze the Results

Bitcoin: Examining Bitcoin's model in different Lookback settings of 10, 30, and 50 is really useful to know its peak efficiency. The table shows the important information that bitcoin has the lowest validation loss with value of 0.00061413 and largest mean absolute percentage error test value of 11.6386.

Ethereum: Based on the evaluations, it is found that the optimal performance of the Lookback setting is 30. The validation loss of 0.00072253 and MAE Test of 0.9699 indicate that Ethereum has striking performance in this analysis.

USDT: Based on the analysis performed using the Lookback settings of 5, 10, and 30, it can be concluded that the optimal parameter for USDT is 5. The USDT model has a validation loss of 0.00002051 and a MAE Test score of 0.00000256, which really indicates its high level of accuracy and effectiveness.

BNB: despite being an emerging phenomenon, displayed slightly higher error metrics than other cryptocurrencies. However, the 30-day lookback period stands out as an ideal span for price analysis, suggesting untapped potential. The validation loss is 0.00062090, and the MAE is 0.1138.

Our findings show that the LSTM model predicts cryptocurrency prices much better than methods like ARIMA and multilayer perceptron neural networks. The proposed LSTM-Dense model is excellent at predicting market changes due to its ability to understand long-term trends and current data, along with improved learning from the LeakyReLU function. However, it hasn't been tested on many

Table 3

Comparison Result with Related Studies

Researchers	Year	Methods Used	Dataset Range	Crypto	Metric Type	Metric Value
Mudassir et al.	2020	SVM, Random Forest	Data from bitinfocharts.com	BTC	MAPE	1.44%
G. Kim et al.	2022	SAM-LSTM	Real BTC data	BTC	MAPE	1.3251%
N. Latif et al.	2023	ARIMA, LSTM	Dec 21, 2020 - Dec 21, 2021	BTC	MAPE	**0.27%**
Our proposal	-	LSTM-Dense	2017-2022	BTC, Ethereum	MAPE	0.030105%, 0. 038678%

cryptocurrencies, and external factors like politics and economics can make predictions less as shown in Table 3.

5. Conclusion

The study focuses on the intricate profound of the network structure of the neurons layman particularly accentuating the proficiency of LSTM and Dense layer in anticipating the volatile drawbacks of the cryptocurrency market. LSTMs go ahead of others thanks to their gating mechanism which you send not only the current information but also the information from the past time. DL's dense layer is particularly claimed as the critical part in DL being very useful for extracting the complex patterns existing in a dataset, which lead to the significant improvement in forecasting accuracy. The research sheds light on the accuracy and the dependability of the DL technique and provides the precision of these past major cryptocurrency. By means of this study setting the benchmark of DL for market forecasting, it has been shown that there is strong correlation in the use of combined advanced algorithms with complex financial sets of data. On the opposite side, expansion to a hybrid model, broadening to others influencing the crypto values and increasing the depth of their work in more cryptocurrencies are the suggestions for the future.

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