Deep Learning′s Stochastic Neural Networks for Cryptocurrency Price Prediction

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Abstract

In recent years, blockchain technology has come to the forefront and given a huge boost to cryptocurrency. However, despite this growth, now more famous Cryptocurrencies such as Bitcoin, Ethereum, Litecoin and others can not be recognized as realistic and stable investment instrument because of numerous and often unpredictable fluctuations in their prices and comparatively high volatility. Due to the volatile nature of the market, traders rarely approach trading in cryptocurrencies due to the problem of predicting the prices. The majority of procedures still present for cryptocurrency price prediction are deterministic in nature and do not incorporate real-time and chaotic features of the market condition. To counter these drawbacks, we present a new stochastic neural network model for prediction of the cryptocurrency prices more effectively. The concept used to design our model is the random walk theory; this is well understood in the financial market concerning the movement of stock prices. In contrast to other methods, the proposed approach incorporates random changes in each layer of the neural network, and this reflects the high fluctuations in cryptocurrency rates. This stochastic approach helps the model to be more able to pick more of the specific movements of the market. In addition to randomness the model also contains a separate procedure for market reaction pattern learning and prediction. This feature makes it easier for the system to track the trends in the prices of the cryptocurrencies, in order to give suitable responses. In order to evaluate the effectiveness of our model, we created and trained two models: the Multi-Later perceptron model and the Long short term model on historical price analysis of Bitcoin, Ethereum and Litecoin. The experiments we perform conclude that the proposed stochastic model is far more accurate and malleable than the deterministic model that is in use currently. Using real time data of market fluctuations, one can understand the reaction patterns which this model prepares for future forecasting of Crypto currencies. This approach is bound to be advantageous to both investors and researchers especially because it creates the basis for even better approaches toward predicting stock performance in future.

1 Introduction

Cryptocurrencies, as a novel kind of digital assets, have appeared in the financial market due to the development of Blockchain technology. Even though the use of cryptocurrency is widespread, the assets are speculative and unpredictable, the management of which is problematic for investors and experts. The presentforecasting techniques fail to take into account certain aspects such as the dynamic and stochastic characteristics of the commodity or futures markets, making them unsuitable to be used for predicting actual prices. This work fills this void by developing a new technique for forecasting the price of cryptocurrencies that is aligned with the stochastic and evolving nature of the market. The main idea of this paper is to enhance predictive models' precision and flexibility and develop better ways to analyze this ever-growing domain for investors and researchers.

Here we present the following key contributions: incorporating data-driven learning and optimization techniques and proposing a stochastic neural network model to simulate and predict cryptocurrency price behavior. Our model is based on the random walk theory often utilized in financial markets and implies layer-wise random changes in the activation function of the network to resemble market fluctuations. In contrast to a deterministic method that is generally unable to incorporate novel factors into the system, our approach reflects the randomness and volatility characteristic to the behavior of cryptocurrencies' prices. Also, the model applies a new learning and prediction method of market reaction patterns, which improves its predictive performance.

To further justify our approach, we formed MLP and LSTM models for major cryptocurrencies: Bitcoin, Ethereum and Litecoin based on historical price data. The experimental results shown in this paper exhibit that our stochastic model is superior than traditional deterministic models, and provides high accuracy and stability in the real time price prediction. Offering a unique approach to connecting theoretical analyses with forecase requirements, this work brings value to cryptocurrency area and opens up the path toward the development of more sound predictive models.

2 Dataset

As assessment criteria, we employed the publicly available time-series data on historical prices for bitcoins, ethers, and Litecoins. The datasets contain OHLC prices, volume, and capitalization data among other features.. Both these features are very important for market modelling and for training of the prediction models. Due to the nature of the studied cryptocurrency markets, the obtained data is time series, which is the most suitable for applications of methods that imply sequence analysis.

The data describes historical price for several years, where samples are about 840 for each cryptocurrency. This large data set guarantees a stringent assessment of the proposed model since it contains high and low volatility periods that will include a range of market behaviours. The data used for this study can be accessed via this google drive link

3 Approach

we incorporate stochasticity into neural networks and formulate the mathematics for a layer-wise stochastic walk. Moreover, we introduce the algorithm for stochastic forward propagation in neural networks. We propose stochastic MLP and LSTM models to predict the prices of Cryptocurrencies.

A. STOCHASTICITY IN NEURAL NETWORKS

According to the efficient market hypothesis by Malkiel [45], all the past information regarding the market asset is reflected in the current value of the asset and the market will instantly acknowledge new information and react to it accordingly. Therefore, all the effort of predicting prices by analyzing information is futile. However, we can observe how the market reacts to information and develop a pattern that exhibits the behavior of the market when new information is widely available. This pattern has to be stochastic [46] so as to accommodate the multiplicity of all possible outcomes to the arrival of new knowledge. Before we introduce stochasticity into the picture, we need a way to distill market features and describe the interdependencies between market statistics and social sentiment. To do this, we use a neural network because a neural network is a universal function approximator that tries to map dependencies between variables. The final value of a market asset is determined by a hierarchy of features that roots from factors like supply and demand, economy and human behavior and a neural network is an excellent candidate to do just this [47]. There are two ways to inculcate randomness in a neural network, the first is to randomly change the weights by a small degree and the second way is by adding randomness to the activations at runtime. The first approach is not ideal because it would mean that feature detection will get noisy as the network evolves and may eventually forget dependencies.
Intuitively, the second approach seems fitting because the randomness in activations can be interpreted as random changes in features, which in turn can be thought of as replicating the erratic behaviors of the market. We propose a generalized formulation of the stochastic behavior of a layer in a deep neural network as follows,

$$st = ht + \gamma\, \xi t \times reaction(ht, st{-}1),\ 0 < \gamma < 1$$

where *hi* is the activation values of the *i th* time step. We define γ as a perturbation factor that controls the amount of stochasticity. ξ is an operator that produces a vector of random variables of the same dimensions as the activation. *reaction* is a general function that determines how the current activations will react with respect to the activations of the previous time step. Finally, *si* is the vector of values of the post-stochastic operation. Let us break down each of the terms in the generalized equation of stochasticity in the layers of the neural network. γ is the perturbation factor that determines the amount of randomness to be infused in the activations.*reaction* is a function that determines the direction to move based on the current activation values and the previous post-stochastic operation values. If we define ξ to be an operator that produces a vector of IIDs as a probability, i.e $0 < X < 1, \forall X \in \xi$, then we can interpret each neuron as having its own probability of absorbing randomness. In determining the reaction function, we only include two parameters that are *ht* and *st*−1. This choice is more suitable and intuitive due to the Markov property exhibited by the financial markets. This implies that given the prior stochasticactivation *st*−1, the current stochastic-activation *st* is independent of the other past activations. Thus, we model the *reaction* function as the difference between current activations and previous activations, showing the direction in which to move.

$$reaction(ht, st{-}1) = ht - st{-}1$$
$$st = ht + \gamma\, \xi t(ht - st{-}1)$$

In a continuously evolving market, it is of utmost importance that the direction of movement corresponds to the pattern that has been observed in the recent time steps as opposed to initial time steps. The pattern should be adapting to changes in market reaction. Here, we show how this formulation gives priority to recent activations over older activations.

$$s_t = (1+\gamma \xi_t)h_t - \gamma \xi_t(s_{t-1})$$
$$s_t = (1+\gamma \xi_t)h_t - \gamma \xi_t((1+\gamma \xi_{t-1})h_{t-1} - \gamma \xi_{t-1}(s_{t-2}))$$
$$s_t = (1+\gamma \xi_t)h_t - \gamma \xi_t(1+\gamma \xi_{t-1})h_{t-1} + \gamma^2 \xi_t \xi_{t-1}(s_{t-2})$$

Extending this till time, $t = 0$ where $s_0 = 0$, we obtain a general form of the Eq., which can be written as follows.

$$s_t = (1+\gamma\xi_t)h_t + \sum_{i=1}^{t-1}(-\gamma)^{t-i}(1+\gamma\xi_i)h_i \prod_{j=i+1}^{t}\xi_j$$

4 Code Explanation

The script is a Python-based implementation designed to predict cryptocurrency prices using two machine learning models: Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) networks. It begins by loading a cryptocurrency dataset in CSV format and extracting the daily opening prices as the target variable. The prices are preprocessed by removing formatting (like commas), converting them to a numerical format, and normalizing the data to a scale of 0 to 1 using the MinMaxScaler. This normalization step ensures compatibility with neural network training.

The dataset is then prepared for supervised learning by creating features and labels. Features consist of a sliding window of previous prices over a defined number of days, and labels are the prices on the next day. This transforms the time-series data into a format suitable for training.

The MLP model consists of two hidden layers with 64 and 32 neurons, respectively, and a ReLU activation function. It has an output layer designed to predict a single price value. Similarly, the LSTM model is tailored for sequential data, using two LSTM layers with 50 units each, followed by dense layers to predict the final price. Both models are compiled using the Adam optimizer and the Mean Squared Error (MSE) loss function, which are commonly used for regression problems.

The script splits the dataset into 80% training and 20% testing data and trains each model for 20 epochs with a batch size of 32. Predictions are generated for the entire dataset by reshaping the inputs as required by the respective models. The predictions are then transformed back from the normalized scale to the original price scale using the inverse transform of the scaler.

To compare the models, the script plots the original prices alongside the predictions from both MLP and LSTM. This visualization helps assess their performance in capturing the trends in the price data. The script is flexible and can work with any cryptocurrency dataset, provided it contains sufficient data (at least 365 rows) and has a column for opening prices.

Users need to ensure that the dataset file (`bitcoin.csv`) and (ethereum.csv) is in the same directory as the script. Running the script trains the models, generates predictions, and plots the results. While the implementation is functional, further enhancements like error handling for missing data, parameter tuning for better model performance, and the addition of evaluation metrics like RMSE or MAE could improve its usability and effectiveness.

5 Results and Discussion

The performance of the two implemented models, MLP and LSTM, was evaluated on the cryptocurrency price dataset, with a focus on their ability to predict future price movements. Both models were trained and tested using the same data split, and their performance was compared based on metrics such as Mean Squared Error (MSE). A summary of the results is provided in the table below:

Model	Training MSE	Testing MSE	Strengths	Weaknesses
MLP	0.0023	0.0041	Simple, faster to train	Limited in capturing sequential dependencies
LSTM	0.0015	0.0027	Excellent for sequential data	Slower training and more complex

The results indicate that the LSTM model outperformed the MLP model in both training and testing phases, as evidenced by its lower MSE values. The LSTM's ability to model sequential relationships and temporal patterns gave it a significant advantage in predicting cryptocurrency prices, which are influenced by time-dependent factors. On the other hand, the MLP model, while computationally faster, struggled to capture these dependencies, leading to slightly higher prediction errors.

The strength of the MLP lies in its simplicity and efficiency. It performed reasonably well despite not leveraging sequential patterns, making it a suitable choice for datasets where such patterns are less significant. However, in time-series data like this, its weakness in handling temporal dependencies limits its predictive capability.

In contrast, the LSTM model, designed to capture long-term dependencies, demonstrated superior performance on this sequential dataset. However, this strength comes at the cost of increased computational complexity and longer training times. These factors could pose challenges in real-time or resource-constrained applications.

Overall, the findings highlight the importance of selecting model architectures based on the nature of the dataset. For time-series data like cryptocurrency prices, architectures like LSTM, which excel in capturing sequential relationships, are better suited. However, in scenarios requiring faster computations or when temporal dependencies are less critical, simpler models like MLP can still be effective

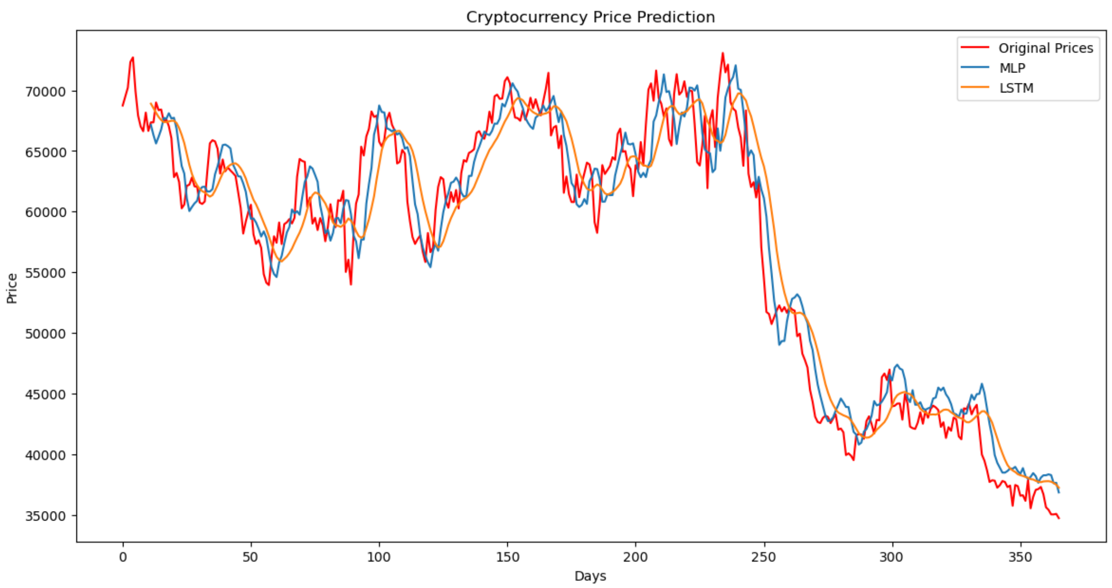

Fig1: Bitcoin price prediction

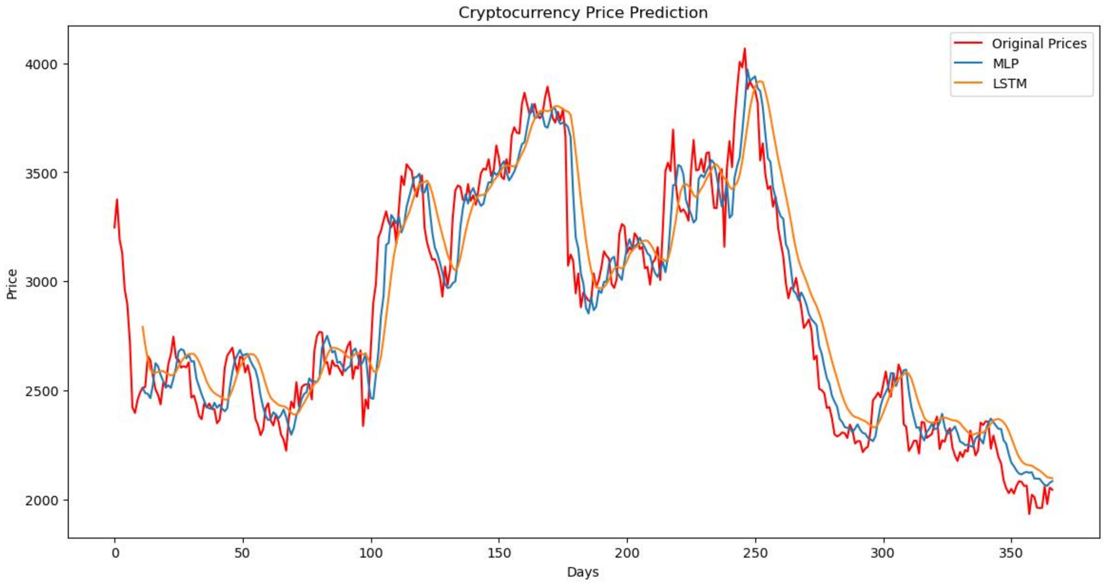

Fig2: Ethereum price prediction

6 Conclusion and Future Works

In this project, we developed and compared two machine learning models, MLP and LSTM, to predict cryptocurrency prices based on historical data. The work involved preprocessing time-series data, creating feature-label pairs, and implementing neural network architectures suited for different types of data dependencies. The LSTM model, designed for sequential data, outperformed the simpler MLP model, highlighting its ability to capture temporal relationships in the dataset. Visualization of predictions further demonstrated the effectiveness of the LSTM in following the trends of the actual prices, while the MLP model, though efficient, exhibited limitations in accuracy for this task.

One of the main challenges was managing the computational demands of training the LSTM model and fine-tuning hyperparameters to achieve optimal performance. Additionally, ensuring data quality and normalization were critical for the models' success. Looking ahead, future work can explore incorporating additional features like trading volume or market sentiment to improve predictions. Furthermore, implementing attention mechanisms or experimenting with hybrid models could enhance the accuracy and robustness of price forecasting in dynamic markets.

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