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The Application of Dynamic Time Warping on Ethereum Price Prediction

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ABSTRACT

This research finds the application of Dynamic Time Warping (DTW) with a Long Short-Term Memory (LSTM) to create a hybrid model for predicting Ethereum (ETH) prices. Cryptocurrencies in general are considered as highly volatile assets, ETH being no exception, which presents challenges and opportunities for investors. Machine Learning models have shown promise in time-series and stock price prediction; however, integrating an algorithm like DTW can enhance the accuracy of the model by finding historical sequences that closely represents the current pattern. The study utilizes daily price data of Ethereum from July 2023 to July 2024, focusing on key metrics such as open, close, high, low, and trading volume. The hybrid and LSTM baseline model were tested for 10 randomly chosen seeds and Root Mean Square Error (RMSE) was used to evaluate performance. The hybrid model better predicted the true ETH price by 23.4% as compared to the baseline LSTM model and statistical evidence further confirms the significance of these results. These findings suggest that the hybrid model provides an approach for Ethereum price prediction, offering new insights for people looking to invest in cryptocurrencies.

Introduction

Ethereum

Following the global financial crisis in 2008, "Satoshi Nakamoto" created Bitcoin as a medium of exchange in response to the crisis (Keogh, n.d.). Ever since, cryptocurrency has increased in popularity and social acceptance. Initially cryptocurrency was made as an alternative to cash but has developed into an alternative investment reaching a market capitalization of USD 528 Billion (Nakamoto, 2008). Since the initial launch of Bitcoin, more than 1600 coins have come into the market (Keogh, n.d.). The focus of this research paper will be on the Ethereum blockchain, the second largest cryptocurrency behind Bitcoin.

Ethereum is different from Bitcoin when it comes to the decentralized finance infrastructure that is built on top of the Ethereum blockchain. This technology often leads to a permissionless protocol stack that can be used for smart contracts (Schär, n.d.). A smart contract is an agreement between the buyer and the seller that will be automatically executed when the terms of agreement are met meaning that there is little to no third-party interference. This allows developers to create decentralized applications and smart contracts quickly, safely, and independently from another party (Rasure, 2024).

Since ETH launched in July of 2015, more than 273 million people have flocked to Ethereum. Investors were attracted to the blockchain's volatility and were interested in getting rich quickly (*Ethereum Cumulative Unique Addresses Daily Insights: Ethereum Statistics*, n.d.). Indeed, ETH was at a low of $122.17 in November of 2019 and then climbed to a peak of $4,644.43 in January of 2023 before falling again to $2,983 in July of 2024. ETH's volatility offers benefits to those looking to profit quickly as well as risks with the possibility of losing money just as quickly. To account for this volatility, it is imperative that we advance our price predicting models using existing machine learning methods with the addition of time-series analysis. Machine learning models are already incredibly powerful in price prediction, however, using time series analysis increases the accuracy and precision of the model decreasing stigma around investing in cryptocurrency (Rasure, 2024; Velasquez, 2023).

Machine Learning Models

When it comes to formulating models for price prediction, there are many options. From the simplest linear regression models to the most complex and intricate machine learning models. Vijh et al. indicated that Autoregressive Integrated Moving Average (ARIMA) and some techniques based on neural networks such as Artificial Neural Network (ANN) or Recurrent Neural Network (RNN) have shown promising results. Similar results were seen with deep neural networks like Long Short-Term Memory (LSTM) (Vijh et al., 2020). Indeed, previous research for ETH price prediction uses RNN and LSTM to predict prices which revealed promising results for price prediction (S. et al., 2023). For this research, a LSTM model will be used. There are many different approaches that researchers have utilized in price prediction, but a comparative analysis done by Mishra et al. concluded an LSTM model outperformed random forest models in predictive analytics especially with time series data (Mishra et al., n.d; Velasquez, 2023).

Dynamic Time Warping

Dynamic Time Warping (DTW) is an algorithm created to measure the similarity between two temporal sequences that may vary in speed, length, or time. DTW is unique in its ability to align two sequences that are not of equal length making it particularly useful for time-series data. The algorithm aligns two non-linear sequences in a way that minimizes the distance between them, allowing for a more flexible comparison of patterns between the two ("Dynamic Time Warping," 2007). DTW was initially developed for speech recognition but has found applications in bioinformatics, gesture recognition, and finance, among others. By identifying the optimal match between sequences, DTW can uncover underlying patterns that might be obscured by time shifts or distortions, providing a useful tool for analyzing complex time-series data in finance and price prediction (Yadav et al., 2018). Indeed, research conducted by Grzejszczak et al. applied DTW to the Warsaw Stock Exchange by linking two related stock prices in hopes that one would predict the other. Using two statistical methods, the researchers found the results to be significant (Grzejszczak et al. 2022). More specifically, Šťastný et al. investigated the application of DTW in cryptocurrencies and employed a method that involved matching two highly correlated cryptocurrencies so that one would predict the other (Šťastný et al., 2022). DTW is slowly increasing its impact in finance and this research paper hopes to increase it even further.

Combining DTW with a LSTM network creates a hybrid model that leverages the strengths of both approaches for time-series prediction. LSTM networks are powerful for modeling sequential data for their ability to handle long-term dependencies and handle short term volatility. By integrating DTW's ability to identify similar historical patterns with LSTM's predictive capabilities, the hybrid model can enhance forecasting accuracy. DTW is used to find historical sequences that closely match the current data, providing adaptive inputs to the LSTM model. The hybrid model can increase understanding of the dynamics of the cryptocurrency, leading to more accurate prediction in intricate time-series datasets. This research explores the effectiveness of the DTW-LSTM hybrid model in predicting Ethereum prices, demonstrating its potential to outperform traditional methods and pure LSTM models.

Methods

Data Collection and Preprocessing

The dataset used in this research was obtained from Yahoo Finance, and it contains daily price data from July 2023 to July 2024 since the most recent prices are more likely to predict future prices. The dataset includes key metrics such as open, close, high, low and trading volume, providing an insight into market dynamics. Here is a sample of the dataset used:

ETH-USD

Date	Open	High	Low	Close	Adj Close	Volume
2023-07-02	1924.448120	1958.160767	1895.906982	1937.438354	1937.438354	6343966490
2023-07-03	1937.883789	1974.775024	1934.688843	1955.389160	1955.389160	7858509087
2023-07-04	1955.524170	1966.365356	1932.611328	1936.633545	1936.633545	5683423776
2023-07-05	1936.796753	1942.432495	1897.124756	1910.588013	1910.588013	6034088075
2023-07-06	1910.417114	1956.012329	1847.850708	1848.636475	1848.636475	8905008384
2023-07-07	1847.512573	1876.963257	1832.025391	1870.602539	1870.602539	6468885150
2023-07-08	1871.002075	1872.501587	1844.641724	1865.539551	1865.539551	4299007854
2023-07-09	1865.594971	1878.668945	1857.748291	1863.009766	1863.009766	4392863807
2023-07-10	1863.240234	1905.460815	1848.777222	1880.556396	1880.556396	6336468234

Figure 1. Ethereum dataset from Yahoo Finance used in the research.

The data was preprocessed and cleansed by removing null values, ensuring data integrity. Necessary adjustments were made to ensure historical prices reflected market conditions.

Feature Engineering

Both raw and derived points were used to be imputed into the model. Among these were the daily closing prices for their predictive power in ETH forecasting and the 5-day and 10-day moving averages (MA-5 and MA-10). These moving averages help smooth out price data to better capture underlying trends removing the day-to-day volatility of price fluctuations, providing more stable input features for the model.

Baseline LSTM Model

The LSTM model was used because it can learn order dependence in sequence prediction problems. The baseline model was initially developed to predict the next day closing price of ETH based on past prices and calculated features like moving averages. The network architecture included two LSTM layers, each with 50 units, to effectively capture both long-term dependencies and short-term trends in the data. To reduce overfitting, dropout layers were created following each LSTM layer. The network culminated in a fully connected dense layer followed by a linear output layer designed to predict the next day's closing price. Training was conducted using the Adam optimizer and mean squared error (MSE) as the loss function, over 50 epochs with a batch size of 32 to optimize learning while maintaining computational efficiency. This baseline LSTM model provided a foundation for assessing the improvements introduced by integrating DTW.

DTW-LSTM Hybrid Model

The hybrid DTW-LSTM model includes the strengths of Dynamic Time Warping with the predictive power of the LSTM model. The DTW algorithm was able to find historical sequences that matched current price patterns of

Ethereum. DTW was able to provide the relevant data points that were used as the additional features for the LSTM model, providing the model with a more accurate representation of past market conditions. The hybrid model was developed like the baseline model, consisting of two LSTM layers with 50 units each, followed by dropout layers to prevent overfitting, and a dense output layer. This combination leveraged the pattern recognition capabilities of DTW and the temporal learning strengths of LSTM, enhancing the overall predictive accuracy. Training and evaluation processes were consistent with the baseline LSTM model, ensuring comparability of results.

Model Evaluation and Validation

The dataset was split into an 80% training set and a 20% testing set to evaluate the model's performance. To increase the model's accuracy, k-fold cross-validation was used within the training phase, allowing the model's performance to be assessed across different subsets of data. The metric for evaluating the effectiveness of the models was the Root Mean Square Error (RMSE), which provides a measure of prediction accuracy by quantifying the average distance between the predicted price and actual price. The formula is below where N is the number of data points, y_i is the actual measurement, and $\hat{y}_i$ is the predicted value.

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{N}}$$

Computational Details

The computational work was carried out using Python 3.8 and python libraries are used: NumPy is used for numerical operations and handling arrays, Pandas manages and manipulates the dataset, Matplotlib is used for data visualization, Scikit-learn was used for data preprocessing and quantifying model performance, TensorFlow and its Keras API are used to construct and train the LSTM model, FastDTW is implemented to use the Dynamic Time Warping algorithm, SciPy's euclidean function is used as a distance metric in this process, and the random library is employed to set seeds for reproducibility of the results. The hardware included an Apple M1 processor which helped in handling the extensive computations. Gitlab was used to publish the code online (Parasrampuria, 2024).

Results

The first model created was a baseline LSTM and DTW model to compare results to. To decrease the likelihood of sampling variability, we choose 10 seeds at random. The table below represents all 10 seeds chosen, along with their individual RMSE values.

Table 1. The seed values used and the RMSE values for both the DTW-LSTM hybrid model and the LSTM Model.

Seeds	RMSE for DTW-LSTM Model in Dollars	RMSE for LSTM Model in Dollars
42	233.4496	367.7576
4231	224.5697	272.6719
3220	262.5823	341.7498
7250	225.6614	279.5361

6401	233.3965	338.7771
3511	236.6863	344.1119
5590	258.2924	416.8193
22	283.0655	333.2917
8024	263.2372	244.4276
2055	303.5304	356.5432

The average RMSE for the DTW-LSTM model is approximately 252.45 while the average for the LSTM model is slightly higher at 329.57. The hybrid model is 23.4% better than the baseline LSTM model using the percentage improvement formula. To determine the significance of these results, a bar graph is constructed below with Standard Error of the Mean (SEM) bars using the for significance. SEM uses a formula to give us a margin of error that we believe the true RMSE value will fall under. By constructing a graph with 2x SEM, we are 95% confident that for both the graphs, the true RMSE values will fall in that margin of error. SEM can be calculated with the following formula where σ is the standard deviation and n is the sample size.

$$SEM = \frac{\sigma}{\sqrt{n}}$$

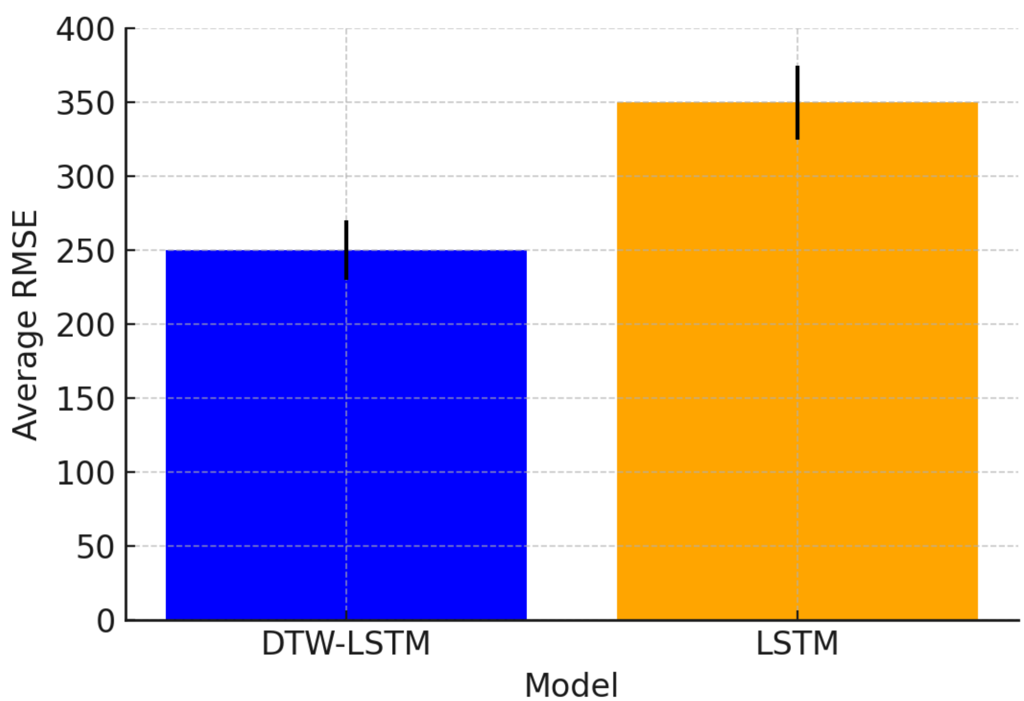

Figure 2. The bar graph represents the average RMSE values for both models with 2x SEM.

The SEM for the DTW-LSTM model was $8.34 which is lower than the value for the LSTM model at $16.07. Looking at the bar graph, there is no overlap between the SEM bars proving that the results and the difference in RMSE values is statistically significant and likely not due to random chance alone.

Discussion

The results from this study demonstrate the potential of combining DTW with LSTM to create an accurate ETH price prediction model. The hybrid model consistently outperformed the already dominant LSTM baseline model across multiple random seed initializations, as evidenced by the lower average RMSE values.

Comparison of DTW-LSTM and LSTM Models

The average RMSE for the DTW-LSTM model was approximately 252.45, while the LSTM model's average RMSE was higher at 329.57. This indicates that the DTW-LSTM hybrid model is approximately 23.4% more accurate than the standalone LSTM model. The results suggest that the DTW algorithm effectively identifies and aligns historical sequences that closely match current price patterns, providing the LSTM network with better input data enhancing the hybrids model predictive accuracy.

Statistical Significance

The Standard Error of the Mean (SEM) for the DTW-LSTM model was 8.34, compared to 16.07 for the LSTM model. The bar graph with 2x SEM bars showed no overlap, implying that we have 95% confidence that the hybrid model is better than the baseline LSTM model and the results are not due to random chance. This statistical evidence strengthens the credibility of the findings that the hybrid model is indeed a better predictor for ETH price than the baseline LSTM model.

Conclusion

The study highlights the advantages of a hybrid model of Dynamic Time Warping and Long Short-Term Memory in predicting Ethereum prices, showcasing the potential to outperform baseline LSTM models. Indeed, the hybrid model had an average RMSE value of 252.45 which is lower than the average RMSE for the baseline LSTM model of 329.57 representing an improvement of 23.4% with the hybrid model. Furthermore, statistical analysis and Standard Error of Mean shows that there is an improvement at the 95% confidence level and that the results are likely not due to random chance. This capability makes the DTW-LSTM model a useful tool in price prediction for cryptocurrencies, potentially increasing profits for investors and traders.

The DTW-LSTM hybrid model provides a foundation for analyzing time-series data and could lead to further research of hybrid models and their potential applications across investments in stocks or digital assets. As the financial industry continues to grow, developing models like DTW and LSTM will be crucial for predicting market dynamics.

Implications for Financial Forecasting

The DTW-LSTM model has a significant impact in price prediction, especially in the volatile cryptocurrency market. This hybrid model is able to make more accurate decisions, offering traders and investors a valuable tool for price prediction. The integration of DTW helps in capturing subtle temporal dynamics that might be overlooked by conventional LSTM models.

Challenges and Limitations

Despite the results of the DTW-LSTM hybrid model, it is not without challenges. The computation complexity of DTW will only get worse with larger datasets, limiting the model's ability to scale. Furthermore, the model's performance is contingent on the quality and quantity of the historical data available and inaccurate or insufficient data can hurt the model's accuracy.

Future Work

Future research would enhance the DTW-LSTM model to make it more accurate and practical. A new approach to the DTW algorithm could help reduce computational complexity, making the model more efficient. The model will become better with additional technical indicators and market sentiment data to enrich the input features. Furthermore, the hybrid model has the ability to be applied across other cryptocurrency and stocks because of its generalizability and robustness. The DTW algorithm can also be tested on other neural network architectures such as Transformers or Convolutional Neural Networks (CNNs), to further improve the accuracy. These further steps in research will help to solidify the role of DTW in finance applications.

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