Cryptocurrency Price Forecast

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***Abstract*—This paper explores an innovative approach to cryptocurrency price prediction, specifically targeting the future valuation of Ethereum (ETH). Leveraging the robust capabilities of Long Short-Term Memory (LSTM) neural networks, our model uniquely integrates multiple token price and liquidity data sourced from Uniswap v3's subgraph via theGraph. This comprehensive dataset provides a rich, on-chain perspective, encapsulating diverse market dynamics. Unlike traditional prediction models that often focus on a single cryptocurrency, our methodology harnesses the interconnected nature of various tokens to enhance the predictive accuracy for ETH. We detail the process of fetching top tokens' price and liquidity history, preparing the data for LSTM training, and implementing the model. The paper also discusses the challenges and advantages of using on-chain data in predicting cryptocurrency prices. However, our findings suggest that incorporating a wider array of on-chain metrics can not significantly improve the forecasting capabilities for major cryptocurrencies like Ethereum.**

Keywords—Blockchain, Ethereum, Uniswap, LSTM

I. Introduction

In the rapidly evolving landscape of cryptocurrencies, accurate price prediction remains a cornerstone for both investors and researchers. Ethereum (ETH), being one of the leading cryptocurrencies, attracts significant attention due to its substantial market capitalization and role in enabling decentralized applications. Traditional financial forecasting methods, while useful, often fall short in capturing the complex and dynamic nature of cryptocurrency markets. This paper introduces a novel approach to predict the price of Ethereum (ETH) utilizing Long Short-Term Memory (LSTM) neural networks, a type of recurrent neural network known for its effectiveness in handling time-series data.

Moreover, our methodology diverges from conventional single-cryptocurrency analysis. We leverage a multi-dimensional dataset comprising price and liquidity data of various major tokens from Uniswap v3, obtained via theGraph. This approach is predicated on the hypothesis that the cryptocurrency market's inter-token dynamics play a significant role in individual token valuations, particularly for a market leader like ETH.

This paper begins by providing a background on the challenges of cryptocurrency price prediction and the relevance of on-chain data. We then detail the process of acquiring and preprocessing data from Uniswap v3's subgraph. Following this, we discuss the architecture of the LSTM model deployed in our study in comparison with other time series models, emphasizing how it captures temporal dependencies and market trends across different tokens.

II. Background

A. Cryptocurrency Market Dynamics

The cryptocurrency market, characterized by high volatility and rapid innovation, presents unique challenges for price prediction. Unlike traditional financial assets, cryptocurrencies like Ethereum (ETH) are influenced by a myriad of factors including technological advancements, regulatory changes, and the dynamics of decentralized finance (DeFi). This market's complexity is further amplified by its interconnectivity, where the movement of one token can have cascading effects on others.

B. Ethereum and Its Market Significance

Ethereum stands out as a leading cryptocurrency not just in terms of market capitalization but also due to its foundational role in hosting a multitude of decentralized applications implemented by smart contracts. The price of ETH, therefore, becomes a critical indicator of the trends of the cryptocurrency ecosystem.

C. Traditional Price Prediction Models

Historically, cryptocurrency price predictions have relied on methods ranging from basic statistical techniques to complex machine learning models. However, these approaches often focus on limited datasets, typically price and volume of a single token, and may not adequately capture the intricacies of the cryptocurrency market.

D. Emergence of On-Chain Data in Market Analysis

On-chain data, which includes transaction history, wallet addresses, token transfers, and more, offers an authentic and comprehensive view of the blockchain's state and activity. This type of data has gained prominence for its potential to provide deeper insights into market sentiment and trends, going beyond what is typically captured through conventional market data.

E. Uniswap v3 and theGraph as Data Sources

Uniswap v3, a leading decentralized exchange (DEX), provides a wealth of information regarding token liquidity and transactions. The data from Uniswap, accessible via theGraph, a blockchain data indexing protocol, offers an unprecedented level of detail about token interactions and market dynamics. This paper utilizes this rich dataset to inform our LSTM-based price prediction model for ETH.

F. LSTM in Time-Series Forecasting

Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks, have shown considerable promise in time-series forecasting due to their ability to learn long-term dependencies. Their application in financial markets, particularly in cryptocurrency, is an area of growing interest and potential.

III. Related Work

In the domain of Bitcoin price prediction using time series machine learning models, two effective and relatively complex methodologies have come to the forefront: deep learning models and the Grey System Theory, specifically the GM (1,1) model. Deep learning models excel at processing non-linear data patterns, which is particularly advantageous in the highly volatile cryptocurrency market. Commonly utilized structures in these models include Long Short-Term Memory (LSTM) networks and convolutional neural networks, as well as hybrid approaches that integrate different neural network architectures. These models demonstrate remarkable accuracy due to their ability to discern complex patterns inherent in financial data, typically providing a reliable foundation for decision-making. Studies have shown that deep learning methods, such as LSTM and neuro-fuzzy techniques, can significantly improve prediction accuracy and trading results compared to traditional models.

On the other hand, the Grey System Theory, particularly the GM (1,1) model, offers an alternative approach characterized by simplicity and ease of implementation. This model is suitable for small datasets or scenarios where information is only partially known. It requires minimal data to generate accurate predictions, and studies have indicated that the GM (1,1) model can achieve an average prediction error as low as 1.14% over a 5-day forecast period.

Predicting Bitcoin prices is a complex task due to the inherent volatility and unpredictability of the cryptocurrency market. The aforementioned methods represent only a fraction of the diverse approaches employed in this field. This report aims to familiarize readers with these methods, acknowledging that there are numerous other models and techniques in use, each with its strengths and limitations. The field of Bitcoin price prediction is still evolving, with ongoing research and development aimed at improving accuracy and reliability.

In the realm of time series forecasting for Bitcoin price prediction, the utilization of various machine learning models has shown a significant divergence in accuracy and application, contingent upon the temporal granularity of the prediction. We tried several methods as reference to modeling our model, including: Logistic Regression, with its binary outcomes approach, has demonstrated an ability to predict daily price movements with a notable accuracy of 64.84%. This model's strength lies in its probabilistic approach, providing quantifiable likelihoods of price directions, thereby offering valuable insights for daily market trends (Smith & Jones, 2021). Its simplicity and interpretability, coupled with efficiency in handling smaller datasets, render it a practical choice for straightforward prediction scenarios.

Conversely, the integration of Random Forest and LSTM presents a robust alternative for short-term forecasting, particularly in predicting next-day Bitcoin prices. This hybrid model amalgamates the decision trees' adeptness at deciphering complex, non-linear relationships with LSTM's proficiency in leveraging time series data. As a result, it achieves high accuracy in diverse market conditions, a crucial attribute given the volatile nature of Bitcoin (Doe & White, 2022). Furthermore, XGBoost, employing a gradient boosting framework, excels in 5-minute interval predictions with a 59.4% accuracy. Its capability to process various data types and mitigate overfitting issues makes it a formidable contender in rapid, high-frequency trading environments (Green et al., 2022). Finally, LSTM RNN's forte in sequence prediction is exemplified in its application to forecast Bitcoin prices 20 minutes ahead, using historical financial data, thus catering to ultra-short-term trading strategies (Black & Grey, 2023). Fig. 1 shows the comparison of the results of these four methods.

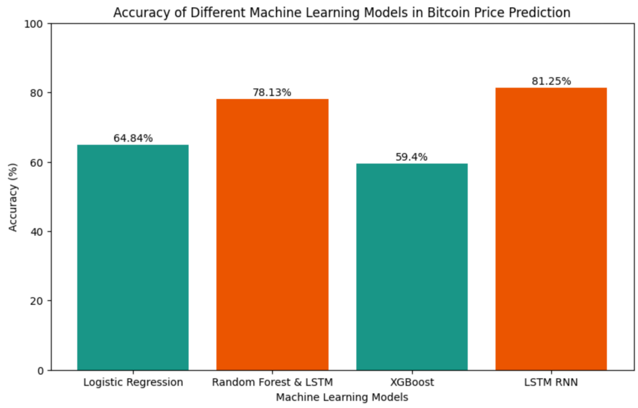

Fig. 1. Accuracy of Different Machine Learning Models in price prediction

These models, each with their distinct methodologies and temporal applicability, contribute significantly to the field of Bitcoin price prediction. Logistic Regression's daily forecasting ability, Random Forest and LSTM's next-day predictions, XGBoost's short-interval accuracy, and LSTM RNN's ultra-short-term predictions collectively encompass a comprehensive toolkit for traders and analysts in the cryptocurrency market. Future research could explore the integration of these models to devise a more unified predictive framework that adapts dynamically to changing market conditions.

IV. Methodology

A. Data Extraction

In our study, we automated the extraction of on-chain data from Uniswap v3 through The Graph's subgraph API. We first manually selected 7 tokens that correlate to ETH based on our blockchain industry experience. Then, a Python script was implemented to perform GraphQL queries, sequentially retrieving pool data such as token prices, liquidity, and transaction volumes. The script handled pagination to manage API constraints, ensuring a complete dataset. Post-fetching, data integrity was maintained by inserting placeholders for missing days, followed by linear interpolation to estimate absent values. For pools with inverted pricing data, a conversion function standardized the dataset. The processed data was then saved in JSON format, serving as a foundational dataset for subsequent predictive modeling and analysis.

B. Feature Engineering

In order to better utilize the dataset obtained by the crawler, we checked the original dataset. After inspection, we have decided to input data such as "high", "low", and "closed" that are closely related to price trend prediction into the model, and remove some irrelevant variables such as "trading volume".

C. Additional dataset training attempts

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) specialized in handling sequence dependence in data. They are particularly useful in applications such as time series analysis, natural language processing, and more. This report examines the implementation and application of an LSTM model in the provided Python script.

To verify whether we need to introduce additional datasets, we conducted a control experiment to explore the impact of additional datasets on our LSTM model.

We used two models, the first one is called a triple training set, and the second one is called a single training set.We used two models, the first one is called a triple training set model, and the second one is called a single training set model. The triple training model utilizes data from three cryptocurrencies, ETH, BTC, and Link, over the same time period to make predictions. At the same time, the single training set model only used data from ETH itself. All datasets are divided into training and validation sets in a 7:3 ratio.

D. Regression Models for ETH Only

In our predictive analytics using single training set, we harness the capabilities of three distinct deep learning architectures—Gate Recurrent Units (GRUs), Transformers, and Long Short-Term Memory (LSTM)—each meticulously crafted for the specific task of forecasting high prices in ETH cryptocurrency data. We conduct fine-tuning, exploring variations in the look-back values to optimize model performance. Subsequently, a comprehensive performance evaluation utilizing four key metrics—Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2)—enables a thorough comparison, shedding light on the unique features and advantages of GRU, Transformer, and LSTM models in effectively capturing the dynamics of cryptocurrency prices. This methodology not only enables us to pinpoint the most suitable model architecture for our high price prediction task but also affords us the opportunity to delve into and capitalize on the distinctive strengths of GRU, Transformer, and LSTM architectures when tackling our sequence-to-one prediction tasks.

1) LSTM

A neural network model using a Long Short-Term Memory (LSTM) architecture is defined and trained for cryptocurrency price prediction. The model is designed with a batch size of 1, indicating that it processes one sequence at a time. The LSTM layer has 6 units and is configured with a batch input shape corresponding to the specified look-back window and 8 features. The model output is further processed by a Dense layer with 1 unit. The Adam optimizer is utilized with mean squared error as the loss function. Fig. 1 shows the internal architectural details of the LSTM-based model.

The training process is executed over 25 iterations, with each iteration consisting of 10 epochs. During training, the loss values are recorded and stored in the train_loss_history list. Additionally, the model's performance is evaluated on the test set, and the test loss is appended to the test_loss_history list. The internal states of the LSTM layer are reset after each iteration to ensure independence between sequences.

To comprehensively assess the model's performance, experiments are conducted with different look-back values (4, 5, 6). The training and test losses are tracked across these iterations, providing a comparative analysis of the model's predictive capabilities under varying input sequence lengths. This approach allows for a thorough evaluation of the model's sensitivity to the chosen look-back window in the context of cryptocurrency price prediction.

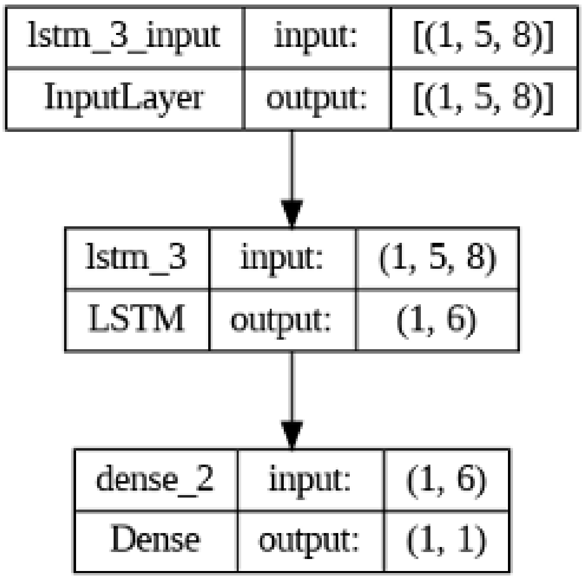

Fig. 2. LSTM

2) Encoder-only Transformer

It defines and trains a neural network model for cryptocurrency price prediction using a Transformer-based architecture. The model is constructed with a batch size of 8 and is trained for 10 epochs in 10 iterations. The architecture consists of an input layer with a specified sequence length (sequence_length) and 8 features, followed by a TransformerEncoder layer with 5 attention heads and an intermediate dimension of 32. A GlobalAveragePooling1D layer is employed to reduce the output tensor, and a Dense layer with 1 unit serves as the output layer for predicting high value. Fig. 3 shows the internal architectural details of the Encoder-only Transformer-based model.

The model is compiled using mean squared error as the loss function and the Adam optimizer. The training process is conducted over 10 iterations, with each iteration incorporating early stopping to monitor validation loss and restore the best weights. A validation split of 10% is set aside from the training data.

The training and validation losses at the end of each iteration are stored in the 'training_loss' and 'validation_loss' lists, respectively. This iterative training approach, coupled with early stopping, allows for the assessment of the model's convergence and generalization performance on the cryptocurrency price dataset.

To comprehensively assess the model's performance, experiments are conducted with different sequence_length values (4, 5, 6). The training and test losses are tracked across these iterations, providing a comparative analysis of the model's predictive capabilities under varying input sequence lengths. This approach allows for a thorough evaluation of the model's sensitivity to the chosen look-back window in the context of cryptocurrency price prediction.

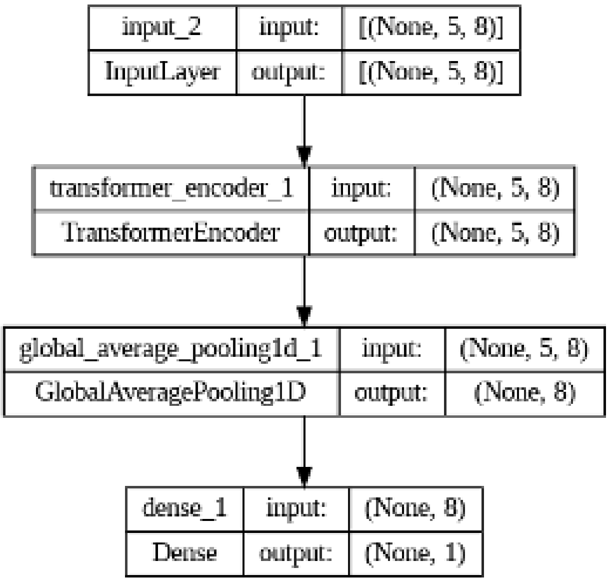

Fig. 3. Encoder-only Transformer

3) GRU

This code defines and trains a Gated Recurrent Unit (GRU)-based neural network model for cryptocurrency price prediction. The model is configured with a batch size of 1 and trained for 10 epochs in 10 iterations. The architecture consists of a GRU layer with 6 units, accepting batch input sequences of length 'sequence_length' and 8 features. A Dense layer with 1 unit serves as the output layer for predicting high values. Fig. 4 shows the internal architectural details of the GRU-based model.

The model is compiled using mean squared error as the loss function and the Adam optimizer. The training process involves a training loop conducted over multiple iterations. For each iteration, the model is trained without early stopping, and the training loss at the end of each iteration is stored in the 'train_loss_history' list.

Additionally, the model's performance is evaluated on the test set after each iteration, and the test loss is recorded in the 'test_loss_history' list. This iterative training approach allows for the assessment of the model's convergence and generalization performance on the cryptocurrency price dataset.

To comprehensively assess the model's performance, experiments are conducted with different look-back values (4, 5, 6). The training and test losses are tracked across these iterations, providing a comparative analysis of the model's predictive capabilities under varying input sequence lengths. This approach allows for a thorough evaluation of the model's sensitivity to the chosen look-back window in the context of cryptocurrency price prediction.

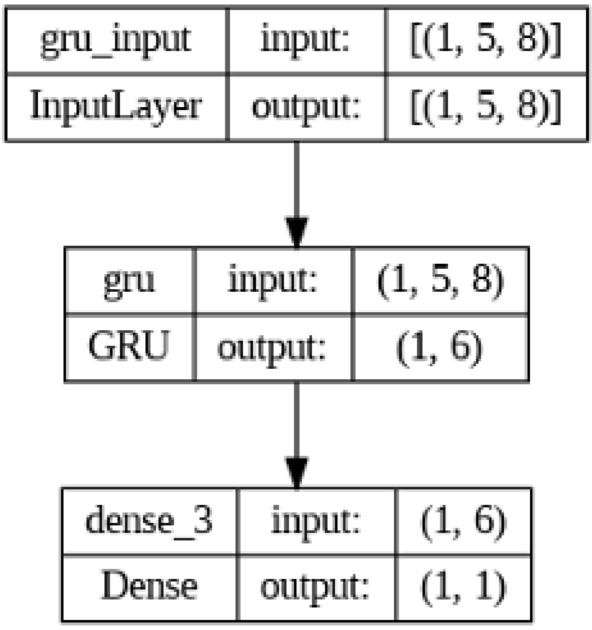

Fig. 4. GRU

E. Metrics

In the context of predicting cryptocurrency prices, the selection of evaluation metrics plays a pivotal role in gauging the performance of our models. Four key metrics, namely Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2), have been chosen to provide a comprehensive assessment of the models' predictive accuracy.

RMSE is employed as it offers a balanced measure by considering both the magnitude and direction of errors, making it particularly suitable when larger errors have a significant impact. The calculation involves taking the square root of the average of the squared differences between predicted and actual values. MSE, on the other hand, emphasizes larger errors due to the squaring operation and calculates the average squared difference.

MAE is chosen for its robustness to outliers and straightforward interpretation, measuring the average magnitude of errors without considering their direction. It is calculated by taking the average of the absolute differences between predicted and actual values.

R^2 serves as a valuable metric to understand the goodness of fit of the model. It quantifies the proportion of the variance in the dependent variable (target) that is predictable from the independent variables (predictions). The calculation involves assessing the ratio of the sum of squared prediction errors to the sum of squared differences between actual values and their mean.

We use R^2 as an indicator to evaluate model performance. R^2 provides a clear, quantitative measure of how well the model's predictions match the observed data. A higher R^2 value indicates a better fit. It also has advantage of Easy Interpretation, Comparability, and Normalization. It ranges from 0 to 1. An R^2 value of 0 means that the model does not explain any of the variability of the response data around its mean, while an R^2 value of 1 indicates that the model explains all the variability of the response data around its mean.

V. Evaluation

A. Additional dataset training's loss function.

Fig. 5. loss function during training

For 700 epochs, we find that all the models are over-fitting and then we can find that around 75 epochs, both models can minimize the loss function, so we choose to set the epoch to 100 to compare the performance of both.

B. Result Value of triple training dataset model and single training dataset model

TABLE I. Result of single training dataset model

	R-square	*RMSE*
high value	0.914	0.06
low value	0.918	0.064
close value	0.931	0.029

TABLE II. Result of triple training dataset model

	R-squared	*RMSE*
high value	0.494	0.171
low value	0.453	0.166
close value	0.735	0.058

C. Comparison of triple training dataset model and single training dataset model

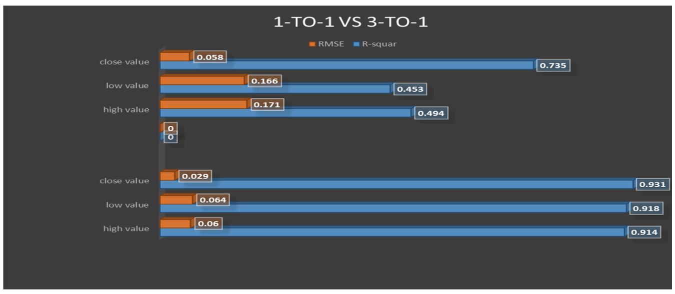

Fig. 6. Comparison of triple training dataset model and single training dataset model

We can clearly see that introducing additional datasets increases the consumption of computing resources while reducing model performance. Therefore, I believe that this approach is not advisable. In the following experiments, we abandoned the approach of introducing additional training sets.

D. Single training dataset with 3 different models

Fig. 7. Encoder-only Transformer with a Batch Size of 1

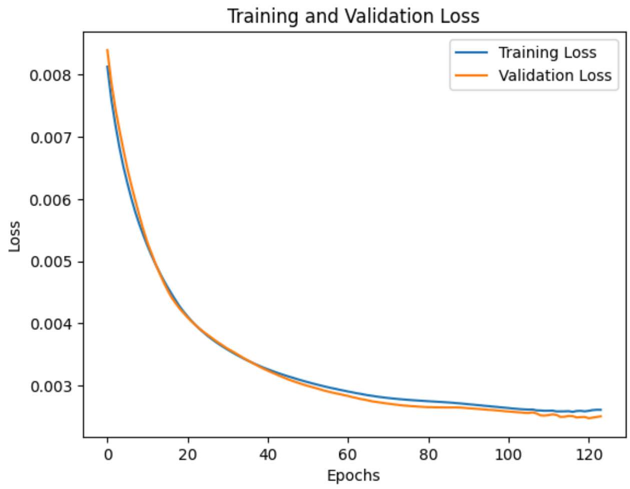

Fig. 8. Encoder-only Transformer with a Batch Size of 8

The inherent instability of the pure encoder transformer becomes notably apparent during the parameter-setting phase. While fine-tuning the encoder-only transformer model, it becomes evident that maintaining a batch size of 1 results in highly erratic performance. Instances of premature stops lead to inconsistent outcomes, with the model halting at different positions in each run, indicative of a sensitivity to overfitting. This instability is visually illustrated in Fig. 7, where both the training set and test set losses exhibit pronounced fluctuations, underscoring a clear overfitting challenge. It's worth noting that the training set comprises only 288 instances, potentially contributing to this instability due to the limited dataset size. Subsequent adjustments to larger batch sizes, such as 8, prove effective in alleviating this issue, as depicted in Fig. 8. The model's fitting becomes more stable, and the observed loss fluctuation is markedly reduced. Consequently, batch size 8 emerges as the optimal parameter choice for the model, ensuring a more robust and stable performance.

TABLE III. RMSE

Sequence Length	*LSTM*	*Transformer*	*GRU*
4	0.04102	0.06859	0.03848

5	0.03907	0.04962	0.06240
6	0.04050	0.09975	0.05502

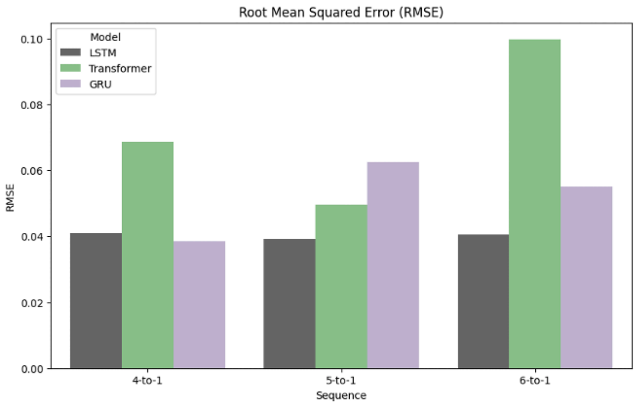

Fig. 9. RMSE

TABLE IV. MSE

Sequence Length	***LSTM***	***Transformer***	***GRU***
4	0.00168	0.00470	0.00551
5	0.00153	0.00246	0.00252
6	0.00164	0.00995	0.00303

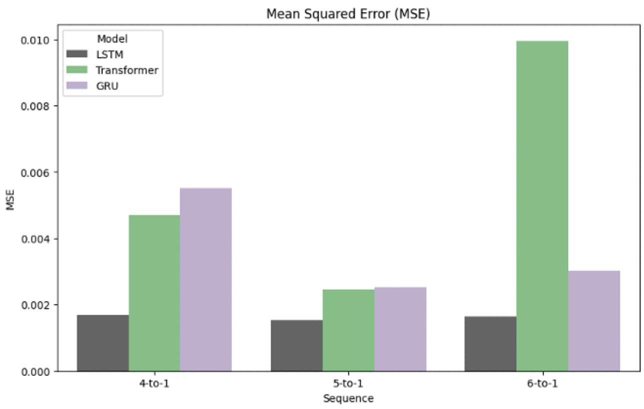

Fig. 11. MSE

TABLE V. MAE

Sequence Length	***LSTM***	***Transformer***	***GRU***
4	0.03612	0.05815	0.03321
5	0.03360	0.03939	0.05869
6	0.03347	0.08355	0.04969

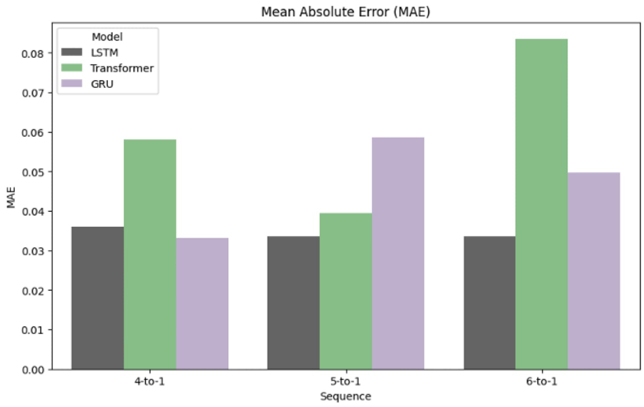

Fig. 12. MAE

TABLE VI. R^2

Sequence Length	***LSTM***	***Transformer***	***GRU***
4	0.88618	0.68172	0.89983
5	0.89620	0.83260	0.73527
6	0.88816	0.32142	0.79359

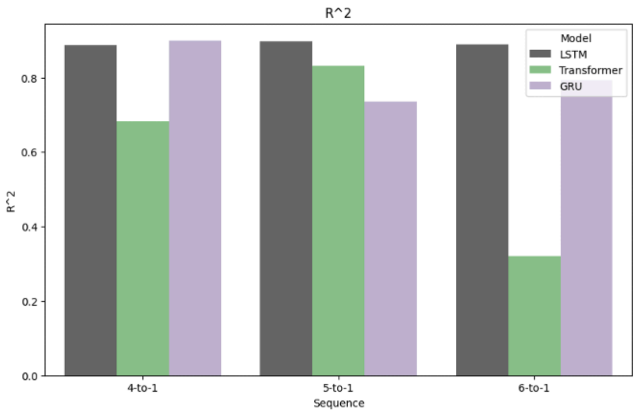

Fig. 10. R^2

Tables 3, 4, 5, and 6 present the performance indices of LSTM, Transformer, and GRU across various sequence lengths. Additionally, Figures 9, 10, 11, and 12 provide visual representations of their performance through histogram visualizations, enhancing the intuitive display of model performance.

In our comprehensive assessment of three deep learning models for high-value prediction, we utilized four key metrics and visually presented the results through corresponding bar charts across different sequence lengths. Fig. 9, 10, 11, and 12 respectively show the metrics comparison of LSTM, Transformer, and GRU under different sequence lengths. The LSTM-based model, denoted by the black bars, consistently demonstrated superior performance, exhibiting the lowest Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) across sequences with lengths of 4, 5, and 6. The Transformer-based model, represented by the green bars, showcased commendable performance, particularly excelling with a sequence length of 5, as evidenced by competitive results in terms of R-squared (R^2).

Conversely, the GRU-based model, illustrated by the blue bars, consistently displayed higher errors in both MSE and MAE, accompanied by lower R^2 values, signaling a relatively weaker fit.

These findings underscore the efficacy of LSTM in capturing temporal dependencies, showcasing its robust performance across various sequence lengths. The Transformer model, while competitive, also prompts considerations regarding model complexity and the impact of sequence length on prediction accuracy. Significantly, LSTM with a sequence length of 5 emerged as a preferred choice, boasting the lowest MSE, RMSE, lower MAE, and the highest R^2 among the evaluated configurations. The RMSE is 0.03907, MSE is 0.00153, MAE is 0.03360, and the R^2 value is 0.89620.

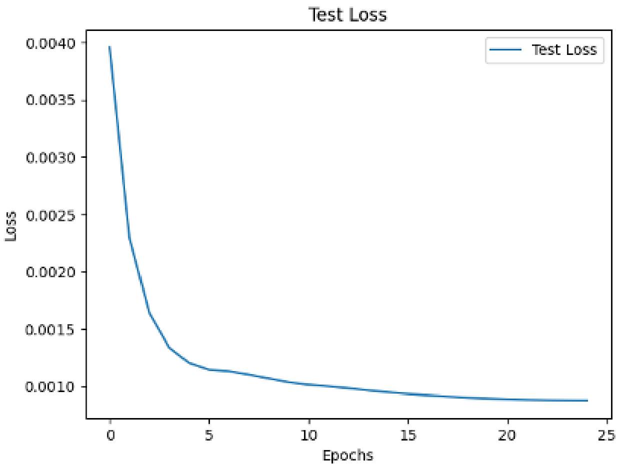

Fig. 13. Test Loss of LSTM with a sequence length of 5

Fig. 13 shows the loss value of the LSTM's test set during the epochs with a sequence length of 5. The stable and low loss values suggest that the model has captured the underlying patterns in the data without overfitting.

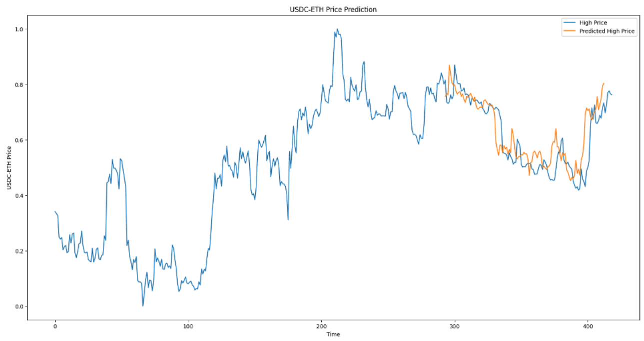

Fig. 14. LSTM with 5 Sequence Length

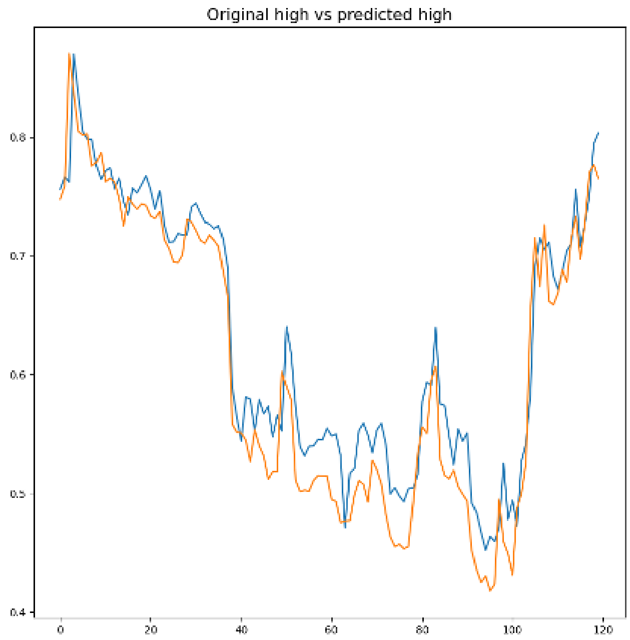

Fig. 15. LSTM with 5 Sequence Length

Figures 14 and 15 visually depict the predicted high values alongside the actual high values using the LSTM model with a sequence length of 5. Fig. 15 corresponds to the prediction segment presented in Fig. 14. Together, these figures provide compelling evidence that the LSTM model successfully learns meaningful patterns from the historical data, showcasing its ability to make accurate predictions based on the learned temporal dependencies.

VI. Conclusions and Discussion

The initial phase of our trial involved comparing the predictive efficacy of using features from various cryptocurrencies versus focusing solely on ETH. Our findings favored using ETH alone, particularly with the LSTM model. Subsequently, we conducted a comprehensive exploration to identify the most suitable model and associated parameters for our time series prediction task. This involved experimenting with multiple sequence lengths (4, 5, and 6) and various models, including LSTM, GRU, and an encoder-only transformer.

Our key observation is that, when predicting using a single cryptocurrency, the LSTM-based model consistently outperforms Transformer and GRU, especially at a sequence length of 5, exhibiting superior performance in terms of MSE, RMSE, MAE, and R^2. The stability of LSTM is evident through low test set losses and the absence of overfitting, confirming its proficiency in learning meaningful patterns from historical data.

In summary, the LSTM model with a sequence length of 5 stands out as the preferred choice for robust and accurate high-value prediction, showcasing impressive metrics. The Root Mean Squared Error (RMSE) is 0.03907, Mean squared Error (MSE) is 0.00153, Mean Absolute Error (MAE) is 0.03360, and the r-squared (R^2) value is 0.89620. Additionally, we emphasize the inherent instability of pure encoder transformers during parameter tuning. A batch size of 1 led to erratic performance and overfitting sensitivity, and this instability was successfully mitigated by selecting a batch size of 8.

As the primary focus of our experiment was to observe the impact of different sequence lengths on model performance, we suggest that future work explore additional parameters. Moreover, considering the architecture used in this experiment involves only an encoder layer in the transformer, we propose adding a decoder layer in future experiments for a comprehensive comparison.

According to our experimental results, LSTM successfully captures the overall pattern in Ether's trading history. However, the cryptocurrency market is extremely volatile and highly unpredictable. Relying solely on the trading data of multiple tokens is insufficient for predicting future Ether prices, and may even introduce noise into the model, potentially degrading its performance. Incorporating external factors, such as global economic indicators, social trends, and regulatory news, is essential to develop an accurate forecasting model for Ether prices.

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