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Application of holt's linear method for forecasting 1INCH cryptocurrency prices

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Abstract
The advancement of digital technology has driven significant innovations in the financial sector, notably the emergence of cryptocurrencies like the 1inch protocol (1INCH). Due to extreme price volatility, forecasting future values remains highly challenging yet crucial for investors. This study aims to predict the price of the 1INCH token from November 2025 to March 2026 using Holt's Linear forecasting method. A total of 58 months of historical data, spanning from January 2021 to October 2025, were obtained from Kaggle and partitioned into 70% training and 30% testing datasets. Through parameter optimization, the optimal smoothing level (α) and trend (β) were identified as 0.925 and 0.175, respectively. The evaluation yielded a training Mean Absolute Percentage Error (MAPE) of 18.33% and a testing MAPE of 19.94%, classifying the forecasting accuracy as "good". Furthermore, the narrow 1.61% generalization gap between these errors demonstrates the model's robustness against overfitting. Consequently, the forecasts indicate a continuing long-term downward trend, with prices projected to decrease from 0.2065 in November 2025 to 0.1771 by March 2026, providing a baseline quantitative reference that can complement broader market analysis.

Keywords: Crypto, 1INCH, Forecasting, Holt's Linear Method.

Abstrak
Kemajuan teknologi digital telah mendorong inovasi signifikan di sektor keuangan, terutama munculnya mata uang kripto seperti token 1INCH. Karena volatilitas harga yang ekstrem, memprediksi nilai di masa depan tetap sangat menantang namun penting bagi investor. Studi ini bertujuan untuk memprediksi harga token 1INCH dari November 2025 hingga Maret 2026 menggunakan metode peramalan linier Holt. Sebanyak 58 bulan data historis, dari Januari 2021 hingga Oktober 2025, diperoleh dari Kaggle dan dibagi menjadi 70% dataset pelatihan dan 30% dataset pengujian. Melalui optimasi parameter, tingkat penghalusan optimal (α) dan tren (β) diidentifikasi masing-masing sebesar 0,925 dan 0,175. Evaluasi menghasilkan Mean Absolute Percentage Error (MAPE) pelatihan sebesar 18,33% dan MAPE pengujian sebesar 19,94%, yang mengklasifikasikan akurasi peramalan sebagai "baik". Selain itu, selisih sebesar 1,61% antara kesalahan-kesalahan ini menunjukkan ketahanan model terhadap overfitting. Akibatnya, perkiraan tersebut menunjukkan tren penurunan jangka panjang yang berkelanjutan, dengan harga yang diproyeksikan menurun dari 0,2065 pada November 2025 menjadi 0,1771 pada Maret 2026, memberikan referensi kuantitatif yang andal untuk pengambilan keputusan investasi.

Kata kunci: Crypto, 1INCH, Peramalan, Metode Holt's Linear.

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1. Introduction

The growth of digital technology has changed the way the world perceives money and financial systems. One of the most influential innovations in this transformation is cryptocurrency, a digital form of currency built on cryptographic algorithms that ensure transaction security and transparency without relying on centralized institutions such as banks or governments (Anam & Jakaria, 2023). At the heart of this system lies blockchain technology, a distributed digital ledger that records transactions permanently across a network of users, ensuring trust and integrity through decentralization (Sari & Gelar, 2024).

Since the introduction of Bitcoin in 2009, cryptocurrencies have grown rapidly from experimental digital assets into an integral part of the global financial ecosystem. The rise of Decentralized Finance (DeFi) has further accelerated this development by enabling transparent, permissionless financial services on blockchain networks. Among the various DeFi platforms, 1INCH has emerged as a key protocol due to its ability to aggregate liquidity and optimize decentralized trading routes across multiple exchanges. Its native token, 1INCH, plays an important role in supporting governance, staking, and incentive mechanisms, making it a fundamental component of DeFi infrastructure (Onishchuk et al., 2024).

Despite its technological significance, the price of the 1INCH token is highly volatile, influenced by internal factors such as trading volume and network activity as well as external forces including regulatory developments, global economic conditions, and investor sentiment (Song, 2025). This volatility highlights the importance of employing robust forecasting techniques to better understand price dynamics in emerging DeFi assets. Previous studies have applied various forecasting approaches to major cryptocurrencies like Bitcoin and Ethereum, ranging from traditional time-series models to modern machine learning and deep learning methods (Anam & Jakaria, 2023; Jin & Li, 2023; Wang, 2025). However, research specifically focused on 1INCH price forecasting remains limited.

Given this gap, studying the price behavior of 1INCH offers meaningful insights not only for investors but also for understanding broader market patterns within decentralized trading ecosystems. The token's role in liquidity aggregation makes its price an indicator of user activity and adoption within the DeFi landscape. Reliable price forecasts can therefore support informed decision-making, risk management, and strategic planning for market participants.

In this study, we aim to forecast the monthly price of the 1INCH token for the period of November 2025 to March 2026 using Holt's Linear Method, a time-series forecasting model suitable for data that exhibit a consistent non-seasonal trend. Historical price data from January 2021 to October 2025, obtained from the Kaggle platform, form the basis of the analysis. By applying this model, the study seeks to develop a reliable and interpretable forecast that captures the underlying trend of 1INCH's market value. The findings are expected to provide practical insights for investors, researchers, and policymakers in navigating the rapidly evolving DeFi environment.

2. Literature Review

Literature on cryptocurrency forecasting has evolved rapidly over the past decade, encompassing classical time-series approaches, advanced statistical smoothing methods, and modern machine learning and deep learning techniques. This section outlines the theoretical foundations and recent developments relevant to forecasting the price of the 1INCH cryptocurrency using Holt's Linear Method.

Forecasting Time Series Data with Trend Patterns

Forecasting plays a crucial role in understanding how variables evolve over time, especially when the data exhibit clear patterns such as trends or seasonality. A *trend pattern* indicates a consistent upward or downward movement in the data over a certain period, often reflecting long-term changes in market dynamics or user behavior (Makridakis et al., 1997). In financial data, including cryptocurrency prices, trends are particularly important because they often capture investor sentiment, technological development, and macroeconomic influences.

For datasets that contain trend components, traditional forecasting methods such as moving averages or simple exponential smoothing may not be sufficient, since they assume tha data fluctuate around a stable mean. More advanced techniques, like Double Exponential Smoothing or Holt's Linear Method, were developed to address this issue by introducing a component that accounts for the changing trend over time (Makridakis et al., 1997). These methods are often preferred for short – to medium – term forcasting because they are computationally efficient and capable of adapting to continuous upward or downward patterns in the data.

Holt's Linear Method

Holt's Linear Method, sometimes called Double Exponential Smoothing, extends the basic exponential smoothing approach by adding two smoothing parameters, α (alpha) for the level and β (beta) for the trend, each ranging between 0 and 1.

The model is expressed as follows:

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1})$$
$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$$
$$F_{t+m} = L_t + b_t m$$

Here, L_t represents the smoothed level of the series, b_t the trend estimate, and F_{t+m} the forecast for m periods ahead. This approach is particularly suitable for datasets that exhibit a relatively consistent trend but no strong seasonal component.

Compared to other time series models such as ARIMA or neural networks (Mohamad Fuad & Din, 2024; Zhang et al., 2021), Holt's method is more interpretable and easier to implement while still maintaining good accuracy in linear trend scenarios. It has therefore been widely used in finance, economics, and business analytics for predicting variables like stock prices, inflation rates, and commodity values.

Error Measurement in Forecasting

The reliability of a forecasting model is typically evaluated using error metrics that measure the difference between predicted and actual values. One of the most widely used indicators is the Mean Absolute Percentage Error (MAPE), which expresses forecast accuracy as a percentage. It is defined as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right| \times 100\%.$$

MAPE is favored because it provides a clear intuitive interpretation – showing, on average, how far the forecast deviate from the actual observations in percentage terms. A smaller MAPE value indicates higher model accuracy. According to Lewis (1982), a MAPE below 10% is considered “highly accurate”, between 10 – 20% is “good”, 20 – 50% is “reasonable”, and above 50% indicates “poor” accuracy.

In studies involving financial forecasting, such as cryptocurrency price prediction, MAPE helps evaluate whether the chosen model, like Holt’s Linear Method, produces forecasts that are reliable enough for decision-making. Since cryptocurrency markets are highly volatile, maintaining a low MAPE value demonstrates that the model can adapt effectively to rapid market changes while preserving overall trend direction.

Advances in Deep Learning for Cryptocurrency Forecasting

Recent developments in cryptocurrency, forecasting have increasingly incorporated deep learning techniques due to their ability to capture nonlinear patterns and long-term dependencies in price data. Architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Recurrent Neural Networks (RNN), and Multi-Layer Perceptrons (MLP) have achieved strong performance in predicting volatile assets. Comparative studies show that GRU models often outperform other architectures in capturing sequential dependencies and adapting to sudden price changes (Pachava et al., 2025).

Hybrid deep learning approaches, such as Variational Mode Decomposition combined with LSTM (VMD–LSTM), further enhance predictive accuracy by decomposing price signals into frequency components before learning patterns (X. Huang et al., 2021). These models highlight the potential of decomposition-based and nonlinear forecasting techniques for capturing complex crypto market behavior. However, they typically require larger datasets and computational resources.

Reinforcement Learning Approaches in DeFi Markets

Beyond predictive modeling, reinforcement learning (RL) has recently been applied to optimize cryptocurrency trading strategies. Hybrid frameworks combining Gradient Boosting Regression Trees (GBRT) with RL-based agents (e.g., DQN, SAC) have demonstrated improved trading performance in highly volatile markets (R. Huang, 2025). These studies emphasize the structural volatility, fragmented liquidity, and rapid market shifts characteristic of decentralized finance (DeFi) tokens.

Although RL offers advantages for dynamic trading environments, its complexity makes it less suitable for producing interpretable medium-term forecasts. For this reason, classical smoothing methods like Holt's Linear remain valuable as foundational tools, particularly for understanding broader market trends rather than micro-level trading dynamics.

Foundational Forecasting Theory

Foundational forecasting studies by Makridakis, Wheelwright, and Hyndman (Makridakis et al., 1997) emphasize that simpler models can outperform more complex ones when the underlying data exhibit a consistent trend and limited seasonality. This principle is especially relevant to cryptocurrency time-series data aggregated at a monthly level, where long-term patterns are more discernible despite short-term volatility.

The use of Holt's Linear Method in this study aligns with this theoretical perspective by focusing on interpretability, trend preservation, and robustness against data irregularities. While advanced models such as LSTM, GRU, and RL-based strategies may offer higher accuracy in specific scenarios, trend-based smoothing models remain reliable baselines in forecasting research.

3. Research Method

Building upon the theoretical foundations discussed in the Literature Review, this study follows a structured quantitative forecasting procedure based on established time-series analysis principles described by Makridakis, Wheelwright, and Hyndman (Makridakis et al., 1997). The procedure also has been applied in recent cryptocurrency forecasting research by Liantoni & Agusti, 2020. The methodology is designed to generate reliable forecasts of the 1INCH cryptocurrency using Holt's Linear (Double Exponential Smoothing) Method, supported by MAPE as the primary accuracy measure. The research procedure can be explained by the following flowchart.

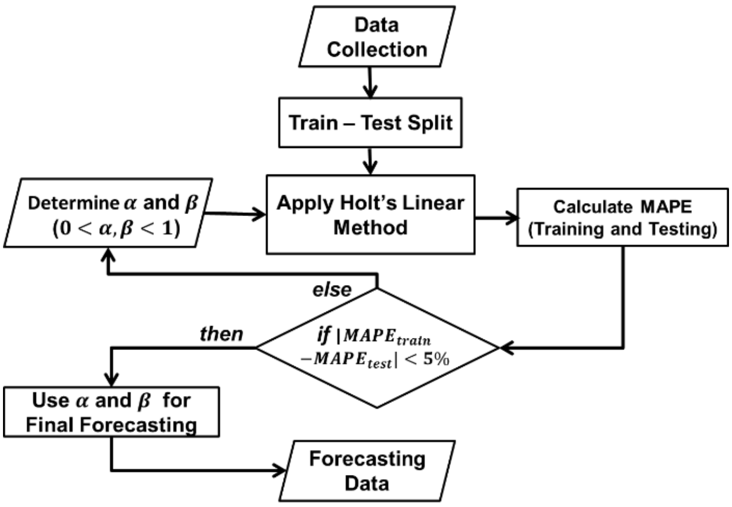

Figure 1. Flowchart of the forecasting procedure

Data Collection

The data used in this study consist of the daily closing prices of the 1INCH cryptocurrency, converted into USD. These data were obtained from the *Kaggle* platform (https://www.kaggle.com/datasets/svaningelgem/crypto-currencies-daily-prices/data) and cover the period from January 2021 to October 2025. The daily prices were then averaged to produce monthly data, which serve as the basis for the analysis. The resulting monthly dataset is presented in Table 1, which summarizes the historical price movements of the 1INCH token.

Table 1. Price of 1INCH Cryptocurrency: January 2021 – October 2025

Month	2021	2022	2023	2024	2025
January	5.0013	1.7210	0.5644	0.4325	0.3079
February	4.8557	1.3362	0.5678	0.4418	0.2619
March	4.6861	1.3334	0.5101	0.4917	0.2109
April	4.4573	1.1822	0.5007	0.4720	0.1806
May	3.1684	1.1386	0.4140	0.4005	0.2215
June	3.0437	0.7282	0.3085	0.4265	0.1932
July	2.2654	0.7677	0.3273	0.3934	0.2662
August	2.9345	0.6636	0.2758	0.2644	0.2587
September	2.9617	0.6211	0.2488	0.2657	0.2504
October	2.6665	0.5832	0.2621	0.2607	0.2109
November	2.1170	0.5490	0.3493	0.3168	
Desember	2.6597	0.5240	0.3914	0.2778	

Pattern Identification

The monthly closing price of the 1INCH cryptocurrency from January 2021 to October 2025 shows a clear trend-dominated behavior. As illustrated in Figure 2, the price begins at a relatively high level, above 4.5 USD in early 2021, and then declines sharply during the following months. Although several short-term fluctuations appear during this initial period, the overall movement remains consistently downward, reflecting a rapid loss of market value and high early volatility.

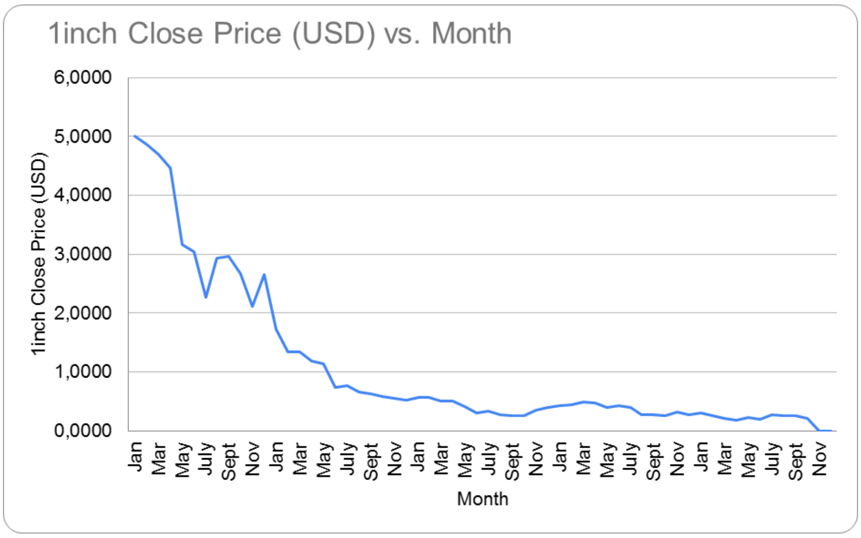

Figure 2. Plot of Monthly 1INCH Closing Price: January 2021 – October 2025

After mid-2022, the price series transitions into a more stable phase. The fluctuations become smaller, and the values remain within a narrow band close to zero, indicating that market volatility has substantially diminished. This pattern aligns with the characteristics described by Makridakis, Wheelwright, and Hyndman (Makridakis et al., 1997), who note that a trend pattern is identified when a time series demonstrates a persistent upward or downward movement over time without recurring cyclical or seasonal components. In this case, the 1INCH price series clearly displays a long-term downward trend followed by a prolonged stabilization period.

Based on these observations, the dataset is well-suited for forecasting methods designed for non-seasonal data with trend components. The absence of seasonal or cyclical behavior and the presence of a monotonic trend support the use of Holt's Linear Method, which incorporates both level and trend smoothing to capture gradual changes effectively. This trend analysis therefore provides a theoretical and empirical basis for selecting Holt's Linear Method as the forecasting approach in this study.

Data Splitting: Train and Test Sets

To ensure an objective evaluation of the forecasting model, the dataset was divided into training and testing subsets using a 70% - 30% proportion. Out of the 58 monthly observations available from January 2021 to October 2025, a total of 40 data points were allocated to the training set (January 2021 – April 2024), while the remaining 18 observations were used as the testing set (May 2024 – October 2025). This separation is intended to evaluate the model's forecasting performance through the calculation of the Mean Absolute Percentage Error (MAPE). As discussed in Section 2.3, a smaller difference between the training MAPE and testing MAPE indicates a higher level of model accuracy and better generalization. Thus, the train-test split provides a reliable basis for assessing whether the model performs consistently across both fitted and unseen data.

Smoothing Parameters Estimation

In this stage, the optimal smoothing parameters for Holt's Linear Method, the level parameter ($\boldsymbol{\alpha}$) and the trend parameter ($\boldsymbol{\beta}$), are determined through an iterative evaluation process. Multiple candidate $\boldsymbol{\alpha}$–$\boldsymbol{\beta}$ combinations are applied to the training dataset to generate fitted values and out-of-sample predictions for the testing dataset. For each parameter pair, the Mean Absolute Percentage Error (MAPE) is calculated for both training and testing data. The optimal combination is selected based on the smallest difference between the training MAPE and testing MAPE, as a smaller discrepancy indicates better model generalization and reduces the likelihood of overfitting or underfitting.

The $\boldsymbol{\alpha}$–$\boldsymbol{\beta}$ pair that yields the most consistent performance across both datasets is then chosen as the best smoothing configuration for Holt's Linear Method. These optimal parameters are subsequently used to construct the final forecasting model, which is employed to project the monthly prices of the 1INCH cryptocurrency for the period from November 2025 to March 2026. This approach ensures that the chosen model not only captures the underlying trend of the data but also maintains stable predictive accuracy when applied to unseen observations.

4. Results and Discussion

4.1. Results

Through the parameter optimization process in the Double Exponential Smoothing method, the optimal smoothing level (α) value was obtained at 0.925 and the smoothing trend (β) at 0.175. Using these optimal parameters, the model produced a training MAPE value of 18.328% and a testing MAPE of 19.938%. Referring to the (Lewis, 1982) evaluation criteria, the actual MAPE value on the test data was in the range of 10%-20%, which classifies the performance of this model into the "Good" category. Furthermore, this model shows an excellent level of robustness. This is evidenced by the very small difference (generalization gap) between the training and testing MAPE, which is only 1.61%. According to Hastie et al., (2009) and Hyndman & Athanasopoulos (2018), the consistency of error rates between the in-sample (training) and out-of-sample (testing) phases is a critical indicator that the model has high generalization ability and avoids overfitting problems.

Using the optimal smoothing parameters ($\alpha = 0.925$ and $\beta = 0.175$), the Holt's Linear model was used to forecast the price of the 1INCH cryptocurrency from November 2025 to March 2026. As shown in Table 2, the results suggest that the long-term downward trend seen in the historical data will continue. Specifically, the forecasted price starts at 0.2065 in November 2025 and decreases to 0.1991 in December. This gradual drop is expected to carry on into early 2026, with the price continuing to fall to 0.1918 in January, 0.1845 in February, and reaching 0.1771 by March. Ultimately, these projected figures provide a clearer analytical basis for anticipating the token's future price movements.

Table 2. Forecast Price of 1INCH Cryptocurrency: November 2025 – March 2026

Year	Month	Forecasting
2025	November	0.2065
	Desember	0.1991
2026	January	0.1918
	February	0.1845
	March	0.1771

4.2. Discussion

The forecasting results generated by Holt's Linear Method provide a clear picture of how the 1INCH token has behaved over time and how it is likely to move in the near future. The model successfully captures the dominant downward trend that characterized 1INCH from 2021 to 2025, followed by a period of relative stabilization. This behavior is consistent with the theory that exponential smoothing techniques are most suitable for non-seasonal series with persistent trend components, as outlined by Makridakis et al. (1998), and supports the method's applicability to DeFi assets.

The comparison between actual and fitted values in Figure 3 shows that the model closely follows the long-term trajectory of the token despite short-term noise. This reflects the typical behavior of Holt-type models, which emphasize level and trend while smoothing out volatility. Similar observations have been highlighted in prior studies using double exponential smoothing for Bitcoin and other cryptocurrencies, where trend-preserving models capture the broader market direction even when daily fluctuations are intense (Liantoni & Agusti, 2020; Prasetyo et al., 2024).

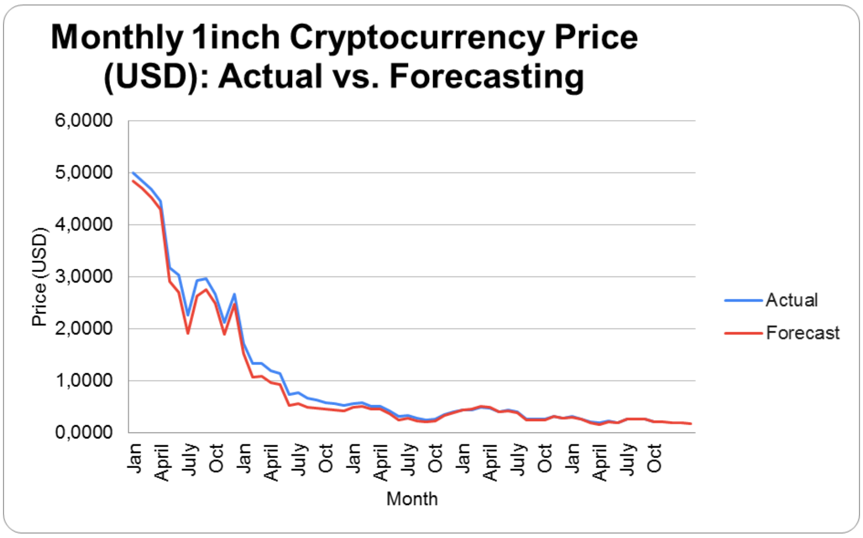

Figure 3. Monthly 1INCH Cryptocurrency Price (USD): Actual vs. Forecast

Although the model does not explicitly capture nonlinear jumps, its ability to maintain a stable structure across both training and testing datasets, evidenced by a narrow generalization gap of only 1.61% between the training and testing MAPE, demonstrates its robustness against overfitting. This suggests that, despite extreme market volatility, the 1INCH price series contains a sufficiently predictable trend component that can be effectively captured using the optimal parameters ($\alpha = 0.925$ and $\beta = 0.175$). This aligns with findings from deep learning studies showing that, while models such as GRU, LSTM, and hybrid VMD–LSTM architectures excel in capturing short-term volatility, the underlying macro-trend of many cryptocurrencies often remains smooth when examined at a monthly resolution (Pachava et al., 2025; X. Huang et al., 2021). In this sense, Holt's method offers a valuable baseline against which more complex models may be compared.

From a market perspective, the projected continuation of a slight downward trend into early 2026 may reflect several structural conditions in decentralized finance, such as declining liquidity aggregation activity, persistent risk aversion, and protocol-level changes documented in recent DeFi analytics research (Onishchuk et al., 2024). Reinforcement-learning-based studies also describe DeFi assets as prone to structural volatility and fragmented liquidity (R. Huang, 2025), reinforcing the idea that long-term price stability within this environment is challenging to achieve.

Despite these challenges, the forecast produced by Holt's Linear Method remains useful for investors and analysts. The relatively smooth predicted trajectory helps outline reasonable expectations of value under normal market conditions, serving as a practical foundation for risk assessment, portfolio adjustments, and strategic planning. While sudden market shocks cannot be captured by this approach, the strong generalization performance and visually coherent fit confirm that Holt's method remains a dependable analytical tool for interpreting long-term price dynamics in the DeFi ecosystem.

5. Conclusion

In this study, the Double Exponential Smoothing method (Holt's Method) was applied to forecast the price of the 1INCH cryptocurrency. Through an optimization process, the best parameters were obtained a smoothing level (α) of 0.925 and a smoothing trend (β) of 0.175. A very high α value (close to 1) indicates that the model places a significant weight on recent price observations. This strongly reflects the extreme volatility of the 1INCH cryptocurrency, where distant past price movements (such as those in 2021) have increasingly less relevance to current price formation. Based on these parameters, the model produced a Mean Absolute Percentage Error (MAPE) of 18.328% on the training data and 19.938% on the testing data. Referring to the forecasting accuracy evaluation criteria established by Lewis (1982), the testing MAPE value of 19.938% falls within the 10% to 20% range, indicating that the performance of this forecasting model is classified as "Good." Furthermore, the very small difference between the training and testing MAPE, at only 1.61%, demonstrates the high robustness of the model. This indicates that the model does not overfit to past data and is capable of effectively generalizing trends when presented with test data (future data not included in the training).

The resulting forecasts show a continued decline in the price of the 1INCH token, reinforcing the downward trend observed in historical values. This pattern may reflect broader structural conditions in the DeFi ecosystem, including shifts in trading volume, reduced liquidity aggregation activity, or changes in investor sentiment, factors that previous studies have also associated with declining cryptocurrency valuations (Kristiawan et al., 2025; Onishchuk et al., 2024). While exponential smoothing models cannot account for sudden market shocks, the model's performance suggests that, in the absence of major external catalysts, the price of 1INCH is likely to remain under downward pressure in the short term. These insights can support investors, analysts, and policymakers in making more informed decisions, improving risk management strategies, and gaining a clearer understanding of market trends within decentralized finance ecosystems.

However, it is important to acknowledge the limitations of this study. The Holt's Linear method is a univariate forecasting model that relies exclusively on historical price data to project future trends. Consequently, it does not incorporate external variables that inherently drive the highly volatile cryptocurrency market, such as macroeconomic indicators, trading volumes, regulatory shifts, or market sentiment. Therefore, while the resulting forecasts offer a valuable mathematical projection of the underlying macro-trend, they should be interpreted with appropriate caution. These findings are best utilized as a complementary analytical baseline rather than a standalone tool for definitive investment decision-making, and future studies are encouraged to integrate multivariate approaches or sentiment analysis to capture external market shocks.

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