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Price Dynamics and Financial Risk Analysis: A Neural Hierarchical Time-Series Forecasting Approach

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ABSTRACT

The highly volatile nature of cryptocurrency prices often causes conventional predictive models to fail in capturing complex nonlinear patterns. This study integrates the Neural Hierarchical Interpolation for Time Series Forecasting (N-HiTS) deep learning model with nonparametric Historical Simulation Value-at-Risk (VaR) method for price forecasting and risk analysis. Using univariate data on daily Ethereum closing prices from January 1, 2021, to January 31, 2025 (N = 1,491 observations), the out-of-sample evaluation was executed using a rolling cross-validation scheme initiated testing from a cut-off point in April 2024 through December 2024, where each evaluation window was set for the next 30 days. The research results show that the N-HiTS model can predict price dynamics with high accuracy, achieving an MAPE of 3.25%, an MAE of 107.825, an RMSE of 136.83, and directional accuracy of 48.28%. Risk analysis using historical simulation yielded a VaR of -6.23% at a 95% confidence level.

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1. INTRODUCTION

As global conditions continue to evolve, digital currencies around the world are developing rapidly. Cryptocurrency is a technology that allows transactions and purchases of digital assets without the need for a third party [1]. Driven by rapid retail expansion, Indonesia ranks third in terms of the highest level of crypto adoption worldwide [2], with annual transactions surging by 335.9% in 2024 and monthly volumes reaching Rp32.45 trillion by March 2025 under official Finance Services Authority (OJK) monitoring [3]. However, this massive market growth is heavily bottlenecked by extreme volatility and speculative retail behaviour. In 2024, a survey was conducted on 1000 respondents who had been investing for more than two years and were of different ages. The survey results revealed that 50% of investors rely solely on social media to make investment decisions [4]. This severe dependency has enabled widespread abuse of trust and market manipulation by unverified influencers, which has been legally proven to cause accumulated financial losses totaling up to Rp72 billion in prominent domestic fraud cases [5]. This situation clearly indicates that a large portion of market participants have not yet utilized objective, scientific approaches in their investment journeys. Therefore, there is a need to implement a price prediction model capable of handling the high volatility of crypto assets, so that investment decisions are not solely based on intuition but also grounded in measurable scientific analysis.

In the development of basic forecasting tools in volatile sectors, traditional deep learning architectures have been extensively explored [6]. Recurrent framework, specifically Long Short-Term Memory (LSTM) networks, were applied to historical crypto market data covering the period from early 2021 until the end of 2025 to identify sequential dependencies, yielding a Mean Absolute Error of 22.59% during the testing phase [7]. However, a critical comparative literature review indicates that traditional recurrent models struggle to adapt to conditions of extreme volatility. While historically effective at mapping long-term linear sequences, LSTM consistently fails to account for the highly dynamic, rapid, and complex structural shifts characteristic of cryptocurrency assets. Furthermore, the iterative and incremental training process of LSTM is relatively time-consuming and highly sensitive to hyperparameter tuning. Therefore, a more adaptive and efficient architectural approach is needed to address the temporal limitations of recurrent models by processing long and short-term patterns simultaneously without heavy sequential dependencies.

To solve the twin challenges of volatility and high computational complexity, recent advances in time-series forecasting have shifted toward pure neural basis expansion architectures. Introduced as a structural improvement over the baseline N-BEATS model [8], the Neural Hierarchical Interpolation for Time Series Forecasting is a model utilizing block-based hierarchical interpolation and multi-rate data sampling techniques [9]. Unlike traditional recurrent networks, N-HiTS breaks down complex temporal signals into distinct frequency components and forecasts them separately, drastically reducing computational overhead while maintaining high precision. The utility of models grounded in hierarchical interpolation has been validated by contemporary research across a diverse array of volatile applications, including precipitation index prediction [10] and flood forecasting [11], as well as in multi-horizon forecasting for hydroelectric reservoir levels [12]. Moreover, current literature reviews highlight that deep learning frameworks now represent the leading methodology for time series analysis, primarily due to their exceptional capacity for capturing intricate, non-linear temporal dynamics [13], [14]. To maximize model performance within large search spaces without incurring high computational costs, contemporary frameworks integrate automated hyperparameter optimization engines like Optuna, which utilizes efficient sampling and pruning mechanisms to achieve peak accuracy [15].

However, deterministic point forecasts generated by neural networks are inherently incomplete for actual asset management; they must be systematically paired with downstream risk quantification. Within the scope of digital asset management, Value at Risk (VaR) serves as the standard quantitative metric for evaluating portfolio exposure, calculating the maximum probable financial loss over a defined period [16], [17]. Traditional parametric risk models consistently fail in crypto markets because they falsely assume that asset returns follow a normal distribution curve. Conversely, the non-parametric historical simulation VaR method offers a definitive advantage through its complete independence from normal distribution of historical returns, directly capturing the heavy tails and volatility clustering inherent in digital asset shocks. While previous studies have successfully applied VaR across banking risk analysis [18], portfolio risk evaluation [19], and alternative methods such as Monte Carlo [20]. There is a significant lack of systems that explicitly integrate advanced deep learning forecasting directly into these downstream risk estimation frameworks [21].

The primary novelty of this study lies in the systematic integration of an Optuna-optimized N-HiTS forecasting model with a non-parametric Historical Simulation Value at Risk (VaR) framework. This study contributes to the literature by implementing the N-HiTS framework for Ethereum price estimation, merging these neural forecasts with VaR-based risk, and offering actionable quantitative insights for cryptocurrency market participants.

2. RESEARCH METHOD

This paper applies a structured sequence of deep learning developments to the N-HiTS model, specifically designed to simulate and project Ether (ETH) market values. Deep Learning is capable of exploring non-linear relationships (latent features) through activation functions and hidden layers [22]. Deep Learning processes data and generates output as solutions to complex problems [23]. This study will begin with data acquisition, data pre-processing, N-HiTS model development, followed by model training and model evaluation, to produce the best error matrix.

To ensure a rigorous evaluation and address reproducibility, the historical dataset from January 1, 2021, to January 31, 2025 (N = 1,491 observations), is evaluated using a time-series rolling cross-validation scheme. The initial model training phase utilizes the historical data from January 2021 through March 2024. Evaluation is then carried out via consecutive cross-validation windows initiated from a designated cut-off point in April 2024 through December 2024. For each monthly evaluation window is set for the next 30 days ahead.

A comprehensive visual representation of the research framework is presented in Figure 1. The flowchart presents the sequential process starting from data acquisition, followed by data preprocessing, model development using N-HiTS, model training, and evaluation. This figure aims to provide a clear overview of how the prediction and risk analysis framework is structured. The arrows indicate the workflow direction, showing how each stage is interconnected in producing the final forecasting and risk analysis results.

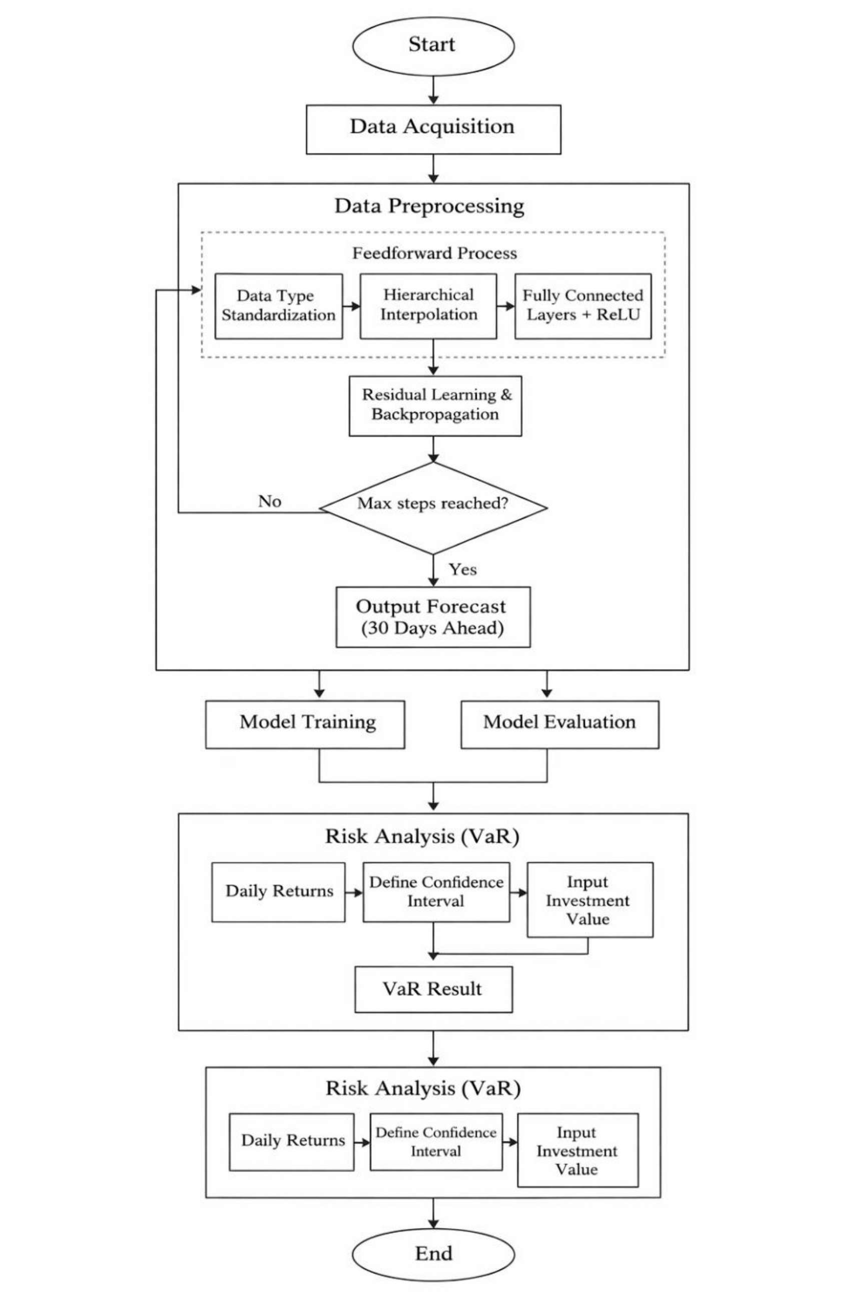

Figure 1.Research Methodology Flowchart
(Source: Developed by the Author)

This prediction period was chosen so that the model not only captures short-term daily patterns but also provides an overview of price movements within a weekly horizon. These estimation results are based on the implementation of the N-HiTS model. The source of Ethereum (ETH) price data was obtained from the yahoofinance website [24]. The yahoofinance website was chosen because of the ease of access to historical data provided, as well as the availability of a Python module called yfinance, which can facilitate the process of retrieving data automatically and efficiently.

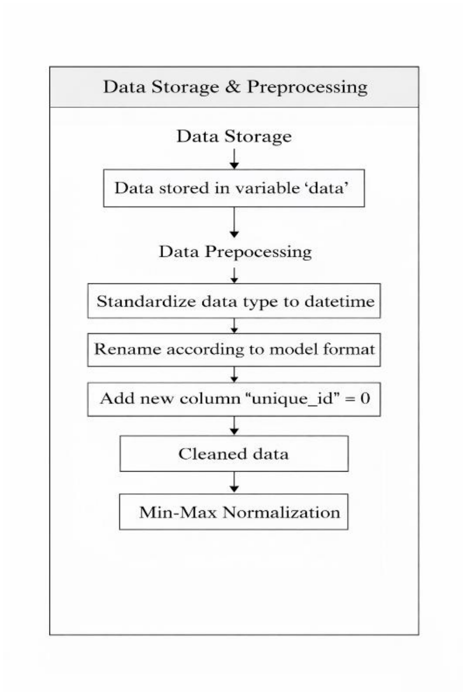

Figure 2. Data Processing Flowchart
(Source: Developed by the Author)

Figure 2 presents the data preprocessing workflow applied before the modelling stage. This figure explains how raw Ethereum price data in CSV format is transformed into a structured format suitable for the N-HiTS model. The process includes data type standardization, variable renaming, and the addition of a unique identifier (unique_id). The flowchart helps readers understand the sequence of preprocessing steps and how the data is prepared for model training.

At this stage, the raw data collected in CSV format will be processed before entering the modeling stage. There are two stages in data preprocessing, namely addressing data type standardization using a robust mechanism and adjusting the parameters that need to be included in the N-HiTS model development. Data type standardization and variable naming are carried out to ensure compliance with the variable requirements in the neuralforecast environment [25]. In addition, the unique_id attribute is also added as a special identifier for the NHiTS model implementation

Before the data was trained, a model fit and the integrity of the model's predictions were validated through a cross- validation framework. At this stage, the time-series scaling technique was used. There are two types of time series scaling available in the neuralforecast environment, namely window scaling and time series scaling. Thus, there are two approaches that will be tried in this analysis to determine the most suitable scaling type while minimizing the level of computation.

The main model used in predicting the ETH price is N-HiTS using the NBEATS comparison model. All modeling and analysis were performed in the neuralforecast environment, a Python library designed for forecasting experiments using PyTorch-based neural models. N-HiTS processes input in the form of historical ETH prices through a series of residual stacks, each consisting of several blocks in N-HiTS using two main components, namely basis expansion to build flexible data representations and hierarchical interpolation to perform predictions at high temporal resolutions in stages.

Before the time series data enters each block in the multilayer perceptron, the data is first downsampled using the MaxPool operation with a kernel size of k_l . MaxPool is a data selection technique that uses the highest representative value in each defined kernel. A high kernel size is more suitable for identifying long-term trends, while a low kernel size is intended to maintain short-term variations. Mathematically, multi-rate signal sampling is formulated as follows:

$$y_{t-L:t,l} = MaxPool\left(y_{t-L:t,l}, k_l\right) \tag{1}$$

In this formulation, l denotes the specific block index, while the initial input for $l = 1$ is represented by $yt{-}L{:}t$, with k_l serving as the designated kernel size. The use of a multi-rate signal sampling system significantly reduces memory and computation usage because the data input for each block is reduced. After multi-rate processing, each block will use non-linear regression with the aim of extracting interpolation coefficients that will drive the forecasting and backcasting outputs. The combined input$y$ (p) is processed in an MLP to produce a hidden representation hl which is then linearly projected into forward interpolation coefficients θ_l^f and backward interpolation coefficient θ_l^b.

$$h_l = MLP_l\left(y_{t-L:t,l}\right) \tag{2}$$

$$LINEAR\ (h) = \mathbf{W}h + \mathbf{b} \quad (3)$$
$$\theta_l^f = LINEAR^f\ (h_l) \quad (4)$$
$$\theta_l^b = LINEAR^b\ (h_l) \quad (5)$$

Where `$h_l$` is the hidden vector or input vector, `$MLP_l$` is the multi-rate signal sampling at block l, `$W$` is the weight matrix, `b` is the bias, `$LINEAR^f$` is the linear layer for forward regression, '$LINEAR^b$` is the linear layer for backward regression, `θ_l^f` is the forward regression parameter, and θ_l^b is the backward regression parameter. This process is capable of capturing complex temporal dynamics that cannot be explained by the use of pure linear interpolation strategies.

The final stage in the N-HiTS model process is the concept of hierarchical interpolation. Hierarchical interpolation is a process of predicting time series data that is created in stages across several different time scales [6]. Each block will output a smaller set of interpolation coefficients, and then in the final forecast, each partial forecast value of each block will be combined through an interpolation function g. The function g maps the time index and forward coefficients to the interpolated forecast values.

$$\hat{y}_{\tau,l} = g\left(\tau, \theta_l^f\right), \quad \forall\tau \in \{t+1, \dots, t+H\} \quad (6)$$
$$\hat{y}_{\tau,l} = g\left(\tau, \theta_l^b\right), \quad \forall\tau \in \{t-L, \dots, t\} \quad (7)$$
$$g\ (\tau, \theta) = \theta[t_1] + \left(\frac{\theta\ [t_2] - \theta\ [t_1]}{t_2 - t_1}\right)(\tau - t_1) \quad (8)$$

Where $\hat{y}\tau,l$ is the predicted value at time τ for block l, $g\ (\tau,\ \theta)$ is the linear regression function in the time domain, $(\tau - t1)$ is the time distance from the starting point, and $\theta[t1]$, $\theta[t2]$ is the parameter value at two points ($t1$, $t2$). Equations 6 and 7 are the outputs of the model at block l for forward prediction and backward reconstruction. These equations are calculated from the regression function$g$ (τ, θ), which is a linear interpolation defined in equation 8. The regression function works by taking two reference points in time

In N-HiTS, there is a backpropagation stage where each block will update its weight so that this model will work by taking the residual error from the previous prediction as input. In this way, the model is able to focus on learning signal components that have not been captured by the previous blocks. To enhance the framework's capacity for identifying intricate data patterns, every block incorporates non-linear ReLU activation functions alongside fully connected layers. After all blocks in the stack have made predictions, the final result is the accumulation of each block's prediction values at a specific time horizon. N-HiTS relies on the power of interpolation and residual learning to avoid overfitting results and makes N-HiTS very efficient in handling time series data.

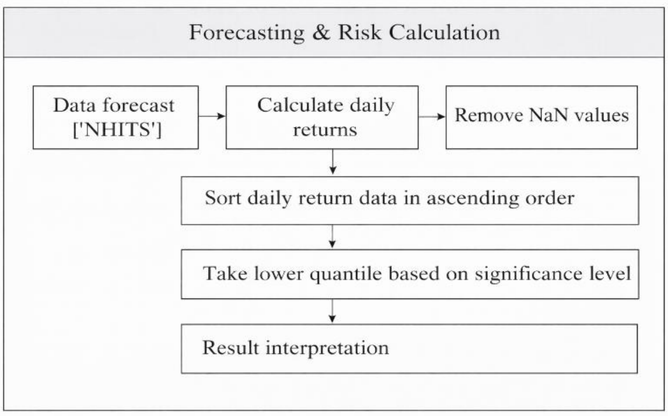

Figure 3. Risk Analyst Flowchart
(Source: Developed by the Author)

In risk analysis using the historical simulation method, there are several steps that need to be taken. The first step is to calculate the return value based on the prediction results by the N-HiTS model. Next, the empty values in the first entry are deleted. The next step is to sort the return values in ascending order. In this study, the confidence level used is 95%, which means that the quantile used is the 5th percentile or the return value that is in the lowest 5% of all data. The final stage is the interpretation of the results, which is to provide an explanation of the risk value obtained. The VaR calculation using the historical simulation method is formulated as follows [26].

$$VaR_{(1-\alpha)}(t) = W_o P_\alpha \,.\sqrt{t} \tag{9}$$

$$P_\alpha = \alpha \,.(n-1) \tag{10}$$

Where $VaR_{(1-\alpha)}(t)$ is the VaR with a confidence level $(1 - \alpha)$ for period t, W_o is the initial amount of funds invested, P_α is the quantile of return distribution in the significance level α, and n is the amount of data. The application of VaR calculation begins with the calculation of the daily return value on crypto assets. The daily return is obtained from the gaps between today's closing price and yesterday's closing price, divided by yesterday's closing price.

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{11}$$

Where rt is the return at time t, Pt is closing price on day t, and $Pt{-}1$ is closing price on day (t-1). After all daily returns are obtained, the data is sorted from the lowest to the highest

3. RESULTS AND DISCUSSION

3.1. Building the N-HiTS Model

This study implements the N-HiTS model to capture patterns and make predictions. The training process uses a cross-validation mechanism where the data is divided into 10 windows, each with a different data range over a horizon defined as 30 days. In determining the best parameters for ETH data, it is necessary to implement several combinations to produce the lowest MAPE. The combinations that will be iterated in the hyperparameter process using Optuna are shown in the table below.

Table 1. Parameter Combinations

No	Parameter	Combinations
1	Input_size_ratio	3 * horizon 4 * horizon
2	Interpolation_mode	Nearest Linear Cubic
3	Windows_batch_size	32 64 128
4	Scaler_type	Minmax Robust
5	Pooling_mode	MaxPool1d AvgPool1d

(Source: Developed by the Author)

3.2. Model Performance Evaluation

The evaluation results of each iteration in the optimization process of selecting the best parameters (hyperparameters) using the MAPE, MAE, and RMSE metrics on the validation set [27], [17]. This allows observation of changes in the performance of the N-HiTS model along with changes in dynamic parameters. The model with the lowest MAPE value on the validation data will be selected as the best model to be evaluated using test data that has never been learned by the model. The results that will be displayed are the MAPE, MAE, RMSE scores, as well as a visualization of the comparison between the model prediction values and the actual data.

Table 2. Result of Hyperparameter

Iteration	Value	Input size	Interpolation mode	Pooling mode	Scaler type	Windows batch size
0	5,26	30	linear	MaxPool1d	robust	128
1	5,27	120	linear	MaxPool1d	robust	32
2	5,49	30	linear	AvgPool1d	robust	32
3	6,58	1	nearest	MaxPool1d	minmax	128
4	6,00	60	cubic	AvgPool1d	robust	64
5	6,58	90	linear	AvgPool1d	minmax	64
6	6,15	90	linear	MaxPool1d	robust	64
7	6,22	120	nearest	MaxPool1d	minmax	64
8	6,06	60	linear	AvgPool1d	minmax	32
9	6,11	60	linear	AvgPool1d	robust	32
10	5,28	30	cubic	AvgPool1d	robust	128
11	5,44	120	linear	MaxPool1d	robust	128
12	5,54	120	linear	MaxPool1d	robust	128
13	5,58	30	linear	MaxPool1d	robust	32
14	6,58	1	cubic	MaxPool1d	robust	128
15	5,33	120	nearest	MaxPool1d	robust	32
16	5,58	30	linear	MaxPool1d	robust	32
17	5,26	30	linear	MaxPool1d	robust	128
18	6,66	30	cubic	MaxPool1d	minmax	128
19	5,29	30	nearest	MaxPool1d	robust	128

(Source: Developed by the Author)

Table 2 presents the results of the hyperparameter tuning process using multiple parameter combinations. Each row represents one iteration, with the corresponding MAPE value and parameter configuration. The "Value" column indicates the MAPE score, where lower values represent better model performance. From this table, the optimal configuration can be identified by selecting the row with the lowest MAPE value, which is 5.26% in iteration 0.

Based on the evaluation results shown in Table 2, there are variations in the combinations produced in the 20 best models in the tuning process using Optuna. Thus, the lowest MAPE value was obtained by the best configuration, namely 'input_size': 30, 'windows_batch_size': 128, 'interpolation_mode': 'linear', 'scaler_type': 'robust', 'pooling_mode': 'MaxPool1d' with a MAPE value of 5.26%. This means that the model uses historical data from the past 30 days as the basis for predicting prices over a 30-day horizon. Dimension reduction is performed by taking the average value of the data. The interpolation mode uses the linear value for estimation, and each training process will process 128 data windows. The use of a robust scaler type indicates that data normalization is performed based on the interquartile range. In cross-validation implementation, there are two main approaches to utilizing information from previous iterations to make predictions in the next time window. This mechanism is closely related to the Refit strategy, which is the procedure for determining the input data used when the model moves to the next cutoff point [28].

Table 3. MAPE of Cross Validation with Refit

Window	*Date Start*	*Date End*	MAPE	MAE	RMSE
1	01-01-2021	05-04-2024	4.453	145.93	181.387
2	01-01-2021	05-05-2024	10.362	338.815	373.54
3	01-01-2021	04-06-2024	11.165	441.892	481.056
4	01-01-2021	04-07-2024	25.752	641.853	728.347
5	01-01-2021	03-08-2024	10.802	314.027	331.74

Window	*Date Start*	*Date End*	MAPE	MAE	RMSE
6	01-01-2021	02-09-2024	5.652	143.563	159.786
7	01-01-2021	02-10-2024	11.649	343.509	379.551
8	01-01-2021	01-11-2024	24.753	631.235	705.027
9	01-01-2021	01-12-2024	5.437	200.148	219.216
10	01-01-2021	31-12-2024	3.252	107.825	136.839
	Mean		11.328	340.870	382.649

(Source: Developed by the Author)

Based on Table 3, using the selected optimal parameters shows varying MAPE values when tested with the temporal cross-validation method with a configuration of 10 windows or cutoffs. It was found that the average MAPE value was 11.328%. The significant difference between the optimization value (5.26%) and the final evaluation average (11.32%) is due to high error fluctuations in several specific periods. In the periods with cutoffs of 04-07-2024 and 01-11-2024, which produced MAPE values of 25.75% and 24.75%, respectively.

Table 4. MAPE of Cross Validation without Refit

Window	*Date Start*	*Date End*	MAPE	MAE	RMSE
1	01-01-2021	05-04-2024	4.453	145.93	181.387
2	01-01-2021	05-05-2024	11.677	371.016	440.555
3	01-01-2021	04-06-2024	16.902	726.746	793.329
4	01-01-2021	04-07-2024	8.719	260.401	315.904
5	01-01-2021	03-08-2024	13.522	405.19	416.474
6	01-01-2021	02-09-2024	5.631	144.175	167.985
7	01-01-2021	02-10-2024	4.984	119.876	148.556
8	01-01-2021	01-11-2024	25.698	649.169	726.085
9	01-01-2021	01-12-2024	5.176	190.064	209.887
10	01-01-2021	31-12-2024	3.519	115.678	143.812
	Mean		10.428	334.352	399.492

(Source: Developed by the Author)

Table 3 and Table 4 show the results of temporal cross-validation with and without the refit strategy. Each row represents a different time window, defined by the start and end dates. The MAPE, MAE, and RMSE columns indicate the prediction error for each window. These tables allow readers to observe how model performance varies across different time periods. Higher MAPE values indicate larger prediction errors, particularly during periods of high market volatility.

Based on Table 4, using the selected optimal parameters shows varying MAPE values when tested with the temporal cross-validation method with a configuration of 10 windows or cutoffs. It was found that the average MAPE value was 10.42%. The significant difference between the optimization value (5.26%) and the final evaluation average (10.42%) is due to high error fluctuations in several specific periods. In the periods with cutoffs of 01-11-2024, which produced MAPE values of 25.698%. The high error rate at the November 2024 cutoff demonstrates that the N-HiTS univariate model stuggles to predict price spikes driven by external sentiment, as sentiment data and trading volume are not captured in historical closing price data.

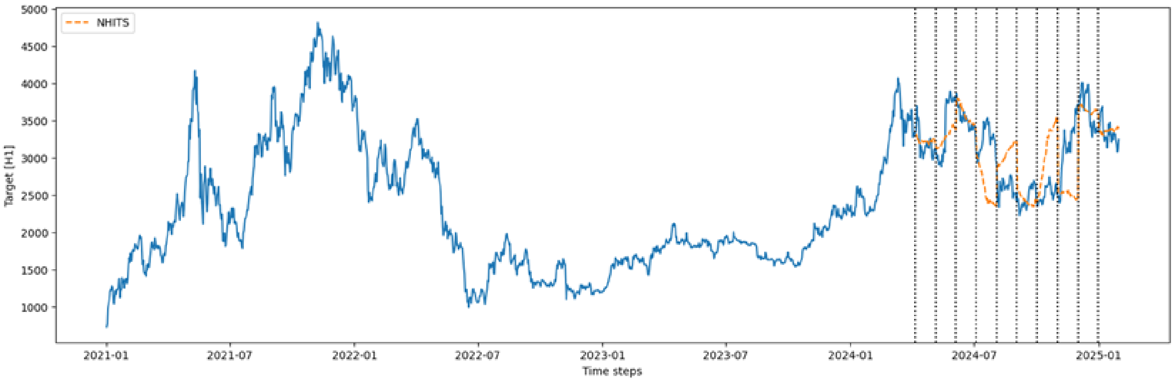

Figure 4. Cross Validation Result
(Source: Developed by the Author)

Figure 4 visualizes the comparison between predicted and actual Ethereum prices across different time windows. The figure helps illustrate how well the model follows the overall trend of the data. The closeness between the predicted and actual lines indicates the accuracy of the model. Deviations between the two lines in certain periods correspond to the spikes in MAPE values observed in the cross-validation results.

This phenomenon shows that even though the model has excellent generalization capabilities in most periods with MAPE values ranging from 3% to 5%, there are changes in patterns in certain time windows. As shown in Figure 4, the visualization results show consistent capabilities in following long-term trends. Despite spikes in MAPE values in several time periods, the model does not experience a permanent decline in performance or model drift.

3.3. Comparison of N-HiTS and N-BEATS

The best model selected will be compared again with the predecessor model N-HiTS, namely NBEATS. Using the test data from the last window, the results are as shown in the table below.

Table 5. Comparison of N-HiTS and N-BEATS

Metric	Result of N-HiTS	Result of N-BEATS
MAPE	3.25%	5.38%
MAE	107.825	194.68
RMSE	136.839	230.28
DA	48.28%	50 %

(Source: Developed by the Author)

Table 5 compares performance of the N-HiTS and N-BEATS models using three evaluation metrics: MAPE, RMSE, and MAE, along with directional accuracy. These metrics can measure the prediction error, where lower values indicate better performance. By comparing the values across both models, it can be observed that N-HiTS consistently produces lower error values, indicating superior predictive accuracy.

These results indicate that the N-HiTS model has excellent generalization capabilities in predicting Ethereum prices. The MAPE value of 3.25% indicates that the average deviation of predictions from actual prices is very low, making this model representative for use in analyzing the price movements of volatile crypto assets.

This performance improvement can be attributed to the architectural design of N-HiTS, which utilizes Multi-Rate Data Sampling and also Hierarchical Interpolation. This approach enables the model to capture short and long-term trends fluctuations more effectively. In contrast, N-BEATS relies on a linear expansion basis, which may limit its ability to adapt to highly dynamic and non-linear patterns commonly found in cryptocurrency data.

On the other hand, N-BEATS, which tends to rely on a linear expansion basis, sometimes has difficulty capturing highly dynamic non-linear pattern changes in crypto data, as reflected in an RMSE value of 230.28, which is much higher than N-HiTS at only 136.83. In addition to the comparison with N-BEATS, the results of this study are also consistent with previous research using the Long Short-Term Memory (LSTM) model. The LSTM model produced a Mean Absolute Error (MAE) of 22.59%, which indicates lower predictive performance compared to the results obtained by N-HiTS in this study. This suggests that N-HiTS is more effective in handling complex volatility patterns in Ethereum price data.

A different insight emerges when analyzing the model's ability to predict the direction of price movements. While N-HiTS outperforms N-BEATS in minimizing error magnitudes, N-BEATS demonstrates a slightly higher Directional Accuracy of 50%, compared to N-HiTS at 48.28%. A Directional Accuracy of 50% implies that N-BEATS ability to forecast whether the price will rise or fall tomorrow is equivalent to a random guess. Meanwhile, N-HiTS falls slightly below this baseline at 48.28%. This phenomenon reveals a common paradox in cryptocurrency forecasting: a model that is highly precise in predicting the exact price level (low MAPE and RMSE) does not necessarily guarantee high accuracy in timing the market's directional momentum. The high noise, rapid trend reversals, and sudden sentiment shifts in the Ethereum market make predicting the exact trend direction a significantly tougher challenge than fitting the historical price values.

Thus, the findings indicate that N-HiTS provides a more effective and adaptive approach for cryptocurrency price magnitude forecasting, particularly under conditions of high volatility, despite its slight limitation in capturing directional trends. However, further validation using different datasets, alternative directional metrics, and longer time periods is required to generalize these results.

3.4.Risk Analyst

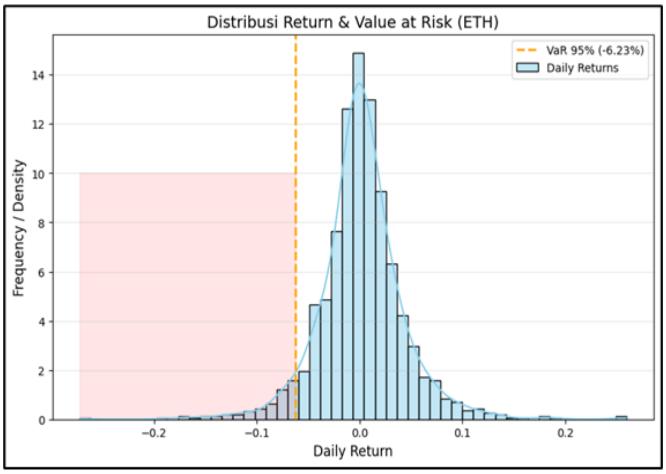

Figure 5. Return Histogram
(Source: Developed by the Author)

The return histogram illustrates the distribution of Ethereum returns along with the kernel density estimation (KDE) curve. The horizontal axis represents return values, while the vertical axis represents frequency. The red shaded area on the left side indicates the tail risk, which corresponds to extreme negative returns. This visualization helps in understanding the non-normal distribution of returns and identifying the risk region used in the Value at Risk (VaR) calculation.

Based on Value at Risk (VaR) calculations at a 95% confidence level, a value of -6.23% was obtained. Empirically, this figure indicates that there is a 5% probability for investors to experience daily losses exceeding 6.23% of the total asset value under normal market conditions. The red shaded area on the left side of the distribution represents tail risk or extreme risk that must be mitigated in digital asset portfolio management.

In the context of financial applications with an investment scenario of $100, the calculation results show a maximum potential loss of $6.23 at a 95% confidence level. This figure indicates that investors have a 95% confidence that in one trading day, the decline in the value of their investment will not exceed $6.23. However, this result also warns that there is still a 5%. probability that the losses incurred could be greater than this amount, indicating the need for additional risk management strategies such as setting a disciplined stop-loss limit.

4. CONCLUSION

Based on the empirical findings, it can be concluded that the N-HiTS model demonstrates superior and highly precise performance compared to the N-BEATS model in forecasting the volatile price dynamics of Ethereum, achieved through its distinctive Multi-Rate Data Sampling and Hierarchical Interpolation architectures. This is evidenced by N-HiTS consistently yielding lower error magnitudes, specifically achieving a Mean Absolute Percentage Error (MAPE) of 3.25%, a Mean Absolute Error (MAE) of 107.825, and a Root Mean Squared Error (RMSE) of 136.839, which significantly outperform N-BEATS' metrics (MAPE: 5.38%, MAE: 194.68, RMSE: 230.28. Furthermore, the integration of risk analysis yielded a quantitative Value at Risk (VaR) threshold of -6.23% at a 95% confidence level, providing an exact maximum potential daily loss projection for portfolio management under normal market conditions. However, because this study relies strictly on univariate closing price data and incorporates limited comparison models, it carries inherent limitations; it omits highly influential external market drivers such as macroeconomic variables, trading volume, and social sentiment data, while also lacking formal VaR backtesting validation. To address these boundaries, future research should transition toward multivariate feature forecasting and incorporate advanced Transformer-based time-series models combined with rigorous statistical backtesting to build a more comprehensive and robust risk-reward framework for highly volatile digital assets.

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