# The Digital Footprint of Public Attention: Forecasting Indonesian Gold Prices using Google Trends Index and Optimized Support Vector Regression

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**Abstract.** To provide actionable forecasting insights for gold prices in Indonesia's public sentiment-driven market, this study developed a machine learning framework using the Google Trends Index (GTI) as a sentiment proxy. We employed an Optuna-optimized Support Vector Regression (SVR) model to comparatively evaluate three feature sets (GTI, historical Lag, and a Mix) across seven forecasting horizons (t+1 to t+30). A key advantage of our approach was the identification of horizon-dependent predictor dynamics: results revealed that while historical data excelled for short-term forecasts (MAPE 0.50% at t+5), the contribution of GTI became vital for long-term accuracy, where the hybrid model achieved its peak performance (MAPE 1.92% at t+30). Notably, the GTI-only model showed solid standalone potential (MAPE < 20%). We conclude that a hybrid approach is most effective, validating GTI as a relevant predictor for Indonesia. Furthermore, the proposed SVR-Optuna framework offers a generalizable methodology for forecasting other sentiment-driven assets, providing a clear, actionable guide for model selection based on forecasting horizons.

**Keyword:** emerging markets, hyperparameter optimization, machine learning, time series forecasting.

## 1. Introduction

Historically, gold (XAU) has played a pivotal role in the global monetary system and investment portfolios as a fundamental safe-haven asset [1], [2]. Its function as a defensive financial instrument has been validated not only throughout history but also during modern crises, including the COVID-19 pandemic, where it demonstrated strong hedging properties against market turmoil [3], [4]. The unique ability of gold to preserve wealth against inflation and geopolitical uncertainty makes it a crucial component for portfolio diversification [5], [6]. These fundamental characteristics drive the high interest of the Indonesian public in gold investment, a trend empirically confirmed in a survey by Zigi.id and the Katadata Insight Center (KIC), which found that gold was the top investment choice for 58.5% of 3,178 respondents [7]. This preference is largely attributed to its perceived security, including its liquidity, low-risk nature [8], its function as a safe substitute for savings [9], and its utility as practical debt collateral (Purnomo, 2013, as cited in [10]). This central role of gold is evident not only at the household level but also on a macroeconomic scale, including its influence on the Jakarta Composite Index (JCI), which further underscores the urgency of accurate price forecasting [11].

The accurate forecasting of gold prices presents a significant challenge due to its complex dynamics. Gold prices are not only influenced by macroeconomic variables [5], [12], but its time series also exhibits intricate statistical properties such as significant structural breaks, where the relationship between gold prices and economic variables fundamentally changes [13]. These complex characteristics often render traditional econometric models like ARIMA or GARCH inadequate [14], [15]. In response, advancements in artificial intelligence have spurred the adoption of machine learning (ML) models. Designed for adaptive learning, ML models have consistently proven superior in capturing non-linear patterns in financial data that are missed by conventional methods [16], [17], [18]. This predictive superiority of ML has been validated through large-scale empirical studies [19].

Among the diverse range of ML models, this study specifically proposes Support Vector Regression (SVR). The choice of SVR is motivated by its underlying principle of structural risk minimization [20], [21], which provides crucial practical advantages for forecasting: high model stability and reproducibility stemming from its convex optimization nature [19], and strong robustness against overfitting, particularly with limited data [22]. These theoretical strengths are empirically validated in the gold price forecasting literature, where SVR has consistently demonstrated strong performance [23], [24], [25], [26], [27], and has even been found to outperform other popular statistical models such as ARIMA, Lasso Regression, and Gaussian Regression [20].

Nevertheless, SVR's performance is highly sensitive to the choice of its hyperparameters [28], [29], a challenge compounded by the curse of dimensionality that renders traditional methods like Grid Search inefficient [30]. To address this, our research integrates Optuna, a modern optimization framework designed to find optimal hyperparameters intelligently and efficiently [31], [32]. The selection of Optuna is based on its specific advantages, including a define-by-run characteristic that enables dynamic search spaces, as well as efficient and cost-effective sampling and pruning mechanisms [32]. Furthermore, Optuna has been shown to provide the best trade-off between performance and computation time in Combined Algorithm Selection and Hyperparameter optimization (CASH) problems [33]. This step is crucial and has been proven to significantly enhance model accuracy across various financial domains [25], [34].

The selection of predictor variables is a crucial aspect of this study. We propose the Google Trends Index (GTI) as a primary predictor, arguing it is a particularly relevant proxy for public sentiment in the Indonesian market. Grounded in behavioural finance, GTI quantifies the information-seeking behaviour that often precedes investment decisions [35], [36]. While the predictive power of GTI for gold prices has been validated in international studies [37], [38], its relevance is especially pronounced in Indonesia. This is due to the market being characterized by high public participation in gold investment and the documented influence of investor sentiment on market returns [39], [40], [41]. Crucially, a recent study confirms that for the Indonesian market, internet-based metrics like GTI provide unique insights into investor behaviour not captured by conventional macroeconomic variables [42]. Therefore, GTI serves as a highly effective proxy for capturing the crucial dimension of public sentiment, including that of investors, which often goes undetected by traditional economic data.

## 2. Research Method

### *2.1. Data Understanding*

This study employs two daily time series datasets, corresponding to gold market trading days, for the period spanning from September 18, 2021, to March 18, 2024:

- Dependent Variable (Y): The price of gold (GAU), denominated as the price per gram in Indonesian Rupiah (IDR). The data were sourced from id.investing.com/currencies/gau-idr.
- Independent Variable (X): The Google Trends Index (GTI), which serves as a proxy for public sentiment and attention. GTI data were manually compiled from Google Trends for several relevant keywords: “emas” (gold), “kurs rupiah” (rupiah exchange rate), “emas batangan” (gold bars), “perhiasan emas” (gold jewelry), and “harga emas” (gold price). Given that Google Trends provides normalized data over shorter intervals, a series of overlapping weekly datasets were collected and subsequently reconstructed to form a single, consistent daily time series. This series was carefully aligned with the period of the gold price data.

### *2.2. Data Preparation*

Prior to the modeling phase, the raw data underwent two primary pre-processing stages: (1) transformation of the time series data into a supervised learning format suitable for multi-step forecasting, and (2) feature normalization using Min-Max scaling.

To evaluate the model's performance in predicting future prices, the forecasting task was framed as a supervised learning problem. This was achieved using a sliding window approach to generate input feature and output target pairs. Specifically, we used t antecedent observations (e.g., t=10) to predict the value h time steps into the future. This process was repeated for multiple prediction horizons (h), namely h ∈ {1, 5, 10, 15, 20, 25, 30}. The selection of 5-day intervals is predicated on the weekly operational cycle of the gold market (5 trading days), enabling an analysis of predictive capabilities from one day (h=1) to approximately six weeks ahead (h=30). These horizons were chosen to assess the model's short- to medium-term forecasting capabilities.

The input variables in our dataset, GTI and GAU, are on different scales. To ensure that all variables contribute equally during model training and to accelerate convergence, we applied Min-Max normalization. This method rescales each feature to a [0, 1] range while preserving the shape of its original distribution.

The normalization procedure strictly adheres to best practices to prevent data leakage. The scaling parameters (i.e., minimum and maximum values) were computed solely from the training set and subsequently applied to transform both the training and test sets. The size of the test set was directly determined by the prediction horizon being evaluated; for an h=1 horizon, the test set consists of the final observation, whereas for an h=30 horizon, it comprises the last 30 observations.

Furthermore, during the hyperparameter optimization phase, a meticulous approach was employed to prevent look-ahead bias. The pre-partitioned, unnormalized training set was further subdivided into two subsets: an optimization training set and a validation set. This nested partitioning is crucial for objectively evaluating different hyperparameter combinations. The Min-Max normalization was applied within this scope using the scikit-learn library: the scaler was fitted on the optimization training set (fit_transform), and the same fitted scaler was then used to transform the validation set (transform). This strategy ensures that the performance evaluation on the validation set accurately simulates real-world conditions with unseen data, thereby enhancing the reliability of the final hyperparameter selection.

The Min-Max transformation for a vector X is mathematically defined as follows [42]:

$$X_{new} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

where $X$ is the vector of input variables

### 2.3. Modelling

The model utilized in this research is Support Vector Regression (SVR). SVR operates on the principle of structural risk minimization to achieve robust generalization performance. To address both linear and non-linear relationships within the data, SVR employs various kernel functions, including the Linear, Polynomial, and Radial Basis Function (RBF), also known as the Gaussian kernel [20]. The general form of the SVR regression function is given by:

$$f(x) = \sum_{i=1}^{N'} (\alpha_i - \alpha_i^*)\, K(x, x_i) + b \tag{2}$$

Where $N'$ is the number of observations in the training set, $f(x)$ is the predicted value for the input data $x$, $a$ and $a^*$ are the Lagrange multipliers, $K(x, x_i)$ is the kernel function, and b is the bias term.

In this study, we evaluate two prevalent kernel functions: Linear and the Radial Basis Function (RBF), also known as the Gaussian kernel. The polynomial kernel was excluded from this analysis due to its requirement for an additional hyperparameter—the polynomial degree—and its significant computational overhead [43]. This decision is further substantiated by the findings of [44], who demonstrated that the RBF/Gaussian kernel typically outperforms the polynomial kernel, provided that the data are appropriately normalized and an optimal RBF width parameter is identified. The formulation for each selected kernel is as follows [45]:

*Linear kernel:*

$$K(x, x_i) = x * x_i + c \tag{3}$$

where $c$ is the penalty parameter of the error term,

*RBF kernel:*

$$K(x, x_i) = \exp\left(-\gamma \left|\left|x - x_i\right|\right|^2\right) \tag{4}$$

where $\gamma$ is a RBF coefficients.

To identify the optimal Support Vector Regression (SVR) hyperparameter configuration, we employed the Optuna optimization framework. The objective of this process was to minimize the Mean Absolute Error (MAE) on the validation set. The search was conducted using a Random Search algorithm over 1,500 trials. The hyperparameter search space defined for this optimization is detailed in table 1.

**Table 1.** Hyperparameter search spaces.

| Hyperparameter | Symbol | Range | Type |
|---|---|---|---|
| Regularization | $C$ | 0.001 , 1000 | Log-uniform |
| Margin of tolerance | $\varepsilon$ | 0.001 , 10 | Log-uniform |
| RBF Coefficients | $\gamma$ | 0.001 , 1 | Log-uniform |
| Kernel function | - | RBF[a], Linear[b] | Categorical |

[a] Indicates the kernel hyperparameter was set to 'rbf' (Radial Basis Function).

[b] Indicates the kernel hyperparameter was set to 'linear'.

### 2.4. Evaluation

The performance of the forecasting models was comprehensively evaluated using a suite of standard metrics: the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). For each of these metrics, a lower value signifies a higher level of prediction accuracy [46]:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{|y_i|} \times 100\% \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \tag{7}$$

where $N$ is the total number of observations, $y_i$ is the actual value, and $\hat{y}_i$ is the predicted value for the $i$-th observation.

The primary evaluation metric adopted in this study is the Mean Absolute Percentage Error (MAPE). The interpretation of the model's performance is benchmarked against the criteria established by [46], as outlined in table 2.

**Table 2.** MAPE Significants.

| MAPE | Significants |
|---|---|
| < 10% | Excellent forecasting ability |
| 10 – 20% | Good forecasting ability |
| 20 – 50 % | Reasonable forecasting ability |
| > 50% | Bad forecasting ability |

## 3. Result and Discussion

The analysis commences with an exploratory data analysis (EDA) to investigate the preliminary relationships between the input variables—the Google Trends Indices (GTI)—and the target variable, GAU (henceforth referred to as the gold price). A Pearson correlation analysis was subsequently conducted to quantify the strength and direction of these linear relationships, with the objective of validating the relevance of each search trend as a potential predictor. The results of this analysis are visualized as a heatmap in figure 1.

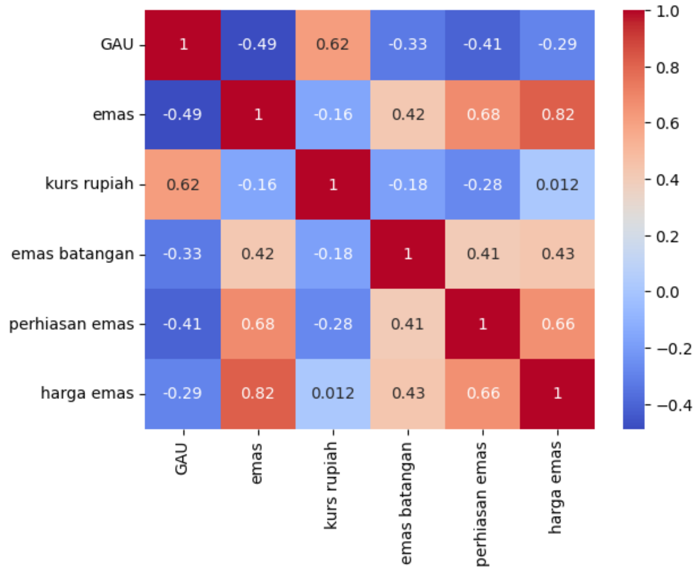


**Figure 1.** Correlation matrix.

The analysis presented in figure 1 reveals several key findings that justify the selection of the input variables. First, a strong positive correlation was identified between the search trend for the keyword "kurs rupiah" (Rupiah exchange rate) and the gold price (r = 0.62). This emerges as the strongest linear predictor, logically indicating that as public search interest in the Rupiah's exchange rate intensifies—often during periods of currency weakening or volatility—the price of gold tends to rise, reinforcing its status as a safe-haven asset.

Second, moderate negative correlations were observed between the gold price and the search trends for the keywords "emas" (gold) (r = -0.49), "perhiasan emas" (gold jewelry) (r = -0.41), "emas batangan" (gold bars) (r = -0.33), and "harga emas" (gold price) (r = -0.29). This is a notable finding, as it suggests that an increase in search volume for gold-related terms often coincides with a decrease in its price. This phenomenon can be interpreted as a "contrarian signal" or a "concern indicator," wherein the public more actively seeks information about gold when its price is declining or during periods of market uncertainty. These significant relationships, both positive and negative, provide a strong empirical justification for utilizing these search trends as features for predicting gold price movements.

Subsequently, a performance evaluation was conducted on three distinct Support Vector Regression (SVR) model configurations: SVR-GTI (using only Google Trends Index features), SVR-Lag (using only historical GAU features), and SVR-Mix (a hybrid of both feature sets) across seven prediction horizons. The comprehensive evaluation results, based on MAPE, MAE, and RMSE metrics, are presented in table 3.

**Table 3.** Performance Comparison of SVR Models Across Prediction Horizons.

| Prediction horizon | Model | RMSE | MAE | MAPE (%) |
|---|---|---|---|---|
| t + 1 | SVR-GTI | 176214 | 176214 | 16.1026 |
| | SVR-Lag | 11995 | 11995 | 1.0961 |
| | SVR-Mix | 12402 | 12402 | 1.1333 |
| t + 5 | SVR-GTI | 170924 | 170370 | 15.6714 |

| | | | | |
|---|---|---|---|---|
| | SVR-Lag | 6399 | 5419 | 0.4976 |
| | SVR-Mix | 23906 | 22726 | 2.0907 |
| t + 10 | SVR-GTI | 128862 | 128515 | 11.8334 |
| | SVR-Lag | 81354 | 81214 | 7.4771 |
| | SVR-Mix | 56574 | 55517 | 5.1132 |
| t + 15 | SVR-GTI | 128374 | 126270 | 11.7572 |
| | SVR-Lag | 64988 | 59548 | 5.5068 |
| | SVR-Mix | 75332 | 70746 | 6.5555 |
| t + 20 | SVR-GTI | 113660 | 104355 | 9.7567 |
| | SVR-Lag | 50940 | 40216 | 3.7205 |
| | SVR-Mix | 58592 | 47065 | 4.3584 |
| t + 25 | SVR-GTI | 111872 | 102998 | 9.7215 |
| | SVR-Lag | 35710 | 28494 | 2.6634 |
| | SVR-Mix | 36115 | 28663 | 2.6787 |
| t + 30 | SVR-GTI | 105564 | 98263 | 9.3262 |
| | SVR-Lag | 33475 | 26436 | 2.4811 |
| | SVR-Mix | 24579 | 20213 | 1.9178 |

The analysis in table 3 reveals that the majority of the developed models exhibit highly accurate forecasting capabilities (MAPE < 10%), in accordance with the significance standards presented in table 2. The optimal performance for very short-term prediction is achieved by the SVR-Lag model at the h=1 horizon, with a MAPE value of just 0.4976%. However, the most compelling finding lies in the dynamics and potential contribution of the GTI features. Although the SVR-GTI model shows comparatively higher error, its standalone performance remains robust. According to the significance criteria, the SVR-GTI model consistently achieves 'good' (MAPE 10-20%) and even 'highly accurate' (MAPE < 10%) performance levels from the h=15 horizon onward. The fact that public sentiment data alone can yield this level of accuracy, without reliance on historical price data, underscores the potential of GTI as an alternative primary predictor.

Nevertheless, the most prominent role of GTI in this study is that of a potent supplementary predictor, which becomes evident upon its integration into the SVR-Mix model. The addition of GTI features demonstrates an ability to significantly enhance accuracy, particularly for medium- to long-term horizons. For instance, at the h=10 horizon, the SVR-Mix model (MAPE 5.1132%) improves upon the SVR-Lag model (MAPE 7.4771%). The most substantial improvement is observed at the h=30 horizon, where SVR-Mix (MAPE 1.9178%) decisively outperforms SVR-Lag (MAPE 2.4811%). This enhancement, however, is not absolute across all conditions. At several horizons (e.g., h=15 and h=20), the SVR-Lag model remains slightly superior. This outcome does not indicate a weakness in the GTI features but rather clarifies their strategic role: they serve as a source of complementary information that becomes particularly valuable when the signals from historical data begin to attenuate or are no longer sufficient to capture market dynamics. It should be noted that the performance degradation with an increasing horizon is non-monotonic; the error values for both SVR-Mix and SVR-Lag models tend to peak at medium-term horizons (h=10 to h=20) before decreasing again at longer horizons. This phenomenon may suggest the presence of specific regimes or cyclical patterns in the test data that are more predictable at longer ranges by a more comprehensive model. Consequently, it can be concluded that GTI features hold excellent potential as a supporting predictor in gold price forecasting, providing significant added value, especially for longer-term predictions.

The visual analysis in figure 2, which displays the comparison between predicted and actual values at representative horizons, corroborates these quantitative findings.

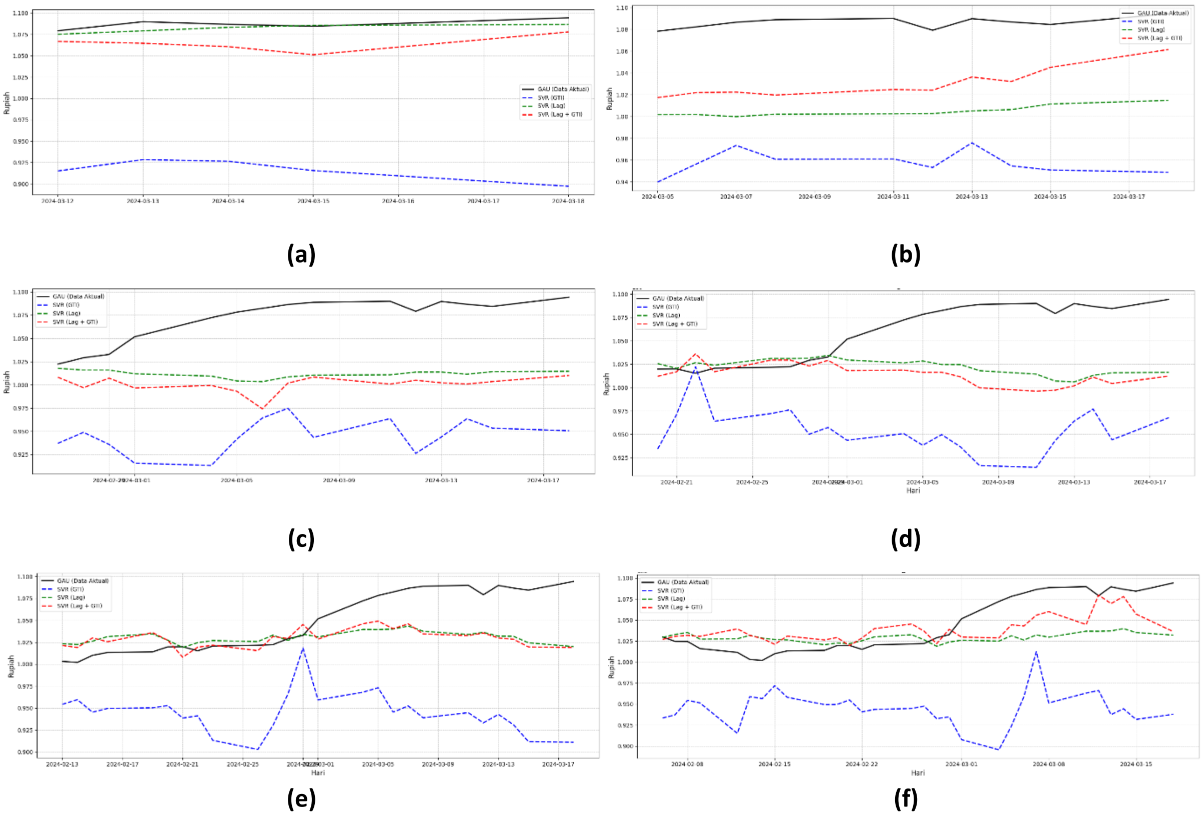


**Figure 2.** Comparison of Predicted vs. Actual Values Across Different Horizons (a) t + 5, (b) t + 10, (c) t + 15, (d) t + 20, (e) t + 25, (f) t + 30

The visual analysis in figure 2 provides strong qualitative support for the quantitative findings. For short-term horizons (h=1 and h=5), the SVR-Lag prediction line (green) is observed to closely track the actual data (black), confirming its superior performance in short-range forecasting. As the prediction horizon extends (h=10 to h=30), a shift in the pattern becomes apparent. Although the SVR-Lag predictions (green) still follow the general trend, they begin to exhibit a noticeable offset from the actual data. In contrast, the SVR-Mix prediction line (red) visually demonstrates the best and most consistent fit to the actual data, particularly at longer-term horizons. The SVR-GTI model (blue) consistently exhibits the largest deviation across nearly all scenarios.

These visual observations confirm the conclusion drawn from the metric analysis: the hybrid of historical and sentiment features within the SVR-Mix model yields the most robust and accurate forecasts overall, especially for long-term prediction.

## 4. Conclusion

To address the challenge of forecasting complex gold prices in Indonesia's public sentiment-driven market, this study developed and validated a forecasting framework that integrates Support Vector Regression (SVR), hyperparameter optimization via Optuna, and the Google Trends Index (GTI) as a sentiment proxy. The principal findings revealed highly specific and actionable insights into model selection based on the prediction horizon. It was found that for very short-term forecasting (h=1 to h=5), a model relying solely on historical data (SVR-Lag) was both highly accurate and sufficient. However, for medium- to long-term forecasting (h=10 and beyond), a hybrid model (SVR-Mix) consistently demonstrated superiority, wherein the contribution of sentiment data (GTI) became crucial for achieving significant accuracy improvements. Furthermore, the study confirmed that a purely sentiment-based model (SVR-GTI) could independently achieve a 'good' performance level (MAPE < 20%), establishing its potential as a robust alternative predictor when historical data is unavailable.

This study offers three unique contributions. Methodologically, it presents a systematic and replicable SVR-Optuna framework for multi-horizon analysis. Empirically, it provides the first quantitative validation of GTI's dynamic, horizon-dependent predictive value for gold prices within the specific context of the Indonesian market. Practically, the findings offer clear, data-driven guidance for investors in selecting a forecasting approach tailored to their investment time horizons.

While offering significant insights, this research acknowledges several limitations that open avenues for future inquiry. Subsequent research could be enriched by integrating fundamental macroeconomic variables to enhance long-term accuracy. A comparative study with deep learning models such as Long Short-Tserm Memory (LSTM) or Gated Recurrent Unit (GRU) is also recommended to address more complex temporal dependencies. Finally, the exploration of more advanced feature engineering techniques or dynamic feature weighting presents a promising avenue for further model optimization.

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