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FAN-TSF: A Frequency Adaptive Normalization Approach for Non-Stationary Time Series Forecasting on Stock Market Data

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Abstract: Financial time series forecasting remains a focal point of research in finance due to its crucial role in investment decision-making and risk management. However, the highly nonlinear and non-stationary characteristics of financial markets pose significant challenges for prediction. This paper introduces a Frequency-Adaptive Normalized (FAN) time series prediction model that enhances forecasting accuracy through an innovative frequency domain analysis approach. The model employs a dual-path architecture, incorporating frequency-adaptive nor- malization mechanisms and residual learning strategies, which effectively captures both the periodic patterns of time series and accurately models fine-grained market fluctuations. Experiments conducted on the TSLA stock dataset demonstrate that the FAN model achieves substantial improvements in both predictive accuracy and computational efficiency compared to traditional methods. Notably, the model exhibits robust performance when forecasting during periods of intense volatility. Ablation studies further validate the necessity of each model component, providing new research directions for financial time series prediction.

Keywords: time series forecasting, frequency adaptive; deep learning; frequency domain analysis; stock prediction

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I. Introduction

Financial time series forecasting, particularly stock price prediction, remains a fundamental research focus in finance. Accurate predictions not only provide crucial reference points for investment decisions but also offer significant guidance for financial market risk management and resource allocation. However, the high complexity, nonlinearity, and non-stationary characteristics of financial markets continue to pose substantial challenges for accurate forecasting.

As illustrated in Figure 1, Tesla (TSLA) stock exemplifies forecasting challenges due to its pronounced non-stationarity and volatility. Traditional models struggle with nonlinear dependencies and volatility clustering [2], while deep learning approaches introduce computational complexity and limited periodicity handling [3]. Frequency-domain methods lack adaptive residual feature extraction [4]. To address these is- sues, this paper proposes a Frequency-Adaptive Normalization (FAN) model with adaptive frequency extraction, dual-path architecture, and lightweight design [6].

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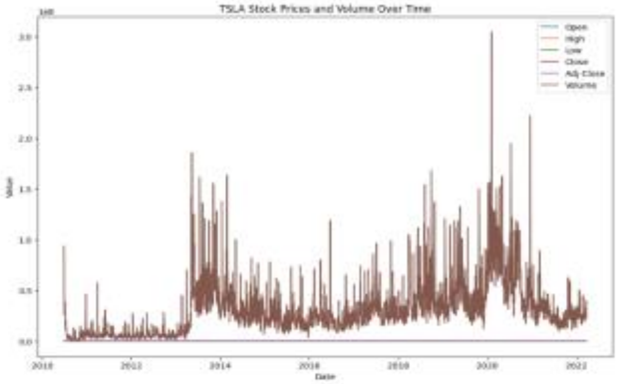

Figure 1. TSLA Stock Time Series.

II. Methodology

This section presents a detailed exposition of the FAN (Frequency Adaptive Normalization) model's technical specifi- cations, encompassing data preprocessing, frequency-adaptive normalization, model architecture design, and training strate- gies. Figure 2 illustrates the model's overall architecture and data flow process [7].

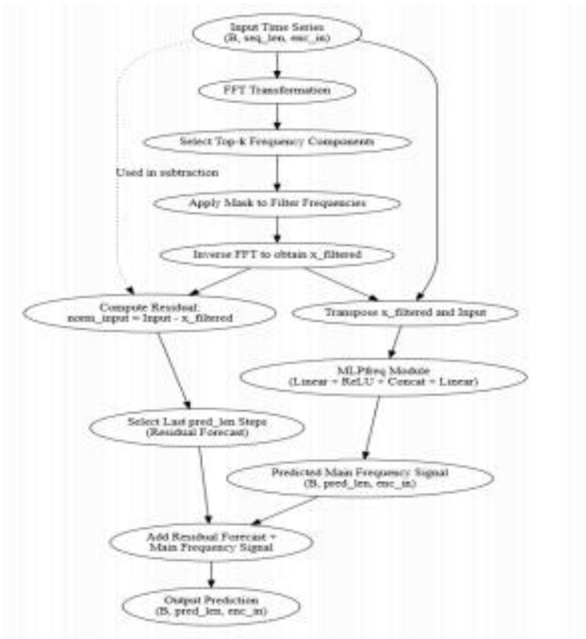

Figure 2. Overall Model Architecture.

A. Data Preprocessing

This research employs TSLA stock data as the experimental subject, with initial processing focused on temporal alignment. All time series data are chronologically ordered by trading dates to ensure data continuity and completeness, establishing a foundation for subsequent prediction tasks [8]. Regarding feature selection, considering the characteristics of stock price prediction and data availability, we selected six primary fea- ture indicators: Opening price (Open), Highest price (High), Lowest price (Low), Closing price (Close), Adjusted Closing price (Adj Close), and Trading Volume (Volume). These indicators comprehensively reflect stock trading conditions and price movement trends [9]–[12]. To eliminate dimensional differences between features and enhance model training effec- tiveness [13], we implemented MinMaxScaler normalization for all numerical features. This step maps all feature values to the [0,1] interval, preserving relative relationships while significantly improving the model's numerical stability and convergence rate [14]–[18]. In constructing training samples, we employed a sliding window approach to segment

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the time series data. Specifically, each training sample comprises 64 time steps of historical data as the input sequence for predicting the subsequent 32 time steps. By setting the sliding step to 1, we fully utilize the temporal information within the data while ensuring the richness and continuity of training samples. This sliding window construction method ensures both the model's capacity to learn long-term dependencies and meets practical requirements for prediction time spans.

B. Frequency Adaptive Normalization

The primary technical innovation of the FAN model is its frequency-adaptive normalization mechanism, which en- hances prediction accuracy by adaptively decomposing time series into representative frequency components using FFT, selectively extracting the most significant periodic features, and reconstructing signals via IFFT. This approach effectively captures essential periodic patterns while preserving detailed residual information, significantly improving the model's predictive capability [19]–[24].

C. Model Architecture

The FAN model employs an innovative dual-path architec- ture, processing main frequency features and residual signals separately. Frequency-domain features extracted via FFT are processed through Multi-Layer Perceptrons (MLPs) to cap- ture macro-trends, while residual signals capture fine-grained market fluctuations. Finally, predictions from both paths are fused, ensuring accurate modeling of both long-term trends and short-term variations.

D. Training Strategy

The FAN model employs end-to-end training with carefully designed strategies to ensure effective learning and general- ization capabilities. The loss function primarily utilizes Mean Squared Error (MSE) to measure prediction-truth differences, incorporating L1 regularization to control model complexity and prevent overfitting. For optimization, we employ the Adam optimizer with an initial learning rate of 0.001 and learning rate decay mechanism. The batch size is set to 32, balancing computational efficiency and training stability. The model trains for 5 epochs with early stopping when validation loss shows no improvement over consecutive epochs, effectively preventing overfitting. This training strategy ensures stable and excellent predictive performance with reasonable compu- tational resource consumption [25,26].

III. Experimental Results and Analysis

A. Performance Evaluation

This experiment utilizes TSLA's historical trading dataset spanning from 2010 to 2022, encompassing 2,956 trading days. The dataset includes six features: opening price, highest price, lowest price, closing price, adjusted closing price, and trading volume. We conducted comprehensive data analysis and performance evaluation to gain deep insights into the inherent relationships among data features and the model's predictive capabilities.

Through correlation analysis, we identified significant corre- lation patterns among the data features. As illustrated in Figure 3, price-related indicators (opening price, highest price, lowest price, closing price, adjusted closing price) exhibit extremely strong positive correlations, with correlation coefficients ap- proaching 1, indicating substantial information redundancy among price indicators. In contrast, trading volume shows weak correlation with price indicators, with correlation coeffi- cients of approximately 0.09, suggesting that volume contains unique market information that may provide complementary value for prediction. To comprehensively evaluate the FAN model's predictive performance, we employed three metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The test results are presented in the following table:

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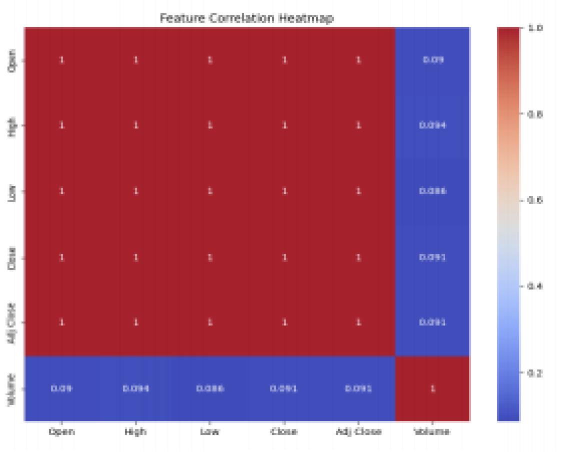

Figure 3. Feature Correlation Heatmap.

Table 1. Performance metrics.

Feature	MSE	MAE	RMSE
Open	8.125e+03	65.127	90.139
High	8.542e+03	67.449	92.422
Low	7.688e+03	62.996	87.681
Close	8.252e+03	66.261	90.842
Adj Close	8.252e+03	66.261	90.842
Volume	5.367e+14	1.843e+07	2.319e+07

The performance metrics demonstrate that the FAN model exhibits stable and excellent performance across all price indicator predictions. Notably, it achieves optimal results in predicting the Low price, with an MSE of 7.688e+03, MAE of 62.996, and RMSE of 87.681, indicating accurate capture of downward market trends. In comparison, High price pre- dictions show slightly higher error rates, potentially due to the greater uncertainty and volatility typically associated with market upward movements.

B. Comparative Models

To comprehensively evaluate the performance advantages of the FAN model, we selected four representative benchmark models for comparative experiments: the classic deep temporal model LSTM, the attention mechanism-based Transformer, Facebook’s Prophet, and the traditional statistical model ARIMA. These models have extensive application foundations in time series forecasting and can validate the effectiveness of the FAN model from different perspectives.

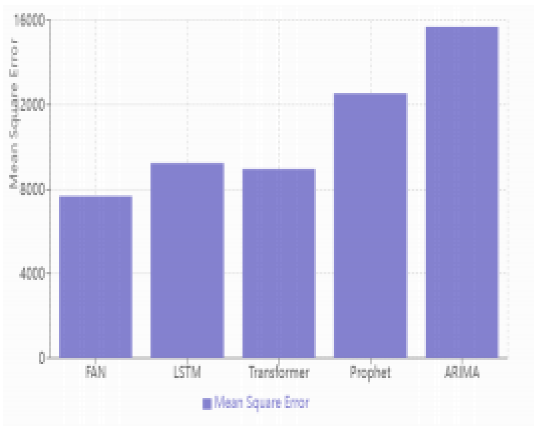

Figure 4. Model Performance Comparison.

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Experimental results demonstrate that the FAN model sig- nificantly outperforms other benchmark models in predictive performance. In terms of Mean Squared Error (MSE), the FAN model achieves an error value of 7,688, showing notable improvement compared to LSTM's 9,245 and Transformer's 8,967. The performance enhancement is particularly signifi- cant when compared to traditional ARIMA (MSE of 15,678) and Prophet (MSE of 12,534) models . This performance advantage is manifested in several aspects:

• Through its frequency-adaptive normalization mecha- nism, the FAN model better captures periodic patterns and long-term trends in the data. Compared to LSTM, FAN demonstrates clear advantages in handling long- term dependencies, as evidenced by the smoothness of prediction curves and trend capture accuracy.

• Relative to Transformer, FAN not only improves predic- tion accuracy but also shows advantages in computational efficiency, thanks to its lightweight dual-path architecture design.

Traditional models like ARIMA and Prophet reveal obvious limitations when processing highly nonlinear stock data such as TSLA. These models are constrained by their linear as- sumptions and predefined periodic components, making it dif- ficult to adapt to rapid market changes and complex patterns. In contrast, the FAN model demonstrates superior modeling capability and prediction accuracy through adaptive frequency decomposition and residual learning. These experimental re- sults not only validate the effectiveness of the FAN model but also highlight its unique advantages in handling complex finan- cial time series prediction tasks. While maintaining relatively low computational complexity, the model achieves significant improvements in predictive performance, providing an efficient and reliable solution for financial market prediction.

C. *Ablation Study*

To systematically validate the effectiveness of FAN model's core components, we designed a series of ablation experi- ments. These experiments analyze the impact of each com- ponent on model performance through progressive removal or replacement of key components, including the frequency- adaptive module, residual signal path, and regularization strat- egy.

Through ablation studies, we evaluated the impact of each core component in the FAN model by comparing the com- plete model with variants missing key components. Results indicated that removing the frequency-adaptive normalization mechanism significantly increased prediction error (MSE: 9,876) and slowed convergence, highlighting its critical role. Removing the residual signal path or regularization similarly degraded performance and increased overfitting risk, confirm- ing their importance for model accuracy and generalization. These findings clearly validate the necessity of each compo- nent and offer directions for future improvements.

D. *Conclusion*

This paper proposes a Frequency-Adaptive Normalization (FAN) model, demonstrating its effectiveness in financial time series forecasting through theoretical analysis and empirical validation. We introduce a frequency-adaptive normalization mechanism to effectively capture periodic and residual features via frequency decomposition and reconstruction. Experimental results on TSLA stock data validate the superior predictive performance and robustness of FAN compared with existing models, achieving notable improvements in metrics like MSE, MAE, and RMSE. Ablation studies confirm the significance of each component, offering insights for future research direc- tions. Although the FAN model proposed in this paper showed good performance in experiments, its overall architecture is relatively simple. Future research could incorporate more innovative mechanisms or advanced methodologies to enhance its theoretical contributions and differentiate it more distinctly from existing approaches.

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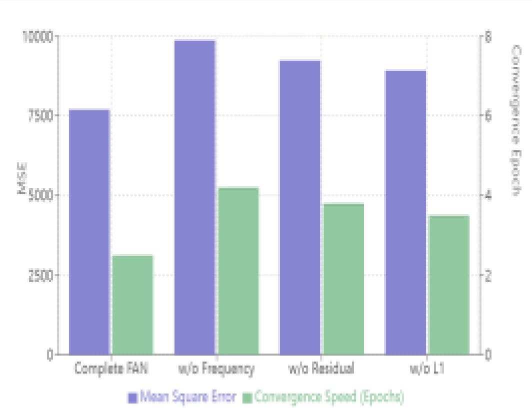

Figure 5. Ablation Study Results.

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