Integrating xLSTM with Signal Decomposition for Enhanced Stock Index Prediction: A Comparative Study with LSTM on the Hang Seng Index

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***Abstract*—This paper investigates whether xLSTM, a recent extension of LSTM networks, provides advantages for financial time series forecasting. Using Hang Seng Index data, we conducted a comparative analysis of xLSTM and conventional LSTM models under multiple signal decomposition frameworks, including EEMD, CEEMD, and UPEMD. Our experimental results demonstrate that UPEMD-LSTM achieves the best performance with a MAPE of 0.52%, and UPEMD-xLSTM follows with a MAPE of 0.72%. The comparison between architectures reveals that the benefits of xLSTM are conditional on proper signal preprocessing. Consequently, architectural improvements alone are not sufficient for financial prediction. The results of this study offer evidence-based recommendations on the deployment of xLSTM architectures for financial prediction tasks and demonstrate that domain-specific preprocessing remains essential to achieve superior forecast performance.**

***Index Terms*—xLSTM, LSTM, Signal Decomposition, UPEMD, Financial Time Series, Stock Prediction, Hang Seng Index**

I. Introduction

Financial time series forecasting remains one of the most challenging problems in both academic research and practical applications due to the inherent complexity of financial markets. These markets are characterized by non-stationary dynamics, nonlinear dependencies, volatility clustering, fat-tailed return distributions, and regime shifts [1]. Long Short-Term Memory (LSTM) networks have emerged as a powerful tool to model temporal dependencies in financial data, demonstrating superior performance over traditional statistical methods [2], [3]. However, LSTM architectures face persistent challenges, including gradient vanishing in very long sequences, limited memory capacity, and difficulties in capturing multi-scale temporal patterns that characterize financial markets [4], [5].

Recently, extended LSTM (xLSTM) was introduced [4], [5] to handle the fundamental limitations of traditional LSTM through two key innovations, exponential gating mechanisms in scalar LSTM (sLSTM) and matrix memory structures in matrix LSTM (mLSTM). These architectural improvements have demonstrated remarkable success in natural language processing (NLP) tasks, achieving performance competitive with state-of-the-art Transformer models while maintaining the computational efficiency of recurrent architectures [4], [5]. The exponential gating allows for stronger gradient flow and more flexible information retention, while matrix memory enables richer representational capacity through structured memory updates. Despite these promising results in NLP, the applicability of xLSTM to financial time series forecasting remains largely unexplored, raising a critical question, i.e., do the architectural improvements of xLSTM translate to better performance in financial prediction, or do financial time series require domain-specific adaptations?

The financial domain presents unique challenges that differ substantially from NLP applications. Financial time series exhibit complex multi-scale patterns, sudden regime changes, and extreme sensitivity to external shocks. These characteristics may require architectural considerations different from language modeling. Furthermore, signal decomposition methods such as empirical mode decomposition (EMD) and its variants have proven to be effective for handling non-stationary financial data by decomposing complex signals into simpler intrinsic mode functions (IMFs) [6]–[8]. However, the interaction between advanced recurrent architectures and decomposition preprocessing techniques has not been systematically investigated.

This paper aims to fill these gaps by conducting a comprehensive empirical study based on data from the Hang Seng Index (HSI). We investigate three key research questions as follows. (1) Does xLSTM outperform traditional LSTM for financial forecasting? (2) How do different signal decomposition methods (EEMD, CEEMD, UPEMD) affect model performance? (3) Which combination of architecture and signal decomposition yields optimal results? Our experimental results reveal that UPEMD-LSTM achieves the best performance with a MAPE value of 0.52%, followed by UPEMD-xLSTM (0.72%). Interestingly, xLSTM demonstrates superiority over LSTM only when combined with EEMD decomposition, whereas LSTM-based models exhibit better performance with CEEMD and UPEMD preprocessing. It suggests that architectural innovation alone is insufficient for financial prediction tasks.

The contributions of this study are as follows.

- We establish a comprehensive experimental framework systematically comparing LSTM and xLSTM architectures combined with various signal decomposition methods (EEMD, CEEMD, UPEMD) for financial time series forecasting.
- We demonstrate that preprocessing quality, particularly UPEMD, contributes more significantly to predictive performance than architectural sophistication, with UPEMD-LSTM achieving the lowest MAPE (0.52%) among all tested configurations.
- We provide empirical insights and practical guidelines for financial forecasting, i.e., (1) prioritizing high-quality feature engineering over complex architectures and (2) identifying that the benefits of xLSTM are method-dependent rather than universal.

II. Related Work

In this section, we briefly introduce related work, including model architectures and signal decomposition methods.

A. Long Short-Term Memory Networks

Traditional recurrent neural networks (RNN) suffer from the vanishing gradient problem, which limits their ability to learn long-term dependencies [9]. Long Short-Term Memory (LSTM) networks [10], deal with the problem of vanishing gradients in RNNs through a gating mechanism that controls the flow of information. The architecture employs three gates, the input gate, the forget gate, and the output gate, to regulate the cell state, allowing the network to selectively retain or discard information over long sequences [11]. The cell state c_t is updated through the forget gate f_t, the input gate i_t, and the cell inputs z_t, while the output gate o_t controls the hidden state h_t as

$$c_t = f_t \odot c_{t-1} + i_t \odot z_t, \quad h_t = o_t \odot \psi(c_t), \tag{1}$$

where $\odot$ denotes element-wise multiplication, and ψ is a nonlinear activation function. This feature makes it the dominant architecture for time series forecasting prior to recent advances such as xLSTM [12].

B. xLSTM Architecture

Extended LSTM (xLSTM), introduced by Beck *et al.* [4], [5], represents a substantial architectural refinement of the classical LSTM framework. The xLSTM incorporates exponential gating functions and higher-capacity memory structures to alleviate intrinsic representational and scaling limitations observed in standard LSTM models. The architecture is organized into two fundamental modules, scalar LSTM (sLSTM) and matrix LSTM (mLSTM), each formulated to overcome specific theoretical and operational limitations of conventional LSTM models.

The sLSTM block introduces an exponential gating mechanism for the input gate, replacing standard sigmoid activation (σ) with an exponential function. This modification enables a more flexible information flow and stronger gradient propagation. Specifically, the input gate is computed as $i_t = \exp(\tilde{\mathbf{i}}_t)$, where $\tilde{\mathbf{i}}_t = \mathbf{W}_i\mathbf{x}_t + \mathbf{R}_i\mathbf{h}_{t-1} + \mathbf{b}_i$ to allow for potentially unbounded activation values. To prevent numerical instability from exponential growth, sLSTM incorporates a normalization mechanism that tracks the maximum gate activation and normalizes the cell state accordingly [4], where $m_t = \max(\log(\mathbf{f}_t) + m_{t-1}, \log(\mathbf{i}_t))$ is chosen to stabilize the exponential function. This design preserves the benefits of exponential gating while maintaining the stability of the training.

The mLSTM block replaces the scalar hidden state with a matrix memory structure, enabling richer representational capacity through covariance-like updates. Drawing inspiration from attention mechanisms in Transformers [13], mLSTM uses query, key, and value projections to update its matrix memory as $\mathbf{C}_t = f_t \odot \mathbf{C}_{t-1} + i_t\mathbf{v}_t\mathbf{k}_t^T$. This formulation allows the model to maintain structured relationships between different feature dimensions, providing greater modeling capacity than traditional scalar-based approaches [4], [5]. The matrix memory can be viewed as storing multiple competing hypotheses about the temporal dynamics, which are then queried at each time step.

Although xLSTM has demonstrated impressive results in language modeling tasks, achieving performance comparable to that of Transformers with significantly fewer parameters [4], its application beyond NLP remains limited. To our knowledge, no prior work has systematically evaluated xLSTM for financial time series forecasting, leaving open questions about its effectiveness in domains with different data characteristics.

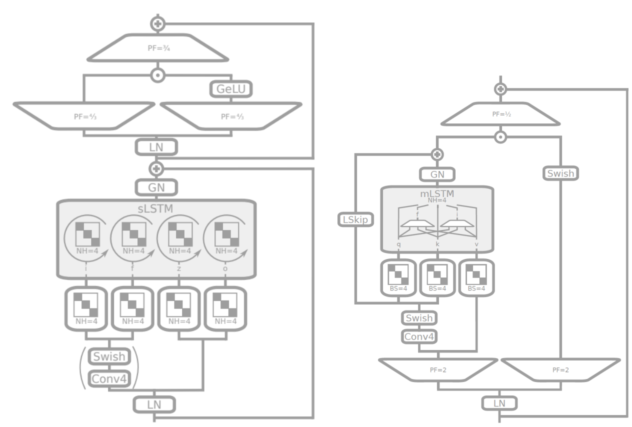


Fig. 1: Structure of xLSTM. (a) The sLSTM Block; (b) The mLSTM Block. (Adopted from [4]).

C. Signal Decomposition for Financial Forecasting

Empirical mode decomposition (EMD) is an adaptive method to decompose nonlinear and nonstationary time series [14]. Although EMD has been widely applied, it exhibits certain limitations when analyzing intermittent signals, leading to the well-known mode-mixing problem [14], [15]. Several modified approaches have been developed to overcome this limitation by introducing controlled perturbations to the original signal. For example, the ensemble empirical mode decomposition (EEMD) employs noise-assisted perturbation to reduce mode mixing [16]. Nevertheless, EEMD can introduce side effects such as mode splitting and residual noise. To solve these problems, further refinements have been developed, including complete ensemble empirical mode decomposition (CEEMD) [17], [18], improved CEEMD (ICEEMD) [19], and uniform phase empirical mode decomposition (UPEMD) [20].

EMD and its variants have gained significant attention for financial time series analysis due to their ability to adaptively decompose non-stationary signals into intrinsic mode functions (IMFs) representing different frequency components. Notable prior studies include applications of empirical mode decomposition (EMD) [6], [21], ensemble empirical mode decomposition (EEMD) [22], and CEEMD [23]. However, prior work has mainly focused on combining decomposition methods with traditional LSTM or simpler neural networks, leaving unexplored potential fusion with more advanced architectures such as xLSTM.

D. LSTM and xLSTM for Financial Time Series Forecasting

LSTM networks have become a popular approach for financial prediction due to their ability to capture long-term dependencies in sequential data [3], [12], [24]–[26], and thus could outperform traditional methods for predicting stock prices. Recent work has explored hybrid approaches that integrate LSTM models with signal decomposition methods such as CEEMD [23]. Combining CEEMD and LSTM or LSTM with the attention layer demonstrated improved prediction accuracy compared to existing empirical studies [27]–[30]. In addition, ensemble frameworks incorporating EEMD with a hybrid model structure consisting of CNN, LSTM, and attention mechanisms show promising prediction results [8].

Despite these advances, LSTM-based methods still face challenges in financial applications. Gradient vanishing continues to restrict the effective context window for long sequences, and the fixed-size hidden state often becomes an information bottleneck when capturing the multi-scale dynamics of financial markets.

Although preliminary studies have demonstrated the application of xLSTM in stock price forecasting with performance comparisons against traditional LSTM [31], [32], these works did not integrate feature engineering or preprocessing methods. Meanwhile, other research has explored xLSTM with series decomposition to extract trend and seasonal components [33], but lacked empirical validation in financial data.

III. Experiments

A. Data

We used daily Hang Seng Index (HSI) data from January 2, 2008 to July 31, 2025, comprising 4,328 trading days. The data set includes standard OHLC features (open, high, low, and close) and spans two major market disruptions, the 2008 global financial crisis and the COVID-19 shock from 2020 to 2021, providing a rich temporal landscape with significant regime shifts. This long-horizon data set captures structurally heterogeneous conditions ranging from sustained uptrends and downturns to high-volatility phases, which enables a comprehensive evaluation of model robustness across different economic scenarios. We divide the data chronologically into training and testing sets using a 90/10 split ratio, with 433 samples in the test set.

For signal decomposition experiments, we applied EEMD, CEEMD, and UPEMD to decompose the closing price into 12 intrinsic mode functions (IMFs) that represent components of different frequencies. To establish a benchmark, we further include models trained directly on the raw OHLC inputs without any decomposition. All features are normalized using the min-max scaling fitted on the training set and applied to both the training and the testing data. This design yields eight experimental settings (OHLC-LSTM, EEMD-LSTM, CEEMD-LSTM, UPEMD-LSTM, OHLC-xLSTM, EEMD-xLSTM, CEEMD-xLSTM, and UPEMD-xLSTM), which facilitate systematic comparison of decomposition methods and model architectures.

B. Model Architecture

The LSTM baseline consists of two LSTM layers with 64 hidden units each, followed by a feedforward network with 32 units using PReLU activation. Dropout (rate=0.2) is applied after the first LSTM layer. The model processes sequences of length 5 with 13 input features and outputs a single prediction value. We use the Adam optimizer with mean squared error loss.

Table I summarizes the xLSTM architecture and training configurations. The model consists of four layers that alternate between sLSTM and mLSTM blocks, with residual connections and dropout regularization. For input based on decomposition, the 12 IMFs and the residual component yield 13 input features; the baseline uses 4 features (OHLC). The architecture outputs predictions one-day-ahead. We use Adam optimizer (learning rate: 0.001), batch size 16, and train for 100 epochs. All models share the same architecture, differing only in input dimensions.

TABLE I: Architecture and Hyperparameters of the xLSTM Model

Component	**Specification**
Model Architecture	
Input dimension	13 IMFs or 4 raw features (OHLC)
Sequence length	5 trading days
Hidden units	32
Network structure	4 layers (2 sLSTM + 2 mLSTM)
Dropout rate	0.1
Output dimension	1 (next-day prediction)
Total parameters	$\sim$26,000
Training Configuration	
Batch size	16
Optimization algorithm	Adam
Learning rate	0.001
Number of epochs	100
Loss function	Mean Squared Error (MSE)

C. Empirical Results

Figure 2 visualizes the forecast results of all eight model configurations in the test set. Panel (a) compares the predictions of four LSTM-based models with actual market prices, and panel (b) presents the corresponding results for xLSTM-based models. Among LSTM variants, UPEMD-LSTM (red line) demonstrates the closest predictions to the actual values (black line), while EEMD-LSTM exhibits the largest deviations. Similarly, for xLSTM architectures, UPEMD-xLSTM produces the most accurate predictions, while CEEMD-xLSTM shows the poorest performance.

To quantify these visual observations, we evaluated all models using the mean squared error (MSE) and the mean absolute percentage error (MAPE). Table II summarizes the performance metrics of the test set for all configurations. The results confirm that UPEMD preprocessing consistently yields superior predictive accuracy across both architectures, with UPEMD-LSTM achieving the lowest MAPE of 0.52%.

The findings can also be supported by Figure 3, which shows the distribution of MAPE values across all model configurations using a heatmap visualization. The lighter colors (yellow and light green) clearly indicate the superior performance of the UPEMD-based models, with both UPEMD-LSTM and UPEMD-xLSTM achieving the lowest prediction errors in the test set. In contrast, the EEMD and CEEMD decomposition methods exhibit consistently higher errors, represented by darker colors on the heatmap. The OHLC model configurations demonstrate relatively stable performance across both architectures with moderate errors.

TABLE II: Predictive Performance Comparison on Hang Seng Index Test Set

Model	MSE	MAPE (%)
LSTM-based Models		
OHLC-LSTM	134,595.10	1.34
EEMD-LSTM	165,975.80	1.79
CEEMD-LSTM	76,719.82	1.23
UPEMD-LSTM	**22,385.15**	**0.52**
xLSTM-based Models		
OHLC-xLSTM	144,371.08	1.48
EEMD-xLSTM	118,720.00	1.59
CEEMD-xLSTM	320,461.00	2.01
UPEMD-xLSTM	**32,064.63**	**0.72**

Note: Bold values indicate the best performance within each model family.

Figure 4 presents a direct comparison between LSTM and xLSTM architectures under identical feature sets. The results reveal that xLSTM outperforms LSTM only when combined with EEMD decomposition; for CEEMD and UPEMD preprocessing, traditional LSTM consistently achieves lower prediction errors. Figure 5 further supports this observation by quantifying the relative performance gain of xLSTM over LSTM across different decomposition methods. The figure clearly shows a positive improvement rate only for the EEMD configuration, while CEEMD and UPEMD exhibit negative values, indicating that LSTM outperforms xLSTM in these cases.

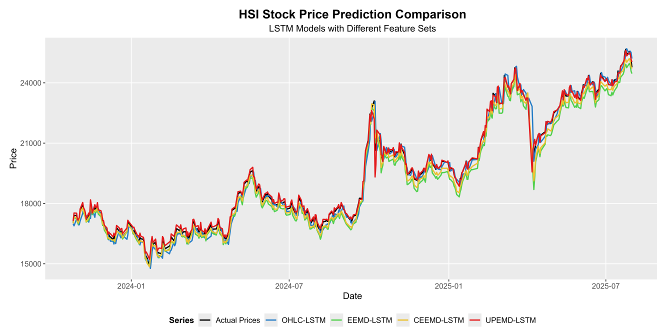
This finding challenges the assumption that architectural sophistication universally translates to improved forecast performance. Specifically, while EEMD-xLSTM demonstrates advantages over EEMD-LSTM, the more refined decomposition methods (CEEMD and UPEMD) enable LSTM to achieve superior accuracy compared to their xLSTM counterparts. These results suggest that the benefits of xLSTM for financial price prediction are conditional on preprocessing quality rather than universally applicable, highlighting that the choice of signal decomposition method may be more critical than architectural complexity for this forecasting task.

In addition, we examine model generalization by comparing performance in training and testing sets to assess potential overfitting. Figure 6 presents this comparison based on MSE values, where the dashed diagonal line represents perfect generalization (training MSE equals testing MSE). Models positioned above this line exhibit overfitting, whereas those below suggest unusual generalization behavior. Our analysis reveals that UPEMD-LSTM and UPEMD-xLSTM both lie nearly on the diagonal line, indicating robust generalization capability with well-balanced training and testing performance. Interestingly, CEEMD-xLSTM exhibits a lower testing MSE than training MSE, a counterintuitive result that indicates the need for further investigation. This phenomenon may arise from random variation in the test set or potential regularization effects during training, although a definitive explanation requires additional empirical analysis. Overall, the figure confirms that UPEMD-based models achieve the best balance between model fitting and generalization, further supporting their superiority for financial forecasting tasks.

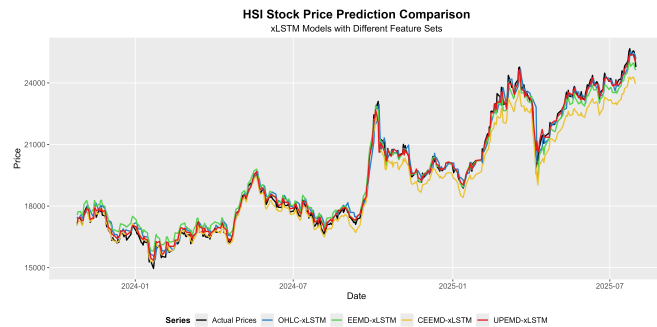
IV. Conclusion

This study aims to investigate the effectiveness of xLSTM architectures for financial time series forecasting through a systematic comparison with traditional LSTM in multiple signal decomposition methods. Using data from the Hang Seng Index during 2008-2025, consisting of major financial crises, we evaluated eight model configurations that combined two architectures (LSTM and xLSTM) with four feature extraction approaches (OHLC baseline, EEMD, CEEMD and UPEMD). Our empirical findings reveal that preprocessing quality, particularly through UPEMD decomposition, dominates architectural sophistication in determining forecast accuracy. UPEMD-LSTM achieves the best performance with a lowest MAPE value of 0.52%, outperforming all other model configurations. Furthermore, xLSTM demonstrates advantages over LSTM only when combined with EEMD decomposition, while traditional LSTM consistently outperforms xLSTM with CEEMD and UPEMD preprocessing. These results challenge the assumption that architectural innovation universally improves performance, highlighting the critical importance of feature engineering in financial forecasting.

Although the xLSTM architecture integrates sophisticated mechanisms such as exponential gating and matrix memory, our empirical evidence suggests that these design innovations do not necessarily yield superior performance in financial



(a) LSTM Models



(b) xLSTM Models

Fig. 2: Comparison of LSTM and xLSTM models for Hang Seng Index one-day-ahead forecasting with different feature sets. (a) shows LSTM predictions; (b) shows xLSTM predictions.

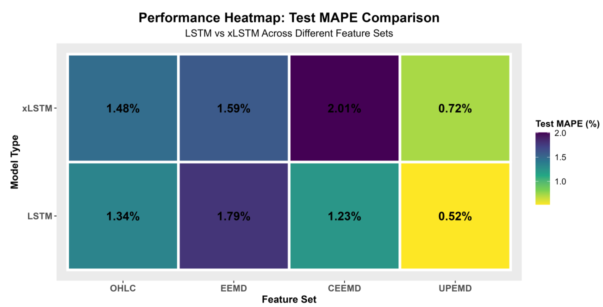


Fig. 3: Test MAPE comparison heatmap across models and feature sets. Lighter colors indicate better performance.

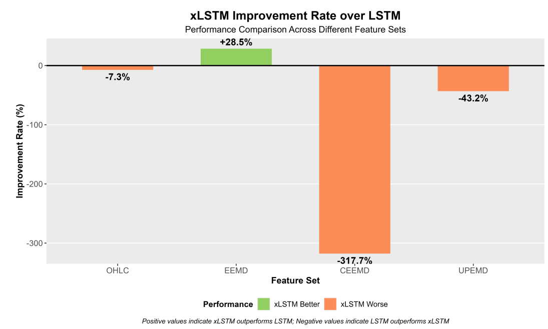
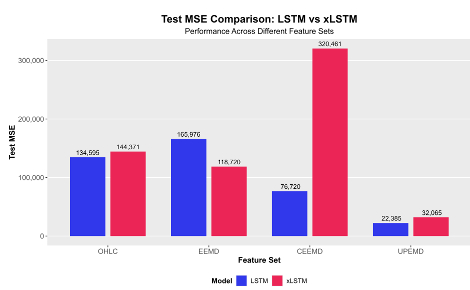
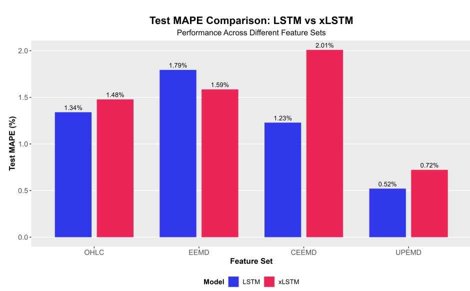


Fig. 5: Performance improvement rate of xLSTM relative to LSTM. Positive values indicate xLSTM outperforms LSTM, while negative values indicate the opposite.



(a) Test MSE comparison



(b) Test MAPE comparison

Fig. 4: Performance comparison between LSTM and xLSTM models across different feature sets. Lower values indicate better performance.

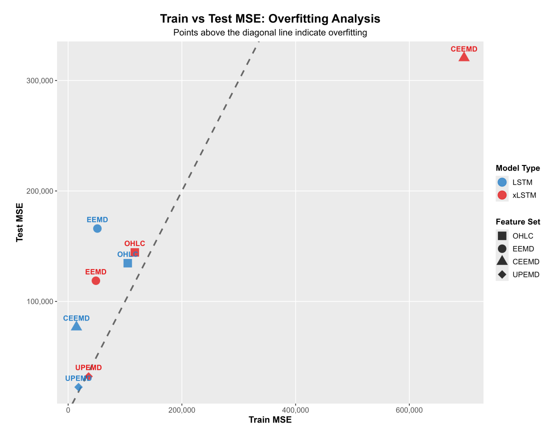


Fig. 6: Training and testing MSE for overfitting analysis. Points above the diagonal line indicate overfitting, with distance from the line reflecting severity.

applications. The performance of xLSTM appears highly conditional, improving only when preprocessing is less refined. In contrast, when preprocessing is inadequate, the improved capacity of xLSTM can partially compensate for the lack of signal refinement. This finding has important practical implications, i.e., practitioners should prioritize investment in robust feature engineering over complex model architectures.

Future work should extend this analysis in several directions. First, investigating different input sequence lengths would reveal how short-term versus long-term temporal dependencies influence model performance. Second, evaluating multi-step-ahead predictions (e.g., 5-day, 10-day, 20-day horizons) would assess model robustness across varying forecast horizons. Third, validating these findings across multiple financial markets and asset classes would establish the generalizability of our conclusions. Finally, exploring the interaction mechanisms between decomposition quality and architectural complexity could provide a deeper theoretical understanding of when architectural sophistication becomes beneficial.

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