A Novel Hybrid HO-CAL Framework for Enhanced Stock Index Prediction

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***Abstract*—The accurate prediction of stock indexes plays a critical role in supporting investment decisions and managing financial risks. This study proposed a novel hybrid deep learning model that integrated the strengths of Convolutional Neural Networks (CNN), the Attention mechanism, and Long Short-Term Memory (LSTM) networks to enhance the modelling of temporal patterns in financial time series. To further improve the prediction performance, the Hippopotamus Optimization (HO) algorithm was incorporated to fine-tune the networks parameters. This is the first application of the CNN-Attention-LSTM (CAL) architecture to stock index prediction. Ablation experiments revealed that the proposed CAL significantly outperformed traditional CNN, LSTM, and CNN-LSTM models, highlighting the effectiveness of the Attention-based architecture. Comparative analyses also demonstrated that the HO-optimized CAL (HO-CAL) model achieved superior predictive accuracy across multiple markets, confirming both the robustness of the hybrid model and the optimization algorithm. These findings underscore the potential of combining deep learning architectures with metaheuristic optimization to improve the prediction accuracy in financial markets, offering valuable insights for real-world investment strategies.**

Keywords*—*Attention mechanism; CNN; LSTM; stock index; hippopotamus optimization algorithm

I. Introduction

With the rapid development of the global economy and increasing maturity of financial markets, stocks play an important role in economic progress [1]. It has become an important investment tool for investors due to its high return characteristics. In the stock market, accurate price prediction is important for investors' decision making and risk management [2]. Nevertheless, the stock market is highly volatile and stock data are characterized by large volume, non-linearity, and noise, which makes accurate prediction extremely challenging [3]. The stock index as an investment weathervane is especially critical. Thus, exploring more efficient and accurate prediction methods has attracted increasing attention from researchers and investors.

Traditional econometric methods, such as ARIMA and GARCH, perform better on low-volatility time series, yet they are unable to deal with high-dimensional and highly nonlinear financial data as complexity and uncertainty increase [4]. Machine learning methods such as Random Forest (RF) and Support Vector Machine can learn the nonlinear relationship between stocks and various impact factors effectively [5]. However, these methods are limited in dealing with noise and missing data and rely too much on feature selection, which leads the prediction accuracy to be difficult to reach the expectation [6]. Recently, deep learning has been shown to perform better than traditional machine learning in stock price analysis because its stronger learning and adaptive capabilities [7]. Most representative neural networks have superior nonlinear generalization abilities. Such as convolutional neural networks (CNN) and long short-term memory networks (LSTM) have become the first choices for handling financial time series, and the applications include stock price, volatility, and trend prediction [8]. However, there are still some significant weaknesses in the existing methods: insufficient modelling of sequence patterns, poor extraction of deep data features, and difficulties in handling large-scale long-term data owing to overfitting and gradient issues [9].

To address these issues, this study proposes a novel short-term stock index prediction model. First, CNN is utilized to extract deep features from stock data, then the Attention mechanism is introduced to assign higher weights to key features, and finally, LSTM is used to mine long-term time series features, that is, the CNN-Attention-LSTM (CAL) hybrid model. The three work in concert to extract more comprehensive and in-depth feature information over multiple time periods, to adapt to the characteristics and requirements of short-term stock prediction and improve the prediction accuracy.

It should be noted that the choice of neural network hyperparameters has a significant impact on the prediction performance [10], and the hyperparameters of CAL are numerous and interrelated. Traditional hyperparameter tuning methods, such as Grid Search and Random Search, are inefficient and prone to falling into local optimal solutions [11]. To address this problem, researchers have used optimization algorithms to automatically find the suitable hyperparameters of the model, such as the Genetic Algorithm and Particle Swarm Optimization (PSO). As an emerging metaheuristic optimization algorithm, the Hippopotamus Optimization (HO) algorithm simulates the feeding and social behaviors of hippos in nature [12]. It shows strong potential for solving complex optimization problems, with the advantages of fast convergence, strong global search capability, and easy implementation [13]. And the HO tends to perform better in dealing with high-dimensional, nonlinear, and multimodal problems than traditional algorithms like Grid Search, PSO and others [14].

As this study intends to enhance short-term stock index prediction, HO was utilized to explore the optimal hyperparameter combination of CAL (HO-CAL). Several international indexes were presented to examine the superiority of the HO-CAL hybrid optimization framework. The contributions of this study are as follows:

- The CAL architecture integrates the advantages of different blocks. It realizes a breakthrough in extracting multi-dimensional features and fully exploits temporal information in the sequence. It not only captures the local features and long-term dependencies but also automatically focuses on the most important parts of the input. It shows good adaptability when facing different markets and effectively improves the prediction performance and generalization ability;
- The pioneering use of HO to optimize the CAL model, which plays a significant role in improving the prediction accuracy and robustness, contributes to the current research on combining optimization algorithms and deep learning.
- The experimental results show that HO-CAL can capture complex relationships and patterns in stock data and accurately predict the international indexes, which can help investors manage their assets more efficiently and allocate capital more adequately.

The remainder of the study is organized as follows: Section II reviews some related work; Section III elaborates on the architecture of the proposed model and the optimization process; Section IV introduces the experimental settings; Section V analyses and discusses the experimental results; and Section VI provides the conclusion of this study.

II. Related Work

A. *Deep Learning Models for Time Series Prediction*

Multivariate time series prediction has a wide range of applications in industry, finance, meteorology and other fields [15]. An increasing number of finance scholars have begun to use neural networks to build stock prediction models, which have achieved remarkable results. Deng et al. [16] utilized a CNN model to extract the structured features of a time series through multilayer convolutional operations and achieved good prediction results. Li et al. [17] proposed an LSTM model for predicting stock prices by preserving historical information through memory cells. Similarly, the integration architecture of CNN-LSTM is applied in stock market analysis [18], which captures the market fluctuation patterns by analyzing stock prices, volumes, and financial data. This assisted investors in formulating scientific investment strategies and effectively reducing investment risk. However, the dynamic interaction modelling ability of CNN-LSTM for temporal features is still limited by its static weight allocation mechanism [19]. Abbasimehr and Paki [20] proposed an Attention-based LSTM time series prediction model that dynamically assigned weights through an Attention layer to focus on key information, resulting in improved prediction accuracy.

B. *Hybrid Deep Learning Architectures*

The use of a single model often makes it difficult to simultaneously consider spatial features, temporal dependence and key information screening needs. Thus, combining CNN, LSTM and Attention has gradually become a research topic. Yi et al. [21] adopted the combined LSTM-CNN Attention model in short-term load prediction, which innovatively used convolutional kernels to extract the stochasticity of the user and solve the problem of non-smooth characteristics. Experiments proved that the model reduced the amount of input data, and the prediction accuracy outperformed the benchmark by more than 10%. Shi et al. [22] predicted stock prices by initially extracting the deep features of raw data through an Attention-based CNN-LSTM model and then fine-tuning them using XGBoost. It improved prediction accuracy, and helped investors realize income growth and risk avoidance. Borré et al. [23] proposed a hybrid LSTM-CNN architecture with the introduction of Attention mechanism and Gated Residual Networks. The experimental results showed that the proposed model performs well in predicting extreme events. Peng et al. [24] used an Attention-based CNN-LSTM model to predict multiple currencies simultaneously, which better captured the correlation between different frequencies and currencies. The model improved the prediction accuracy, and reduced the transaction cost and investment risk. LÜ et al. [25] used CNN-LSTM-Attention to effectively capture the spatial-temporal correlation of soil moisture, and its RMSE was reduced by 49% and 57% compared to LSTM and CNN-LSTM models, respectively.

C. *Metaheuristic Optimization*

Alongside advances in deep learning models architecture, the application of metaheuristic optimization for hyperparameter tuning in models has also received increasing attention. Although HO is still in the early stages of research, it has attracted attention owing to its simple structure and ease of integration with deep learning models. Maurya et al. [14] used HO to optimize distributed power planning and network reconfiguration under different load models and then compared it with PSO, whale optimization, grasshopper optimization, zebra optimization, coot bird optimizer, and firefly algorithms, proved the superiority of HO. Mashru et al. [26] proposed a multi-objective hippopotamus optimizer and compared it with six well-known swarm intelligence algorithms, which demonstrated the effectiveness of HO in dealing with structural optimization problems.

With the rapid evolution of deep learning, CAL model has emerged as a powerful tool for dealing with time series due to their capacity to jointly capture local patterns, sequential dependencies, and key feature importance. Meanwhile, the HO algorithm offers an efficient method for tuning hyperparameters of such deep architectures, further enhancing their performance in noisy stock market environments. While existing research still faces several limitations. Many hybrid models inadequately address the challenge of hyperparameter adjusting, often relying on inefficient or limited optimization strategies. Moreover, few studies systematically evaluate the integration of attention-based deep learning models with metaheuristic algorithms in the context of stock index prediction. To bridge this gap, this study proposes a novel HO-CAL model that combines the CNN-Attention-LSTM model with hippopotamus optimization algorithm for hyperparameter tuning. This approach is designed to enhance model robustness, accuracy, and adaptability across diverse market environments, offering both theoretical advancement and practical guidance for financial prediction.

III. Methodology

HO-CAL is a hybrid optimization deep learning framework that combines three different types of neural network layers as well as an optimization algorithm to fully capture financial information and temporal features in the data with the following basis.

A. Convolutional Neural Networks

A CNN can effectively extract local patterns and features from a time series by sliding a convolutional kernel over the input data to scan it, as shown in Fig. 1. And pooling layer is usually added after the convolutional layer to reduce the feature dimension of the data and reduce the computational complexity [27]. Therefore, in this study, when facing a large amount of stock time series, a 1D-CNN was used to extract features and reduce their dimensionality to make the learning effect more accurate and concise.

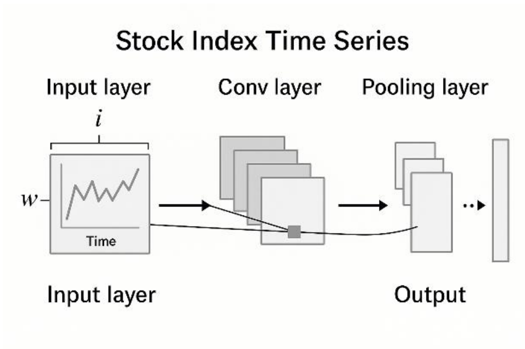

Fig. 1. CNN process structure.

B. Squeeze-and-Excitation Attention

CNN cannot distinguish the importance of information during learning [28]. While the Attention is extremely specialized in capturing critical nodes in sequence processing [29]. SE Attention is designed to improve the model performance by adaptively adjusting the weights of the feature channels. The Squeeze part extracts the global features by reducing the features size to 1×1 through a global average pooling operation. This step compresses the features of each channel into a scalar value to form a channel description vector. The Excitation part learns the channel weights through a series of fully connected layers and activation functions. These weights are used to weight the features and enhance the important feature channels. Its core formulas are as follows:

$$\mathrm{s} = \sigma\big(\mathrm{W}_2 \cdot \delta(\mathrm{W}_1 \cdot \mathrm{z})\big) \tag{1}$$

$$z_c = \frac{1}{H\times W}\sum_{i,j} U_c(i,j) \tag{2}$$

$$\widetilde{U}_c = s_c \cdot U_c \tag{3}$$

where H, W are the feature dimensions and C is the number of channels. Attention enables the proposed model to automatically focus on the key features in massive information, significantly improving the relevance of data processing. Therefore, the introduction of Attention is expected to further enhance the accuracy of stock index predictions.

C. Long Short-Term Memory Networks

LSTM is used to process the temporal correlation of the sequence data. It adopts a unique gating mechanism to effectively manage the flow and memory of information, avoiding the loss of important information [30]. The gating unit of the LSTM consists of an input gate (i_t), forgetting gate (f_t), output gate (o_t) and cell status (C_t). The following equations express the relationship between these four:

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \tag{4}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{6}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{7}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{8}$$

$$h_t = o_t * \tanh(C_t) \tag{9}$$

where x_t is the input at the current moment, h_{t-1} is the output at the previous moment, σ is the sigmoid function, and W, b are the weight and deviation of the neuron respectively. The i_t determines the degree of acceptance of new information, the f_t controls the reservation ratio of historical information, and the o_t filters out critical information for current decision making. This sophisticated gating mechanism enables LSTM to effectively deal with long-term dependencies in sequence data.

D. CNN-Attention-LSTM

The accurate prediction of stock prices is crucial and previous studies have verified the effectiveness of various single models. However, there is still much potential to improve prediction accuracy, especially in the context of model integration and complementarity. Therefore, this study proposes an enhanced stock index prediction method based on the CAL architecture as shown in Fig. 2. And the specific implementation steps are as follows:

Step 1: Input: stock historical data $[T \times F \times 1]$, where T denotes the time step and F denotes the feature dimension;

Step 2: Feature extraction (CNN): local features are extracted from the input data and deep temporal features are gradually extracted through two convolutional layers with an activation function to improve the model expression ability;

Step 3: Attention weighting (Attention): extraction from the last step is fed into the SE Attention module. The importance weights of each channel are calculated and are weighted by fusion with the original features, thereby enhancing the key features and suppressing redundant information;

Step 4: Sequence modelling (LSTM): the weighted feature sequences are input into the LSTM network to further model the long-term dependencies in the time dimension and extract the time series information;

Step 5: Prediction output: the LSTM output is mapped through the fully connected layer to obtain the final predicted price.

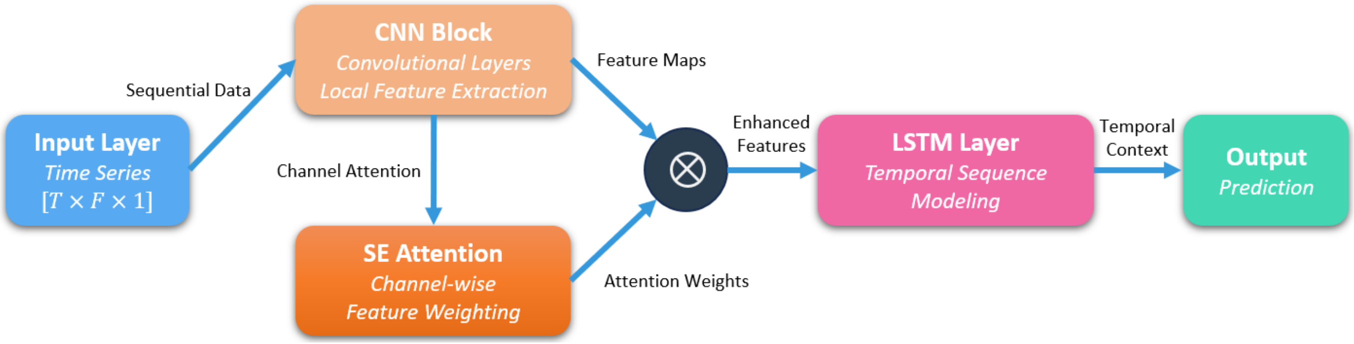

Fig. 2. CAL architecture for stock index prediction.

It can be found that CAL integrates the feature extraction capability of CNN, the channel feature weighting capability of Attention mechanism, and the temporal modelling capability of LSTM. Its innovation lies in integrating different types of neural network layers to form an efficient temporal prediction architecture, which can improve prediction accuracy.

E. Hippopotamus Optimization Algorithm

CAL has a complex hyperparameter space, and the combination of these hyperparameters can significantly affect the prediction accuracy and generalization ability of the model. HO is the newest metaheuristic optimization algorithm proposed by Amiri et al. [12] in 2024. It simulates the dynamic response strategy of hippos under different environmental conditions, which is an SI algorithm based on stochastic search. The HO algorithm consists of the following three stages:

The initialization of HO involves the generation of stochastic initial solutions, and the decision variables are

$$x_{ij} = lb_j + r * (ub_j - lb_j), i = 1,2,\cdots,N; j = 1,2,\cdots,m \quad (10)$$

where r is a random number within $(0,1)$, lb_j and ub_j are the upper and lower bounds of the jth dimension respectively.

Phase I: Position updating (Exploration). The dominant hippo individual in the group (the optimal solution) guides the other individuals to update positions, which can be expressed as

$$x_{ij}^{M} = x_{ij} + y_1 \cdot (D_{hippo} - I_1 \cdot x_{ij}) \quad (11)$$

where x_{ij} denotes the position of the ith hippo in the jth dimension, D_{hippo} is the position of the dominant male hippo, y_1 is a random number within $[0,1]$, and I_1 represents the distance reduction factor. The position update formula for a female or immature hippos is as follows:

$$x_{ij}^{FM} = \begin{cases} x_{ij} + h_1 \cdot (D_{hippo} - I_2 \cdot MG_i), & T > 0.6 \\ \Delta, & \text{else} \end{cases} \quad (12)$$

$$\Delta = \begin{cases} x_{ij} + h_2 \cdot (MG_i - D_{hippo}), & r_6 > 0.5 \\ lb_j + r_7 (ub_j - lb_j), & \text{else} \end{cases} \quad (13)$$

$$T = \exp\left(-\frac{t}{\text{Maxiteration}}\right) \quad (14)$$

where I_2 is an integer between $[1,2]$, MG_i denotes the average position of some randomly selected hippos from the population, r_6 and r_7 are random numbers between $[0,1]$, and h_1 and h_2 are randomly selected numbers. The following equation describes the update of the position of hippos in the population:

$$x_i = \begin{cases} x_i, & F_i^M < F_i \\ x_i, & \text{else} \end{cases} \quad (15)$$

Phase II: Defence against predators (Exploration). Avoiding the algorithm falling into a local optimal solution by simulating the hippos' defence strategy when threatened by a predator. The predator position is denoted by

$$\text{Predator}_j = lb_j + \mathbf{r}_8 \cdot (ub_j - lb_j) \quad (16)$$

where $\mathbf{r}_8$ is a random vector within $[0,1]$. The hippos respond to a predator as

$$x_{ij}^{HippoR} = \begin{cases} \mathbf{RL} \oplus \text{Predator}_j + \frac{f}{c - d \times \cos(2\pi g)} \cdot \frac{1}{\mathbf{D}}, & F_{\text{Predator}_j} < F_i \\ \mathbf{RL} \oplus \text{Predator}_j + \frac{f}{c - d \times \cos(2\pi g)} \cdot \frac{1}{\mathbf{D} + \mathbf{r}_9}, & \text{else} \end{cases} \quad (17)$$

where **RL** is a random vector with a Lévy distribution to model the fast-acting behaviour of hippos during attacks, and f, c, d, and g are random numbers to control the intensity and direction of the hippos' response. The position of the ith hippo is updated by

$$x_i = \begin{cases} x_i^{HippoR}, & F_i^{HippoR} < F_i \\ x_i, & \text{else} \end{cases} \quad (18)$$

Phase III: Escaping from predator (Exploitation). Focus on efficient localized search in the solution space to improve the accuracy and quality of the solution. Hippos escape position update:

$$x_{ij}^{hippo\varepsilon} = x_{ij} + r_{10} \cdot (lb_j^{local} + s_1 \cdot (ub_j^{local} - lb_j^{local})) \quad (19)$$

$$lb_j^{local} = \frac{lb_j}{t}, ub_j^{local} = \frac{ub_j}{t} \quad (20)$$

Fig. 3 shows the specific process of HO adjustment of the CAL hyperparameters. HO begins by randomly initializing a population of hippo individuals, where each represents a set of CAL hyperparameters. In the fitness evaluation section, each individual's hyperparameter configuration was used to train the CAL, with the RMSE on the validation set serving as the fitness value. The algorithm then updates each individual's position according to HO principles, effectively adjusting the CAL hyperparameters. This process iterates until the convergence criteria are reached, and the optimal hyperparameters that minimize the prediction error are obtained.

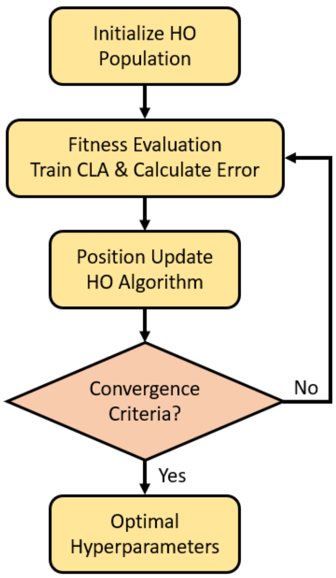

Fig. 3. CAL hyperparameter optimization via the HO algorithm.

IV. Experimental Process

For stock index prediction evaluation, all experiments were conducted on a Windows 11 system using a CPU (13th Gen Intel Core i7-13700H) and GPU (NVIDIA GeForce RTX 3050 4GB). And the prediction models were implemented in MATLAB (R2024b).

A. Data Pre-Processing

This study targets the CSI 300 Index in China, which is regarded as a trend indicator for the Shanghai and Shenzhen markets. It covers 300 A-shares with large market capitalization and high liquidity. The research period is from January 7, 2019 to December 27, 2024, with 1,451 trading days. The proposed model is based on technical analysis and is premised on the identification of behavioral patterns in historical series. Thus, referring to Paiva et al. [31], Table I summarizes 21 technical indicators were used as inputs for the prediction, including return rate indicators calculated based on opening (O), closing (C), high (H) and low (L) prices, as well as momentum, volatility, and volume related indicators etc.

There is a considerable difference in the scale of the above features. The normalization process helps to speed up the convergence of the loss function, prevent gradient explosion in network training, and improve the computational accuracy [5]. Therefore, this study applies the Min-Max normalization method to transform the data between [0,1], and the calculation process is as follows:

$$\mathbf{X}_{\text{new}} = \frac{\mathbf{X}-\mathbf{X}_{\text{min}}}{\mathbf{X}_{\text{max}}-\mathbf{X}_{\text{min}}} \tag{21}$$

where X is the original technical indicators matrix, X_{max} and X_{min} are the maximum and minimum values of X, respectively, and X_{new} is the new value after normalization.

TABLE I. Summary of Stock Index Prediction Variables

Return Rate Indicators		Technical Indicators
$v_1 = ln\left(\frac{C_t}{C_{t-1}}\right)$	$v_8 = ln\left(\frac{H_{t-1}}{O_{t-1}}\right)$	Momentum (close price, period = 10)
$v_2 = ln\left(\frac{C_{t-1}}{C_{t-2}}\right)$	$v_9 = ln\left(\frac{H_{t-2}}{O_{t-2}}\right)$	Relative strength index (close price, period = 14)
$v_3 = ln\left(\frac{C_{t-2}}{C_{t-3}}\right)$	$v_{10} = ln\left(\frac{H_{t-3}}{O_{t-3}}\right)$	Parabolic SAR (high and low price, acceleration = 0, maximum = 0)
$v_4 = ln\left(\frac{H_t}{O_t}\right)$	$v_{11} = ln\left(\frac{L_t}{O_t}\right)$	Average true range (high, low and close price, period = 14)
$v_5 = ln\left(\frac{H_t}{O_{t-1}}\right)$	$v_{12} = ln\left(\frac{L_{t-1}}{O_{t-1}}\right)$	True range (high, low, and close price)
$v_6 = ln\left(\frac{H_t}{O_{t-2}}\right)$	$v_{13} = ln\left(\frac{L_{t-2}}{O_{t-2}}\right)$	Chaikin A/D line (high, low, and close price; volume)
$v_7 = ln\left(\frac{H_t}{O_{t-3}}\right)$	$v_{14} = ln\left(\frac{L_{t-3}}{O_{t-3}}\right)$	On balance volume (close price, volume)

B. Sliding Window and Evaluation Metrics

This study uses the technical indicators of the past 20 days to predict the closing price of the next day. And a sliding window approach was conducted for the six-year index data: the first three years of data were used to train the model; the following year was used as a validation set for optimally tuning the CAL hyperparameters; and the subsequent year is used as a test set to examine the prediction ability. And each completed cycle slides forward for one year, ultimately obtaining daily predicted closing price for 2023 and 2024.

In order to evaluate the model prediction performance, this research employed six evaluation metrics. They are Mean Absolute Error, Mean Absolute Percentage Error, Mean Square Error, RMSE, R^2 and Relative Error, which are calculated as follows:

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N} |r_t - \hat{r}_t| \tag{22}$$

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N} \left|\frac{r_t-\hat{r}_t}{r_t}\right| \tag{23}$$

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{N} (r_t - \hat{r}_t)^2 \tag{24}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N} (r_t - \hat{r}_t)^2} \tag{25}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{N} (r_t-\hat{r}_t)^2}{\sum_{t=1}^{N} (r_t-\bar{r})^2} \tag{26}$$

$$\text{Relative Error} = \frac{\hat{r}_t-r_t}{r_t} \tag{27}$$

where r_t, $\hat{r}_t$ represent actual close price and predictive close price at time t respectively.

V. Experimental Results and Discussion

This section presents and discusses several experimental evaluations of the proposed HO-CAL framework through systematic analysis across multiple perspectives, including ablation studies, optimization effectiveness comparisons, and robustness across international stock markets. Beyond the quantitative outcomes, we also contextualize these findings by comparing them with existing literature and by evaluating how the model addresses the challenges identified in earlier sections.

A. *Ablation Experiment*

In order to verify the effectiveness of the proposed CAL model for short-term stock index prediction, Table II presents a comparison of the ablation results against several baseline and state-of-the-art methods, including econometric (ARIMA), machine learning (RF), and deep learning (CNN, LSTM, CNN-LSTM).

TABLE II. COMPARISON OF ABLATION RESULTS FOR CAL MODEL

Model	MAE	RMSE	MAPE(%)	R^2
ARIMA	122.86	166.63	3.41	0.897
RF	101.32	139.78	2.75	0.923
CNN [16]	82.04	129.96	2.20	0.947
LSTM [17]	69.25	109.43	1.89	0.957
CNN-LSTM [18]	59.73	91.82	1.49	0.971
CAL	52.41	80.57	1.31	0.978

Among the baseline models, ARIMA shows the worst performance, with an MAE of 122.86 and R^2 of 0.897, indicating its limited capacity to capture the nonlinear characteristics of stocks. In contrast, the RF model significantly improved the prediction accuracy (MAE: 101.32, R^2: 0.923), highlighting that machine learning methods are better suited for modelling the complex relationships among technical indicators. Meanwhile, CNN achieved an MAE of 82.04, whereas LSTM further reduced it to 69.25, reflecting the effectiveness of temporal modelling in financial time series. All all deep learning models outperformed RF, underscoring their enhanced learning capability and adaptability. The combination of CNN-LSTM resulted in a substantial boost in performance (MAE: 59.73, R^2: 0.971), confirming prior findings that hybrid architectures can integrate complementary strengths of individual components [18], [22].

Building on these findings, the ablation study clearly demonstrates that the CAL model delivered the most accurate and reliable performance, with the lowest MAE (52.41), RMSE (80.57), MAPE (1.31%), and the highest R^2 (0.978). This proves that the addition of the Attention mechanism dynamically allocates weights to important time-dependent features—addressing the static limitation in CNN-LSTM architectures, as previously highlighted by Abbasimehr and Paki [20]. These results align with [21] and [24], who reported that attention-based models significantly improve prediction accuracy by enhancing the model's ability to focus on relevant input segments.

B. *Model Optimization Effectiveness Comparison*

After proving the validity of the CAL model, HO was used to optimize CNN-LSTM and CAL for comparison. Fig. 4 shows the hyperparameter tuning process on the validation set, and it can be seen the HO2 (belonging to CAL) demonstrates markedly superior performance from the initial iteration, with a starting fitness value of 72.35 compared to HO1 (belonging to CNN-LSTM) initial value of 87.29. Throughout the optimization process, HO2 consistently maintains lower fitness values than HO1, ultimately achieving a final fitness value of 50.41 compared to HO1's 55.73, demonstrating the superior optimization ability of HO algorithm. This 10.55% improvement, as well as the consistent and substantial performance differential between the curves, provide strong empirical evidence that the CAL architecture possesses inherently better representational capabilities owing to its Attention mechanisms. Remarkably, both models exhibited rapid convergence within 6 iterations without extensive computational overheads. And the steep descent during the first two iterations followed by gradual stabilization highlights HO's exceptional search efficiency and ability to effectively balance exploration and exploitation phases, which proves that HO is particularly well suited for CAL hyperparameter optimization tasks.

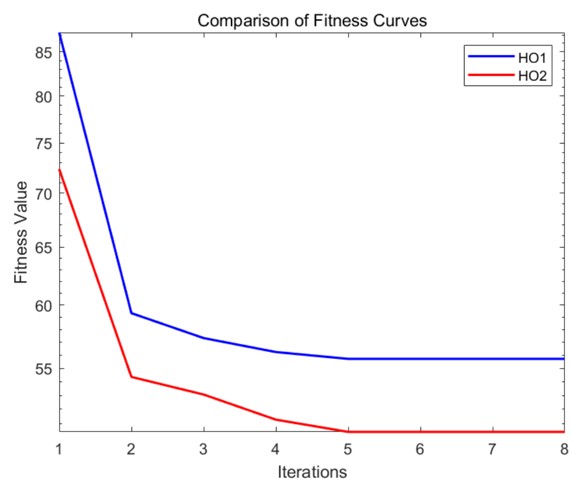

Fig. 4. Convergence analysis of HO for CNN-LSTM and CAL.

The training period spanning from 2019 to 2022 in Fig. 5 demonstrate exceptional model convergence, with all models exhibiting remarkably close alignment with the actual price trajectory. Notably, the models successfully capture major market movements, including the significant upward trend from early 2020 to mid-2021 (reaching peaks around 5,700) and the subsequent downward correction through 2022. The observable differences on the training set are minimal, suggesting that all models have sufficient price recognition capabilities and all have learned effectively.

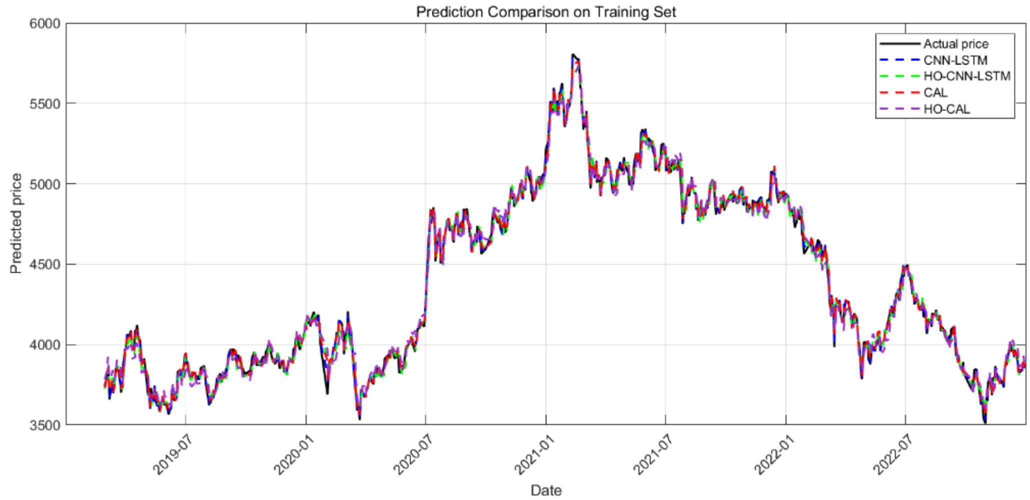

Fig. 5. Prediction performance comparison on training set (2019-2022).

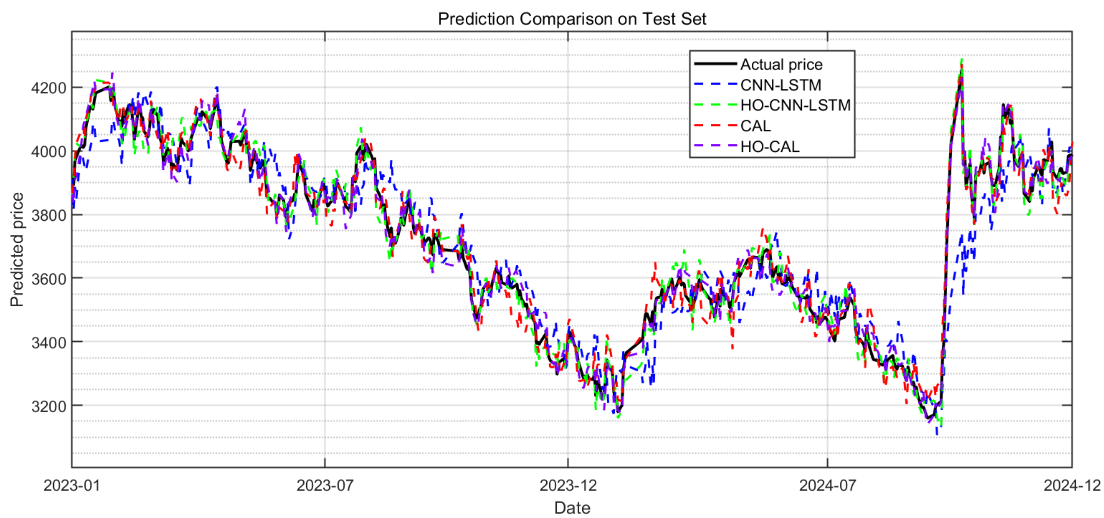

Fig. 6. Prediction performance comparison on testing set (2023-2024).

The testing results for 2023-2024 in Fig. 6 reveal more pronounced performance differentials. The HO-CAL demonstrates superior tracking accuracy, maintaining the closest alignment with actual price movements throughout the testing period. Particularly notable is the model's performance during high-volatility periods, such as the sharp decline in mid-2023 (from ~4,000 to ~3,200) and the subsequent market recovery phases, which captures such extreme events in line with the study in [23]. The CNN-LSTM baseline shows the most significant deviations, particularly during rapid price transitions, while the HO-CNN-LSTM demonstrates improved stability over its non-optimized counterpart. The CAL performs moderately well but lacks the precision achieved by its HO-optimized version. The hyperparameter optimization significantly enhances prediction accuracy, HO-CNN-LSTM and HO-CAL showing reduced prediction volatility and better trend-following capabilities.

The comprehensive performance evaluation presented in Table III demonstrate a clear hierarchical structure. Specifically, HO-CAL attains the lowest MAE of 40.03, representing substantial improvements of 33.0% over CNN-LSTM, 13.5% over HO-CNN-LSTM, and 23.6% over CAL. And the HO algorithm's contribution is consistently significant, with HO-CNN-LSTM showing 19.7% RMSE improvement over CNN-LSTM, and HO-CAL achieving 22.0% improvement over non-optimized CAL. These results confirm the complementary value of model architecture (CAL) and optimization strategy (HO). In line with Maurya et al. [14], who validated HO's superior performance in engineering optimization problems, our results highlight its promising extension to stock prediction.

TABLE III. HO EFFECTIVENESS TEST

Model	MAE	RMSE	MAPE(%)	R^2
CNN-LSTM [18]	59.73	91.82	1.49	0.971
HO-CNN-LSTM	46.29	73.69	1.18	0.984
CAL	52.41	80.57	1.31	0.978
HO-CAL	40.03	62.86	0.99	0.991

The visualization in Fig. 7 provides an intuitive multi-dimensional performance comparison, clearly illustrating the dominance of HO-CAL across all metrics. The radar chart reveals that HO-CAL (represented by the innermost polygon for error metrics and outermost for R^2) consistently achieves optimal or near-optimal performance boundaries. Notably, the visualization emphasizes the substantial performance gap between the optimized and non-optimized models, with both HO-enhanced variants showing marked improvements over their baseline counterparts.

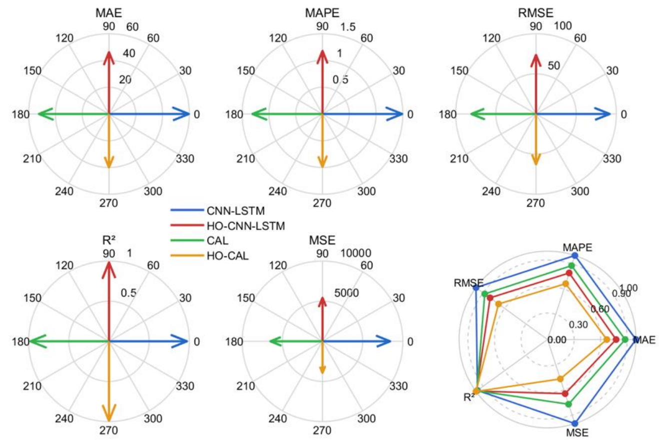

Fig. 7. Multi-dimensional performance evaluation.

The comparison in Fig. 8 provides crucial insights into the temporal distribution and magnitude of relative errors across four models. The error distribution around the zero baseline indicates minimal systematic bias across all models, with relatively balanced positive and negative errors suggesting unbiased prediction behavior. However, the frequency and magnitude of extreme errors vary significantly. The CNN-LSTM exhibiting the most pronounced error volatility, displaying frequent extreme deviations reaching ±4%. These large-magnitude errors are particularly concentrated during periods of high market volatility, indicating the baseline model's limited capacity to handle rapid price fluctuations. In contrast, HO-CAL demonstrates remarkably constrained error boundaries, with the majority of errors confined within ±2% range, representing a 50% reduction in maximum error magnitude compared to CNN-LSTM. The chronological analysis reveals that HO-CAL maintains consistent error stability throughout the entire testing period, with notably reduced error spikes during critical market transitions observed in mid-2023 and late 2024. The HO-CNN-LSTM shows intermediate performance, exhibiting improved stability over the baseline but lacking the precision consistency achieved by Attention-based models. CAL demonstrates moderate error reduction compared to CNN-LSTM, though it occasionally exhibits error spikes that are effectively mitigated in its optimized counterpart HO-CAL. The comparison between optimized and non-optimized model pairs clearly demonstrates the HO algorithm's effectiveness in error reduction, with HO-CAL achieving the most significant improvement in error containment.

The HO-CAL framework integrates CAL networks with the HO algorithm, achieving lower error metrics and improved predictive accuracy. It excels at capturing market turning points and maintaining stability during transitions, effectively modelling complex temporal and nonlinear dynamics. Consistent performance gains across metrics highlight both statistical and practical relevance, reducing prediction errors and financial risk. The relative error reduction throughout the testing period confirms the stability of the proposed framework for stock time series prediction applications.

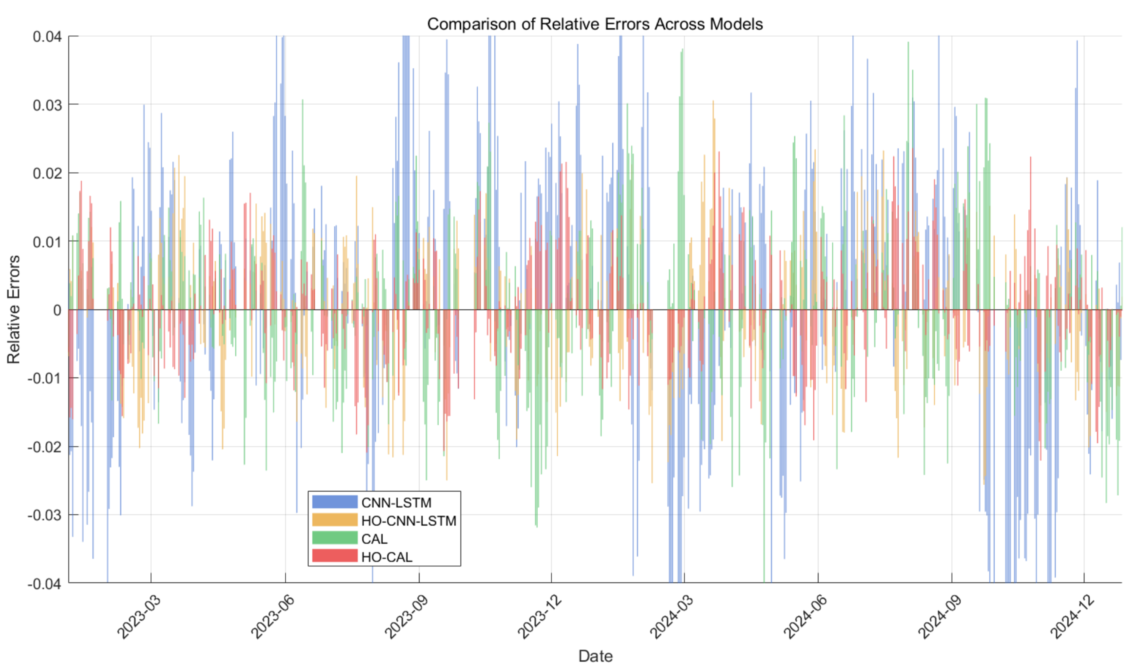

Fig. 8. Temporal distribution of relative prediction errors across models.

C. Robustness Test

To further validate the accuracy and robustness of the HO-CAL framework, this study extends the evaluation to four major international stock indexes: the S&P 500 (Standard & Poor's 500 Index), FTSE 100 (Financial Times Stock Exchange 100 Index), Nikkei 225 (Nikkei 225 Stock Average), and KOSPI (Korea Composite Stock Price Index). These indexes represent a diverse range of market structures and efficiency levels across developed and emerging economies.

TABLE IV. COMPARISON OF PREDICTIONS FOR INTERNATIONAL MARKETS

Stock Index	MAE	RMSE	MAPE(%)	R^2
CSI 300	40.03	62.86	0.99	0.991
S&P 500	75.26	113.85	1.42	0.983
FTSE 100	129.48	194.20	1.56	0.982
Nikkei 225	471.21	706.85	1.24	0.989
KOSPI	28.15	42.75	1.06	0.990

The experimental results in Table IV confirm the robustness and generalizability of the proposed framework. HO-CAL achieved strong predictive performance across all markets, with high R^2 values (≥ 0.982) and consistently low MAE, RMSE, and MAPE values. Notably, KOSPI (MAE: 28.15, R^2: 0.990) and CSI 300 yield the best results, followed by Nikkei 225 (MAE: 471.21, R^2: 0.989), whereas S&P 500 and FTSE 100 showed slightly higher error metrics. The differences between these international markets are consistent with the findings in [32], and can be interpreted through the lens of market efficiency: the S&P 500 (USA) and FTSE 100 (UK) are generally classified as semi-strong to strong-form efficient markets, where price patterns are quickly arbitraged away, making predictive modelling more challenging. In contrast, Nikkei 225 (Japan), KOSPI (Korea) and especially CSI 300 (China), often considered weaker-form efficient or less efficient due to higher market volatility and behavioral factors, may retain exploitable patterns that the HO-CAL framework can effectively capture. This also suggests that deep learning methods like HO-CAL, tend to perform better in markets with lower informational efficiency. These results underscore the practical value of the proposed hybrid framework in real-world financial predictions, particularly in scenarios that involve diverse data distributions and varying market dynamics.

VI. CONCLUSION AND FUTURE WORK

Stock markets are crucial to global financial systems, and accurate stock index prediction remains a challenging yet valuable task for investors, policymakers, and researchers. This study proposed a novel hybrid HO-CAL framework for enhance the predictive accuracy and generalizability of stock index. Through comprehensive experiments, the HO-CAL achieved consistently superior performance across multiple evaluation metrics (e.g., MAE, RMSE, R^2), outperforming baseline models including CNN, LSTM, CNN-LSTM, and even CNN-LSTM-Attention variants. The Attention mechanism significantly enhanced the model's ability to focus on key temporal patterns, while HO effectively optimized parameters to avoid local minima. Ablation studies and visual analyses confirmed the individual and synergistic contributions of each component. In robustness tests across five major global stock markets, HO-CAL maintained high predictive accuracy, demonstrating strong generalization ability even in markets with differing volatility and efficiency levels. These results validate the model's applicability in real-world investment and confirm its alignment with behavioral finance perspectives.

From a theoretical standpoint, this research contributes to the growing body of literature on deep learning in financial prediction by (1) empirically demonstrating the benefits of attention-enhanced feature selection in volatile stock series, (2) proposing the first integration of the CAL architecture with the HO algorithm, and (3) verifying the feasibility of metaheuristic optimization in tuning deep learning models for financial applications. Practically, the proposed framework offers a scalable and accurate solution that can assist investors in managing portfolio risk and timing market entry more effectively.

Nevertheless, this study has certain limitations: the model relies exclusively on technical indicators, without incorporating macroeconomic or firm-level fundamental variables, which may limit its comprehensiveness in capturing long-term market dynamics; while HO showed strong performance, its computational cost is non-negligible, especially when applied to large-scale or high-frequency datasets. Future work could address these limitations in several ways. First, integrating fundamental financial indicators (e.g., ROA, PE ratios) and macroeconomic variables (e.g., inflation, M2 growth) could improve the model's explanatory power. Second, the model can be extended by exploring other deep learning architectures such as Transformers, Temporal Convolutional Networks, or Graph Neural Networks, which may offer enhanced capabilities in modeling complex dependencies. Finally, comparisons with other powerful metaheuristic optimization, such as Grey Wolf Optimizer or Whale Optimization Algorithm, can further refine the optimization strategy.

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