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An innovative method for highly accurate stock price forecasting: a case study on HSI

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Abstract: Volatility in the stock market is attributable to many interrelated factors operating in the background. Changes in the unemployment rate, global economic data, immigration policies, public health conditions and monetary policies that impact nations are all potential causes. All participants pursue a comprehensive stock market assessment to increase profits and decrease risks. The globe is searching for a precise and trustworthy forecasting model encompassing the highly variable and nonlinear market behaviour inside a comprehensive framework. This study predicts the close price of the Hang Seng Index (HSI) the following day using a hybrid model called Long Short-Term Memory (LSTM) with a combination of the artificial bee colony. The proposed model achieved optimal outcomes by utilising conventional factors, including a Root Mean Square Error (RMSE) of 180.21, a Mean Squared Error (MSE) of 32474, a coefficient of determination of 0.9941 and a Mean Absolute Error (MAE) of 135.61.

Keywords: stock exchange; financial market; stock future price; long short-term memory; artificial bee colony.

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Biographical notes: Shuyu Hu obtained a Master's degree from Hunan University in China. Now, she works in School of Economics and Management of Hunan Open University. Her research interests include financial and economic management.

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1 Introduction

The global stock market, often called the equity market, comprises several stock exchanges. The general public and investors buy and sell shares that fluctuate due to supply and demand. Owning stock or shares in a company or organisation is called ownership. Purchasers want to purchase a share at the most affordable cost, while vendors strive to sell it for the most amount. Forecasting the stock market is especially difficult due to the numerous uncertain factors that affect the pricing on the market, including political developments, economic conditions and investor moods (Gandhmal and Kumar, 2019; Arévalo et al., 2016). Erratic changes in the price of stocks on the market caused this. In its natural state, the stock market is lively and boisterous (Chourmouziadis and Chatzoglou, 2016). Cutting-edge stock knowledge is needed to anticipate the stock exchange. Investors steer clear of stocks whose worth gradually declines

over time and instead purchase stocks whose price increases in the future. Additionally, diverse factors that affect the stock market's volatility may influence the exchange market. Another difficulty in predicting the future price of stocks is incomplete information regarding stock market data. Investors employ a diverse array of technical indicators to anticipate fluctuations in the stock price.

Forecasting market trends is challenging, even if these indications are utilised to evaluate the stock. Stock fluctuations are affected by both economic and non-economic variables (Emin, 2011). New tactics drawing on Artificial Intelligence (AI) and Machine Learning (ML) were developed in response to the prediction mistakes of previous strategies. These tactics decreased these errors and improved forecast accuracy. A sort of Artificial Neural Network (ANN) known as a Recurrent Neural Network (RNN) uses a looped design known as a recurrent network to enable the information of prior knowledge. RNN considers the current

input while making a decision and generates outputs based on the inputs it has previously learned. LSTM is one of these algorithms. LSTMs are a more sophisticated kind of RNNs, as first presented by Hochreiter and Schmidhuber (1997). They are intended to understand temporal sequence data and their long-term connections more effectively than traditional RNNs (Kratzert et al., 2018). An LSTM comprises forget, input and output gates, three nonlinear gates that manage information transfer within and outside the neuron having a self-recurrent connection known as a memory cell. LSTM can identify long-term dependencies that other RNNs cannot recognise because the forget gate, also known as cell memory, determines the data from previous stages to be disregarded.

The output gate chooses the extent to which the cell state contributes to the output value, whereas the input gate governs the data required for updating the cell state. Therefore, by preventing the exploding or disappearing gradients issue that significantly impacts standard RNN architectures, a more significant memory may help LSTMs learn long-term dependencies (Xu et al., 2020). LSTM was employed by Yadav et al. (2020) to predict time series in the Indian stock market. LSTM was utilised by Zou and Qu (2020) for quantitative trading and stock prediction. An optimiser is an algorithm or technique used to minimise or maximise an objective function in machine learning and optimisation issues. The objective function gauges the scheme's productivity, and optimisation entails modifying the scheme's parameters to provide the optimal result.

Optimisers are essential when training machine learning schemes since the main objective is frequently to minimise a loss function. The loss function displays the disparity between the scheme's projected output and target values. The optimiser modifies the scheme's parameters throughout training to lessen this loss. Typical optimisers include the following: Examples of these optimisers include: the Whale Optimisation Algorithm (WOA) (Mirjalili and Lewis, 2016), Genetic Algorithm (GA) (Mitchell, 1998), Biogeography-Based Optimisation (BBO) (Simon, 2008), battle royale optimiser (BRO) (Rahkar Farshi, 2021), Particle Swarm Optimisation (PSO) (Kennedy and Eberhart, 1995), Artificial Bee Colony (ABC) (Karaboga, 2010), Grey Wolf Optimisation (GWO) (Mirjalili et al., 2014).

To solve numerical difficulties, Karaboga (2005) invented the ABC method. The algorithm is a metaheuristic that takes its cues from bees' curious foraging habits. The program views the food sources as answers. The ABC's three types of honey bee agents in the colony are scouts, hired bees and bystanders. The bees are divided into two sections, each containing an equal number of bees ABC algorithm. The

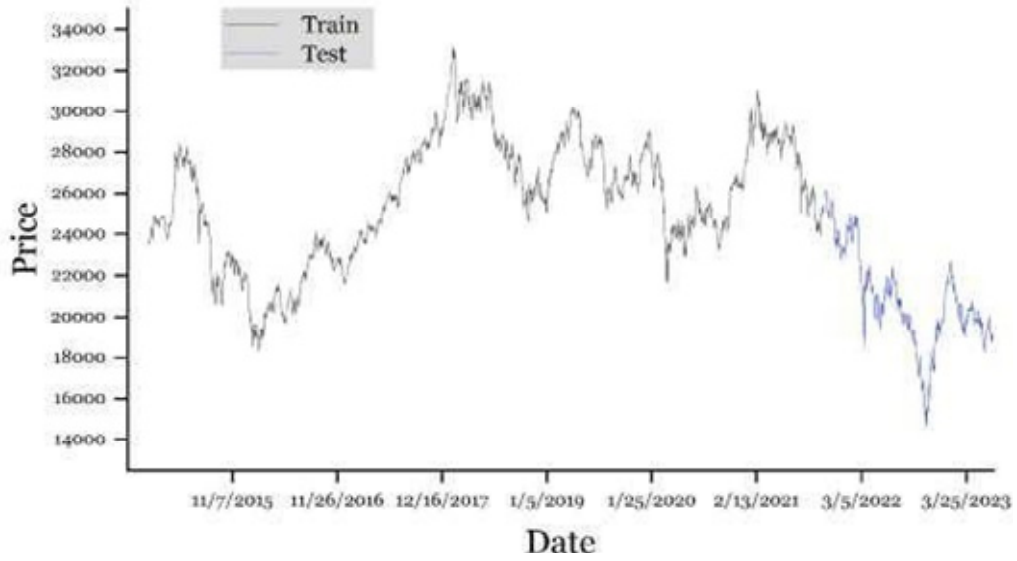
bee's food supply is a solution whose properties must be maximised inside the ABC. A problem's objective function that has to do with the standard of the food supply may be determined by looking at the fitness level of a proposed solution.

Stated otherwise, the procedure of determining the optimal response is comparable to the foraging efforts made by bees to locate a high-quality food source. The bee agents utilise the initial solutions as sustenance sources, which are generated at random. After the bee agents are started, they undergo three essential processes of repeating operations: reevaluating the accessible possibilities, choosing workable solutions and avoiding less-than-ideal options. To evaluate each model's dependability, the current study examined many schemes, including LSTM, PSO-LSTM, GWO-PSO and ABC-LSTM. The scheme that has been chosen for this article and has shown exceptional performance is the ABC-LSTM. This study uses the HSI, a well-known Hong Kong stock market index, as its data set runs from 1st January 2015 to the end of June 2023. The following portion thoroughly examined the investigation, data source and all relevant elements. Numerous analytical tactics were used for the data, such as the Decision Tree (DT) model, assessment metrics and optimiser strategies. The study's outcomes are presented and compared with outcomes from other strategies in the following section. An overview of the research's conclusions is provided in the last paragraph.

2 Methods and metrics

2.1 Data set preparation

A type of bar chart known as an Open-High-Low-Close (OHLC) chart shows the share prices at each opening, closing, high, low and volume point during a given period. This study employs a well-known Hong Kong stock market index, the HSI, as the data set. Leaders across various industries within the Hong Kong economy comprise the diversified collection of corporations that make up the HSI. These industries include manufacturing, telecommunications, technology, real estate and finance. The productivity of the Hong Kong stock market can be significantly projected by looking at the HSI, which also shows movements in the regional economy. Eight years of data have been gathered from 1st January 2015 to the end of June 2023. A partitioning strategy was employed in this experiment, as Figure 1 illustrates. Expressly, 20% of the data was set for validation and testing. However, the remaining was allocated to training.

Figure 1 Dividing up the data into distinct training and testing segments

2.2 LSTM

Time series, audio, and text are sequential data types that may be processed using an ANN called LSTM. It is beneficial for processing data with enduring dependencies, meaning that information from earlier time steps is necessary. By utilising memory cells, along with input, output and forget gates, LSTM can retain this knowledge for extended periods. By managing data flow both within and outside of memory cells, these gates allow the network for data retrieval and storage selectively as needed, as shown in Figure 2. An LSTM network consists of the following components (Gers et al., 2000; Yu et al., 2019):

Input manages data entry into the memory cell.

$$\text{input gate} = \sigma(W_i \times [ht - 1, xt] + bi) \quad (1)$$

Data flow out of the memory cell is regulated by forget.

$$\text{forget gate} = \sigma(W_f \times [ht - 1, xt] + bf) \quad (2)$$

Output: manages the memory cell's output to the other networks.

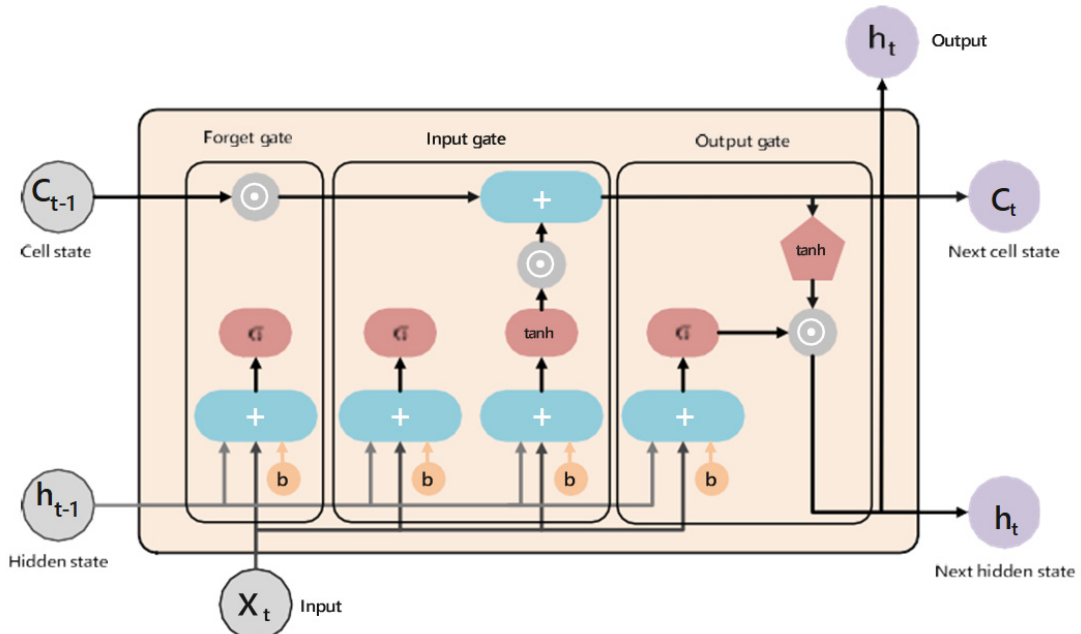
$$\text{output gate} = \sigma(W_o \times [ht - 1, xt] + bo) \quad (3)$$

Cell state: The memory cell serves as the storage location.

$$\begin{aligned} \text{memory cell} &= ft \times ct - 1 + it \\ &\times \tanh(Wc \times [ht - 1, xt] + bc) \end{aligned} \quad (4)$$

Hidden state: The LSTM unit's output forecasts or transfers data to the subsequent LSTM unit.

$$\text{hidden state} = ot \times \tanh(ct) \quad (5)$$

Figure 2 The LSTM model's architectural shape and organisational structure (see online version for colours)

2.3 PSO

PSOs are frequently employed in machine learning schemes to optimise hyperparameters (Elaraby et al., 2022; Otair et al., 2022). This method is inspired by the collective behaviour seen in fish schools and bird flocks, where particles move around in a search domain until they find the best answer (Poli et al., 2007). PSO seeks to effectively examine the parameter space and use a population-based technique to converge on the best answer. The PSO in this paper computes the hyperparameter space of ML schemes to select the best hyperparameter values and promote variety in ensemble learning. The particle acceleration and deceleration in the PSO algorithm can be calculated using the following formula:

$$vt + 1 = vt + C_1 rt(Pbest - xt) + C_2 rt(Gbest - xt) \quad (6)$$

The symbol vt displays the frequency of the i -th particle at a particular moment in time repetition in a d -dimensional search domain. A representation of the position and ideal particle are specified for each cycle of the i -th function by the variables $Pbest$ and $Gbest$. The parameters control particle velocity C_1 and C_2 , while rt and rt represent random values between 0 and 1. Additionally, the particles within the PSO algorithm might 12 adjust their placements by utilising the subsequent equation:

$$xt + 1 = xt + vt + 1 \quad (7)$$

In a d -dimensional search domain, the coordinates of space of the i -th particle during the cycle t are indicated by the variable xt .

2.4 GWO

GWO is easy to use since it is straightforward in theory, searches quickly, has a high degree of accuracy and is simple to explore. The four groups of wolves (potential solutions) in GWO are rated based on their strength (fitness function): alphas, betas, deltas and omegas. The pack is led by the alpha wolves, who hold the highest rank in the social structure. The second most powerful wolves are the beta wolves. It helps maintain the pack's discipline and backs the alpha wolf. Weakness-prone Omega wolves are generated at the bottom of the hierarchy (Sharma et al., 2016).

$$W(t + 1) = Wp(t) - A \times D \quad (8)$$

$$D = |C \times Wp(t) - W(t)| \quad (9)$$

$$C = 2 \times \text{rand} 2 \quad (10)$$

$$A = 2 \times \alpha \times \text{rand} 1 - \alpha \quad (11)$$

$$\alpha = 2 - 2 \times (t - T) \quad (12)$$

The variables t and T depict the count of cycles completed thus far and the total count of cycles; W and Wp stand for the wolf's and its prey's respective position vectors; $\text{rand} 1$ and $\text{rand} 2$ are uniformly created random values between $[0, 1]$. A randomly generated number from $[0, 2]$ is represented by C .

2.5 Artificial bee colony

To solve optimisation problems, Karaboga (2005) invented the ABC method. The algorithm is a metaheuristic driven by bees' inquisitive foraging behaviours. The software sees the food sources as solutions. Two bee groups are present in the ABC algorithm, each containing an identical quantity of bees. Bees are classified as either worker bees or spectator bees, depending on how many are present. Inside the ABC, the sustenance source for the bees is viewed as a solution whose qualities need to be optimised. In other words, figuring out the best course of action is similar to bees searching for a high-quality food source through foraging. The bee agents employ the first solutions, which are produced at random, as food sources. There are four stages to the algorithm:

Phase of initialisation: Using the function, a first set of solutions is generated at random:

$$S_i = S_{\min} + \text{rand}(0, 1)(S_{\max} - S_{\min}) \quad (13)$$

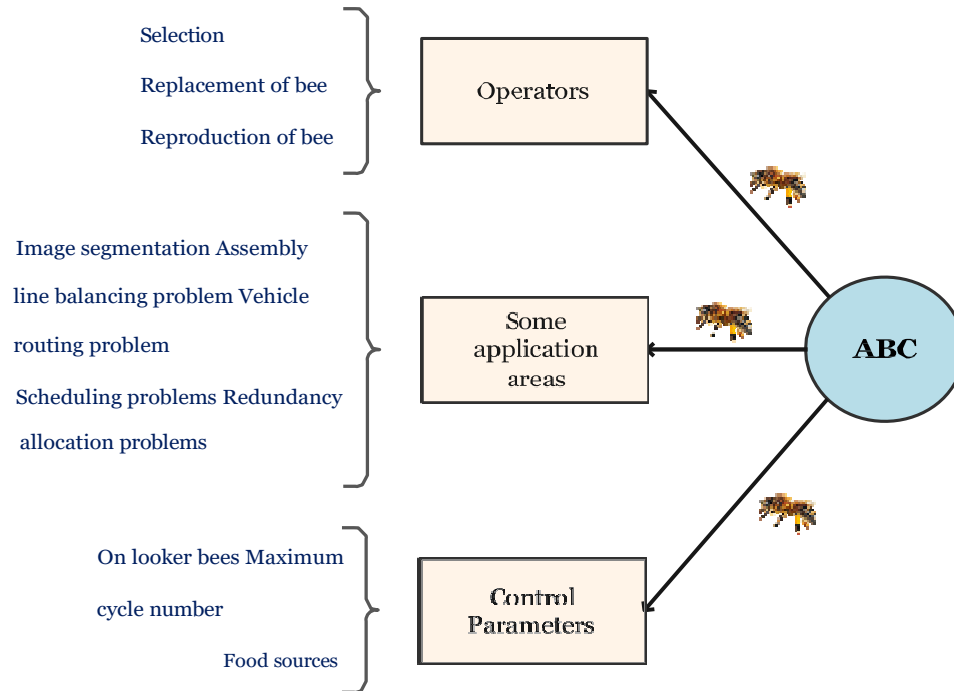
where S_i depicts the i -th solution and $S_{\max}$ and $S_{\min}$ depict the corresponding upper and lower limits on the solutions. Phase one of the used a bee look for a solution: The employed bees use the following function to look for a new solution around i -th solution:

$$\text{New}_i = S_i + \emptyset_i (S_i - S_j) \quad (14)$$

The variables New_i , S_i and S_k represent the New_i -th and randomly picked solutions from the swarm, respectively, while $\emptyset_i$ is a random integer with a range of $[-1, 1]$. The cost analysis and comparison of the new solution, New_i , and the previous remedy, S_i , will be performed. If the new solution is less expensive than the old one, the group will adopt it. The trial number will be raised if the solution is abandoned in the final step. Every other solution follows this method in the swarm. Phase of observer bee solution search: Using roulette wheel selection, the onlooker bees use probability to explore solutions. These bees base their search strategy on more effective solutions. Equation (15) may be used to calculate the selection chance of every resolution in the swarm.

$$P(S_i) = \sum_{i=1}^n f(S_i) \quad (15)$$

$P(S_i)$ displays the likelihood of the i -th resolution, and $f(S_i)$ depicts the i -th solution's fitness value. For a chosen solution, the observer uses the previous solution, S_i . The scout bee's phase seeks a remedy: If the trial count is over the threshold, the previous answer will be eliminated from the throng, and a new one will be calculated. The improved solution will be sent to the swarm. Figure 3 offers an overview of the operation and functionality of the ABC optimiser. Figure 4 presents a flowchart illustrating the functionality of the ABC optimiser.

Figure 3 An overview of the operation and functionality of the ABC optimiser (see online version for colours)**Figure 4** A flowchart illustrating the functionality of the ABC optimiser (see online version for colours)

2.6 Evaluation metrics

Two methods are used to assess a model's performance: examination of net value and forecast accuracy. By contrasting the projected values with the actual data in the testing collection, the prediction errors and the correctness of the predictions can be calculated. To assess the performance, three typical markers for prediction errors are employed:

- Mean Absolute Error (MAE):

$$MAE = \frac{\sum_{i=1}^N |y_i - \hat{y}_i|}{N} \quad (16)$$

where N signifies the sample size, y_i signifies the real value and $\hat{y}_i$ signifies the projected value. The mean absolute difference between the expected and actual numbers, or MAE, can prevent errors from cancelling out on top of one another. It displays the total projected mistakes (Willmott and Matsuura, 2005).

- Mean Squared Error (MSE):

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (17)$$

N displays the sample size, y_i displays the real value and $\hat{y}_i$ displays the projected value. MSE is a frequently used metric to assess how well time series forecasting works. It gauges the prediction of absolute errors like that of MAE (Lehmann and Casella, 2006). In this case, the loss function for training the scheme is MSE.

- Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (18)$$

A model's fit to the data is shown by its R^2 . The computation entails gauging the overall among the squares showcasing the discrepancies between the projected and observed values, subtracting it from the total squares that illustrate the variations between the actual readings and the

mean, and then subtracting this amount from 1. The more closely this number strategies 1, the more accurate the scheme is considered to be.

- Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N}} \quad (19)$$

RMSE is a widely used assessment measure for regression issues since it shows the impact of big mistakes and computes the mean disparity between the projected and actual values. Significant errors will impact the RMSE value. The outcomes are better when the RMSE value is nearer 0.

3 Result and discussion

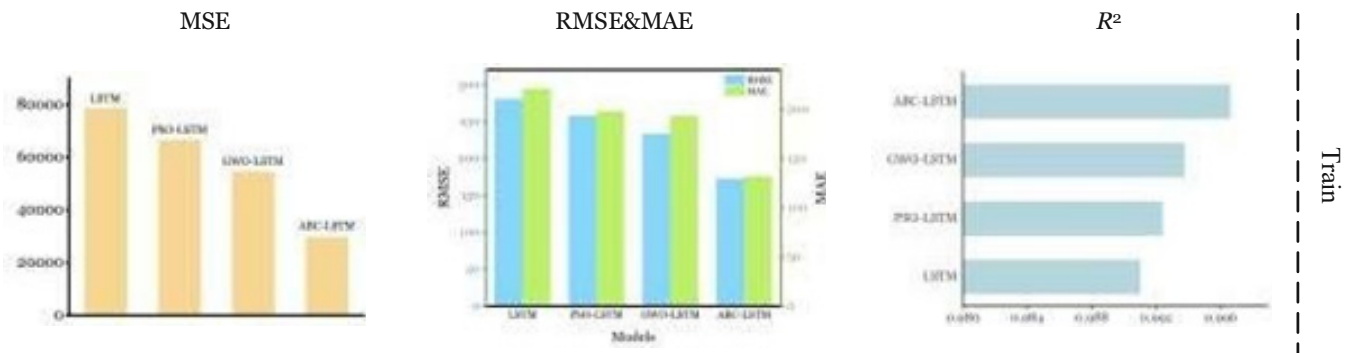
3.1 Compare and analysis

Table 1 displays the accuracy of the forecast of ABC-LSTM for all stock prices in terms of R2, MAE, MSE and RMSE. The findings show that the suggested method performs well because of its low error rate and strong correlation. The date is displayed on the horizontal axis in Figure 7, and the stock price is shown on the vertical axis. The tight match between the actual and projected stock prices indicates a low mistake rate in stock price prediction. The date is displayed on the horizontal axis in Figure 8, and the stock price is displayed on the vertical axis. There are a few mistakes in the stock price prediction due to the tight match between the actual and forecasted stock values. The paper thoroughly examines many schemes to protect the productivity of the Hong Kong HSI market in the future. To assist investors in making better investment selections, the study comprises projections, table 1 and Figures 5 to 8 that summarises the outcomes. With a reported R2 of 0.9941, RMSE of 180.21, MAE of 135.61, and MSE of 32474, the ABC-LSTM model outperformed all other assessed schemes. The scheme is the most accurate alternative for forecasting the stock price and HSI index from the first of 2015 to the end of June 2023 since it had the greatest accuracy rate out of all the examined schemes.

Table 1 The evaluation outcomes of the schemes for training and testing sets.

Scheme/Metrics	Training Collection				Testing Collection			
	R2	RMSE	MAE	MSE	R2	RMSE	MAE	MSE
LSTM	0.9910	280.35	220.83	78593	0.9830	306.37	281.42	93865
PSO-LSTM	0.9924	257.85	198.24	66485	0.9866	272.01	206.47	73987
GWO-LSTM	0.9937	233.59	193.55	54564	0.9906	227.5	194.35	51758
ABC-LSTM	0.9966	172.57	131.87	29781	0.9941	180.21	135.61	32474

Figure 5 The training outcomes of the schemes encompass many measures, including R^2 , MAE, MSE and RMSE (see online version for colours)



The illustration shows a comparative performance evaluation of four predictive models, LSTM, PSO-LSTM, GWO-LSTM and ABC-LSTM, based on three key performance metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), and the coefficient of determination (R^2). The first plot shows MSE values for each model, with baseline LSTM having a high value, representing relatively poor predictive accuracy. In contrast, predictive models optimised with algorithms PSO-LSTM, GWO-LSTM, and ABC-LSTM show successively lesser values for MSE, with ABC-LSTM having a minimum value, representing a high level of performance in minimising prediction errors. The following plot is a two-dimensional evaluation for RMSE and MAE, both important predictive accuracy and overall performance evaluation factors. Regarding RMSE and MAE, plots for LSTM reveal its poor performance compared to its counterparts. PSO-LSTM and GWO-LSTM reveal a fair improvement, with GWO-LSTM outdoing PSO-LSTM in minimising both types of errors marginally. ABC-LSTM plots reveal minimum RMSE and MAE values for the fourth successive case, effectively reducing discrepancies between actual and predicted values.

The third plot describes the coefficient of determination (R^2), a performance criterion that assesses a model's effectiveness in explaining variance in a data set's dependent variable. The results consistently illustrate that ABC-LSTM outperforms all other models regarding the three-performance metrics mentioned. Therefore, ABC-LSTM proves to have high predictive accuracy and dependability. Implementing optimisations, including PSO-LSTM and GWO-LSTM,

yields performance improvements; however, ABC-LSTM outdoes them in attaining an ideal balance between predictive accuracy and minimising errors. On the other hand, baseline LSTM, with no optimisations, proves to have poor performance and therefore confirms improvements achieved in forecasting efficiency through time series analysis with a combination of methodologies.

The following Figure 6 shows a comparative performance evaluation between four specific models, LSTM, PSO-LSTM, GWO-LSTM and ABC-LSTM, using three specific performance evaluation metrics – Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and the coefficient of determination (R^2). In the first panel, it can be seen that the values for MSE illustrate that the traditional LSTM model shows the largest value for its error, thus representing its poor performance. With PSO-LSTM and GWO-LSTM, a decrease in MSE is seen, with ABC-LSTM having the least value, representing its high accuracy. In the second plot, values for RMSE and MAE are shown, supporting the same observation; in this case, for RMSE and MAE, the LSTM model shows the largest values, then PSO-LSTM and GWO-LSTM and ABC-LSTM show the minimum errors, thus supporting its effectiveness in minimising prediction errors. In the third plot, values for R^2 have been displayed, in which ABC-LSTM holds the largest value, representing the best model fit, then GWO-LSTM and PSO-LSTM, with LSTM having its minimum value. These observations reveal improved predictive performance for optimised LSTM variants, with ABC-LSTM proving to be most effective in all performance evaluation values.

Figure 6 The testing outcomes of the schemes encompass many measures, including R^2 , MAE, MSE and RMSE (see online version for colours)

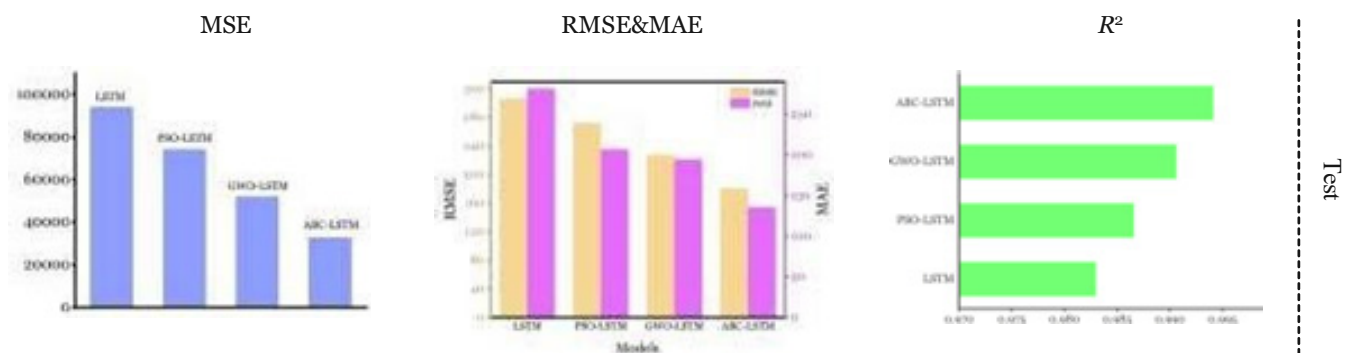


Figure 7 is a comparative graphical plot of actual and predicted stock prices over some time. On the x -axis, a date index is represented and the y -axis shows the stock price. Two curves have been drawn: one for the actual price (in brown) and one for the predicted price (in blue). How closely these two sets of curves coincide signifies that the predictive model effectively captured trends and fluctuations in stock price. How closely actual and predicted values coincide signifies a high level of correlation with little deviation, meaning that trends in fluctuations in stock price have been captured effectively through generalisation in a model. There could be, at most, negligible deviations; nevertheless, the model shows high predictive accuracy. The graphical plot confirms the forecasting potential in a model and, therefore, its usability in financial forecasting operations.

Figure 8 is a comparative graphical plot of actual and predicted stock prices over some time. On the x -axis, a date index is represented, and the y -axis shows the stock price. Two curves have been drawn: one for the actual price (in brown) and one for the predicted price (in blue). How closely these two sets of curves coincide signifies that the predictive model effectively captured trends and fluctuations in stock price. How closely actual and predicted values coincide signifies a high level of correlation with little deviation, meaning that trends in fluctuations in stock price have been captured effectively through generalisation in a model. There could be, at most, negligible deviations; nevertheless, the model shows high predictive accuracy. The graphical plot confirms the forecasting potential in a model and, therefore, its usability in financial forecasting operations.

Figure 7 Through the implementation of the ABC-LSTM methodology, the forecasting curve is generated during the training phase (see online version for colours)

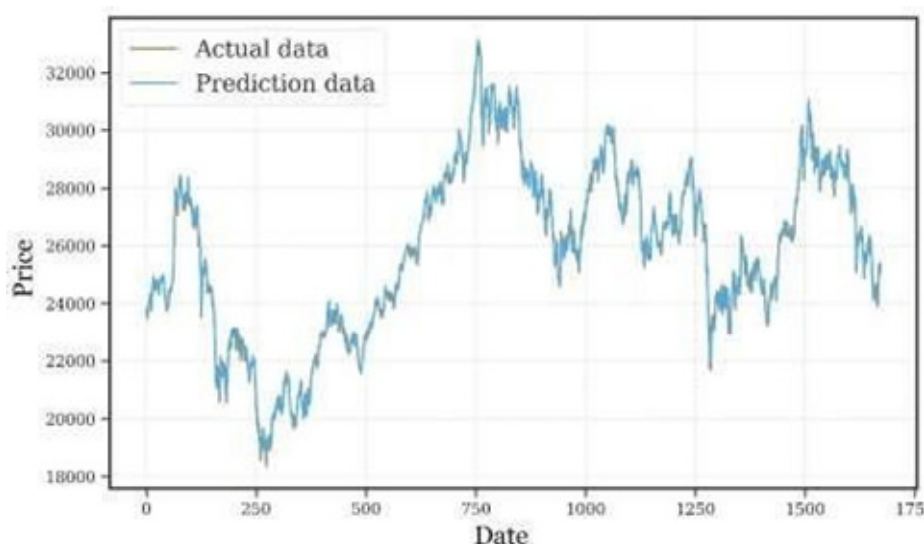
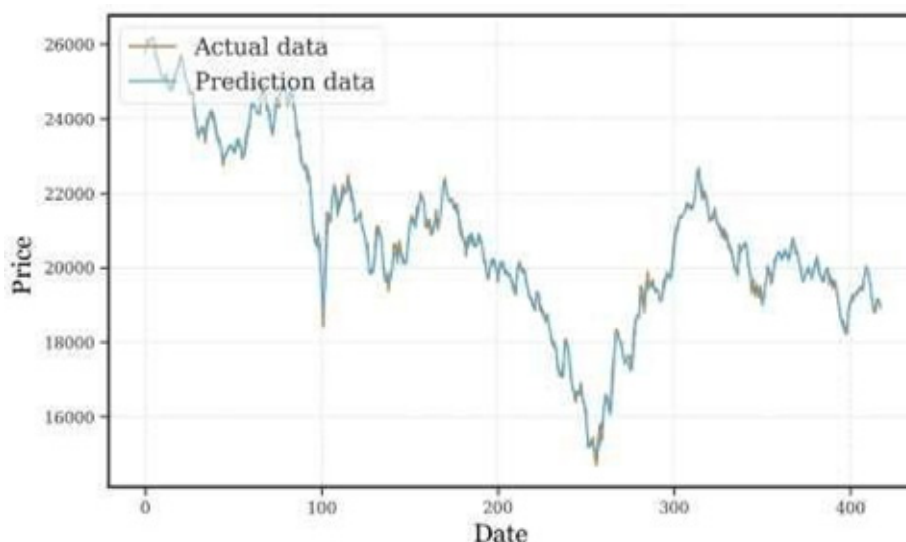


Figure 8 Through the implementation of the ABC-LSTM methodology, the forecasting curve is generated during the testing phase (see online version for colours)



4 Conclusions

The financial industry in which the acquisition occurs is referred to as the stock market, and the sale of shares of companies with public listings is conducted. By evaluating the operations of individual enterprises and the overall business climate, it functions as a metric for a nation's economic well-being. Stock prices are contingent upon the equilibrium between supply and demand. While stock market investing carries some risk, there is long-term potential for substantial profit. Predicting stock trends has been a significant issue for the financial industry. This investigation tries to offer a novel blended scheme, ABC-LSTM, in which ABC is used to boost the hyperparameters of LSTM. This model has a high ability to project the stock market value. Data from the stock market is employed to forecast the HSI index stock price. The data set spans the months of 1st January 2015, and 30 June 2023. The data spans eight years and is split into 80% train and 20% test data. This suggested model was compared to LSTM with the combination of the PSO and GWO optimisers to evaluate its effectiveness. The outcomes indicated that ABC-LSTM was the most effective scheme and produced precise forecasts.

- The four-assessment metrics RMSE, R^2 , MAE and MSE, in addition to the data collected during the scheme assessment, were displayed form in the article's outcomes segment. The most effective model among the strategies that have been proposed for the estimation of time series is the ABC-LSTM method, with the least number of errors with RMSE (180.21), R^2 (0.9941), MAE (135.61) and MSE (32474).

Acknowledgement

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Declarations

All authors declare that they have no conflicts of interest.

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