Stock Price Prediction Using Deep Learning

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ABSTRACT

Stock price prediction remains an arduous undertaking due to nonlinear market patterns and volatility. This study develops a combined deep learning framework that integrates a Long Short-Term Memory (LSTM) network with optimization principles derived from the Sparrow Search Algorithm (SSA). The concept in this paper stems from modern technology created to enhance prediction techniques based upon social media sentiment analysis and historical pricing data and technical indicators (moving averages, exponential moving averages, MACD and relative strength indexes). The combination of historical price data with technical indicators permits traders and investors to build predictive models for their respective trading methods. Historical price data and technical indicators represent the trends derived from time-series and technical analysis and allow analysts to make forecasts regarding future price levels. Testing results indicate that, in terms of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), models using Long Short Term Memory (LSTM) with recurrent networks that employ an optimization/addition technique outperform standard LSTM models. We have shown through our findings that optimization/addition-based recurrent neural networks (i.e., LSTM) offer a legitimate approach to short-term stock price forecasting given the rapidly evolving dynamics within the financial markets.

KEYWORDS: Daily Stock Price Forecast, Long Short Term Memory, Senescence Supported Algorithm (SSA), Artificial Neural Networks, Deep Learning, Time-Series Forecasting; Financial Statistical Analysis

I. INTRODUCTION

The stock market typically demonstrates random, chaotic behaviour over time which is influenced by many external influences including the economy, response of the investor/customer to financial factors (i.e., macroeconomics) and stock market activity (noise).

Random behaviour makes it challenging for statistical models to predict future prices from historical prices; however, research has shown that LSTM networks are capable of capturing the sequential relationship (dependencies) in time-series databases containing historical price data from stock exchanges. LSTM performance is contingent upon several hyperparameters including the learning rate, the number of hidden units and dropout settings used. Selecting inappropriate hyperparameter values may lead to reduced rates of convergence for the model and also affect prediction stability across time. In addition, multiple studies have confirmed through experimentation that implementing an optimization method (e.g., SSA) within a DNN significantly enhances the accuracy of the model when making future value predictions based upon statistically based input data (e.g., historical prices and indicators).

The MS-SSA- LSTM architecture introduced in earlier research shows that adaptive parameter tuning guided by SSA improves generalization and reduces error rates in fluctuating markets (2). Motivated by these developments, the present work designs an SSA-guided LSTM model using only historical numerical indicators, without sentiment data, and evaluates its suitability for short-term stock trend forecasting.

2. LITERATURE SURVEY

Conventional statistical models frequently find it challenging to volatile, nonlinear and highly dynamic nature of financial markets. As deep learning has advanced, researchers have progressively shifted away from conventional statistical methods. toward neural architectures capable of modeling long-term dependencies and nonlinear patterns.An overview of previously conducted research that relates to the proposed SSA-LSTM model is provided below. For ease of reference, this overview has been divided into different areas of research as follows: (1) Deep Learning Models; (2) Hybrid Neural Network Models; (3) Sentiment-Enhanced Models; (4) Technical Indicator-Based Systems; (5) Optimization Frameworks; and (6) Applications of SSA Variants to Predicting Financial and Non-financial Time Series. Traditional and Statistical Methods for Stock Price Prediction. Prior to the advent of deep learning, traditional statistical forecasting methods such as ARIMA, VAR, GARCH and Exponential Smoothing were widely used to predict stock prices. These types of models produced satisfactory forecasts in relatively stable market environments but were inadequate for predicting stock prices in more volatile market environments due to their reliance on linearity. Due to their limitations in being able to model more complex time-based patterns and abrupt shifts/deviations associated with fluctuations in stock prices, traditional models have consistently produced poor generalization capabilities for actual stock trading activity. In order to overcome the limitations of traditional linear models, several machine-learning models, including Support Vector Regression (SVR), Random Forest (RF), and K-Nearest Neighbour (KNN), have been employed. However, these types of algorithms rely on a pre-set, fixed-length feature representation of each time point and thus cannot take into account the sequential dependency of time-series data

as can be done with sequence-learning algorithms, which makes their ability to generalize beyond the testing data limited relative to more advanced sequence-learning models.

2.2 Deep Learning for Financial Time-Series Forecasting

The rise of deep learning marked a major shift in stock prediction methods. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are often preferred because they can learn long-term dependencies within time series. The way LSTMs manage this is by using gating mechanisms to prevent the vanishing gradient technique of RNNs, thereby allowing the model to maintain and utilize significant historical information during training. Current research evidence demonstrates LSTM networks outperform traditional forecasting models such as ARIMA, SVM, and conventional artificial neural networks when forecasting stock market indicators and stock prices across companies. It has also been established via research that when we provide additional technical indicators, these will further enhance deep learning models when performing stock forecasting.

Technical indicators, including RSI, MACD, moving averages, and ratio of volatility measure, assist LSTMs with the detection of trends and momentum and the ability to anticipate reversals in price trends. All of these findings suggest that deep learning models built around using technical indicators would also be advantageous for such applications and support the approach taken in our study.

2.3 Architectures for Hybrid Deep Models

As research into deep learning continued to develop, researchers began creating hybrid architectures by integrating two or three architectures together, thus leveraging the complimentary advantages of all hybrid architectures created.

For example, the LSTM network leverages its ability to model long-term dependencies and develop spatio-temporal relationships with features extracted using a convolutional neural network (CNN) before using that information to create an LSTM input parameter model (4). Rephrased:

By using a convolutional neural network (CNN) to create short-term temporal filters through the application of convolutional layers, the CNN–LSTM provides a mechanism for developing a model based on short-term patterns and spatio-temporal relationships.

Out et al. (1) developed an LSTM-XGBoost hybrid model incorporating Twitter sentiment, achieving improved directional accuracy across multiple technology stocks. Their findings show that emotional responses expressed online correlate strongly with short-term market movements.

The primary source for this research, Mu et al. (2), developed an MS-SSA-LSTM architecture combining investor sentiment indices, technical indicators and SSA-based optimization.

2.4 Technical-Indicator-Based Models

Technical indicators remain fundamental in forecasting models due to their interpretability and low computational requirements Numerous studies show that indicators like MA7, EMA12, EMA26,

MACD and RSI enhance the accuracy of models when incorporated as inputs for LSTM and GRU frameworks. Researchers have observed that well-designed indicators lessen the workload on neural networks by emphasizing trend directions , momentum fluctuations and divergence patterns. Approaches based on indicators also serve as the foundation for numerous hybrid models. For example, CNN–LSTM systems utilize technical indicators as multivariate sequences, allowing convolutional filters to identify co-movement patterns among the indicators. This study similarly adheres to this established methodology by employing a selection of common indicators as the main inputs for the model.

The Importance of Metaheuristically Optimized Models

Metaheuristic algorithms are among the best optimization methods for hyperparameter optimization of deep learning algorithms. Deep learning models, including recurrent neural networks (RNN) like LSTM and GRU, are sensitive to hyperparameters such as learning rate, dropout rate, sequence length, and number of neurons. Hyperparameter selection traditionally involved time-consuming manual tuning, which often leads to suboptimal models.

To circumvent these limitations, researchers integrated methods of metaheuristic optimization (the use of algorithms that mimic natural processes to discover optimal solutions) with LSTM and GRU ML/DL Algorithms. Each of these studies noted significant improvements in model performance due to the methods' ability to discover and optimally choose a model's hyperparameters with relative accuracy even in extremely large search spaces. PSO LSTM Models have been developed and widely adopted to increase accuracy when making predictions regarding stock and cryptocurrency values. Using GA for hyperparameter optimization has resulted in reduced training errors and improved the ability to prevent early convergence problems. These studies demonstrate the importance of automated optimization of hyperparameters, especially when handling extremely volatile financial markets.

Sparrow Search Algorithm (SSA) and its Applications

The Sparrow Search Algorithm is a relatively recent metaheuristic inspired by the foraging behaviour of sparrows. SSA introduces a producer–scrounger mechanism, enabling global and local search balance. Cheng et al. (5) introduced modified SSA variants to improve convergence speed, escape local minima and enhance performance on time-series forecasting tasks.

Mu et al. (2) demonstrated that SSA-based optimization significantly enhances the performance of sentiment-driven LSTM models for stock prediction. SSA's strong convergence behaviour, adaptability and resilience make it an attractive candidate for hyperparameter tuning in deep learning models.

Although SSA has been applied to numerous optimization problems, including engineering tasks, image processing and classification, its adoption in pure technical-indicator- based stock prediction remains limited. This creates a research gap that the current work

addresses Summary of Research Gap. The review reveals a clear opportunity for developing an optimized, technical-indicator-based deep learning model that requires no external sentiment sources, while still achieving competitive accuracy. Integrating SSA-inspired optimization with a clean, LSTM-driven forecasting pipeline allows for a robust and computationally efficient approach to stock price prediction.

The present study builds directly on the insights from Mu et al. (2), extending the optimization capability to purely numerical time-series inputs, thereby offering a practical forecasting system suitable for real-time financial analysis.

3. METHODOLOGY

The operational workflow used in the developed program is mirrored in the methodology. The process starts with gathering daily historical stock prices and calculating technical signs that are essential for evaluating trends, momentum, and volatility. Close price, MA7, EMA12, MACD, and RSI are among the features that are employed. During network training, the dataset is scaled using Min–Max normalization to preserve numerical stability. In response to findings that long- sequence modeling improves predictive reliability, supervised training sequences are created using a sliding time frame of 60 days (3). 20% of the dataset is used for testing and 80% is used for training.

The architecture of the model features two LSTM layers stacked on up of each other, separated by a dropout layer, and concludes with a dense output layer. The Mean Squared Error (MSE) is employed throughout the training procedure,along with the Adam optimizer.training.

Optimization incorporates SSA- inspired hyperparameter tuning to determine appropriate learning rates, hidden units, and dropout ratesOnce the best hyperparameters are chosen, the final LSTM model is trained for multiple epochs with early stopping to prevent overfitting. After training, a recursive forecasting approach is applied to generate a seven-day forecast, where each predicted value is fed back into the model as input for predicting the next day.

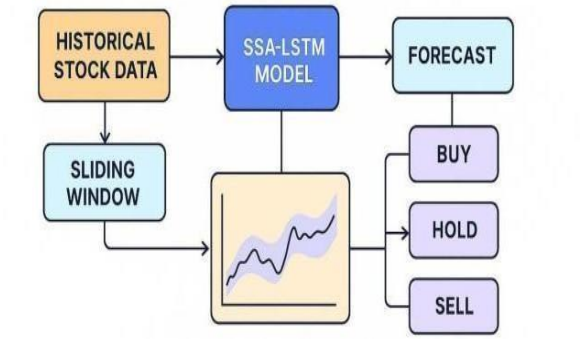


Figure 3.1: Block Diagram of SSA-LSTM Based Stock Price Forecasting and Trading Decision System

INITIALIZATION (SSA + LSTM)

The initialization of the proposed LSTM model optimized by the Sparrow Search Algorithm (SSA) happens in two steps. Technical indicators, which consist of Moving Averages (MA), Exponential Moving Average (EMA), and Average True Range (ATR), along with Normalized Closing Prices, are calculated using a standard set of formulas. By using the technical indicators and the normalized closing prices to create the initial feature data, these feature data sets will then be reshaped into the LSTM's input sequences. The next step defines the

Search Space for the Sparrow Search Algorithm, where each sparrow represents one possible hyperparameter configuration of the search algorithm. The hyperparameter configuration contains four variables: Learning Rate, Number of Layers (LSTM) in 1st Layer, Number of Layers (LSTM) in 2nd Layer and Dropout Rate. The starting boundaries for these parameters are selected based on stable convergence behaviour reported in previous experimental studies: **Learning rate:** 0.0005–0.005
Units (Layer 1): 30–80

Units (Layer 2): 20–60

Dropout: 0.10–0.30

These ranges form the initial swarm population. The fitness of each agent is measured by training a lightweight LSTM model for three epochs and calculating the RMSE. SSA then updates the positions of the agents using producer and scrounger movement rules, gradually steering the population toward better-performing hyperparameter combinations. The agent with the lowest RMSE is selected as the final hyperparameter configuration for training the complete LSTM model.

4. Algorithm for FAST_SSA_LSTM_ Optimization

Input: X_train, y_train, X_val, y_val, scaler

Output: Best parameters (lr*, units1*, units2*)

1. Set population size: pop_size = 3

2. Set iterations = 1

3. Define hyperparameter bounds:

lr ∈ [0.0005, 0.0050]

units1 ∈[32, 96]

units2 ∈[32, 96]

4. Initialize population P randomly within the bounds

5. For every sparrow Pi in the population: Compute the fitness(Pi) using :

a. LSTM parameters = Pi

b. Train LSTM for 1 epoch (fast objective)

c. Predict y_val

d. Compute RMSE → fitness(Pi)

6. Identify best sparrow P_best (lowest RMSE)

7. For iter = 1 to iterations do:

a. Compute mean fitness of entire population

b. For every sparrow Pi:

If fitness(Pi) < mean_fitness: Pi =

Pi + rand() * (P_best - |Pi|) Else:

Pi = P_best + randn() * |Pi - P_best| Apply

bounds: Pi = clip(Pi, lb, ub).

Recompute fitness(Pi) c. Update P_best with best fitness 8. Return best parameters P_best End Algorithm

Algorithm for LSTM_7_Day_Forecast

Input:

Historical closing prices P = {p1, p2, …, pT}

Lookback window L = 60

Forecast horizon H = 7

LSTM hyperparameters: lr, units1, units2

Output:

7-day future forecast $\hat{Y} = \{\hat{y}1, \ldots, \hat{y}7\}$

Model accuracy metrics: RMSE, MAPE, R^2

1. Normalize prices using Min-Max scaler:

   P_norm = Normalize(P)

2. Construct supervised learning dataset:

   For i = L to T–H:

   X[i] ← P_norm[i–L : i]

   y[i] ← P_norm[i : i+H]

   End For

3. Reshape dataset for LSTM: X shaped to (samples, L, 1) y shaped to (samples, H)

4. Split into training and validation sets:

   (X_train, y_train), (X_val, y_val)

5. Build LSTM model:

   Model:

Layer1:LSTM(units1, return_sequences=True)

Layer 2: LSTM(units2)

Output: Dense(H)

Loss = MSE Optimizer = Adam(lr)

6. Train model using early stopping:

   Fit model on (X_train, y_train)

   Validate on (X_val, y_val)

7. Predict on validation set:

   y_pred = model(X_val)

8. Compute model accuracy:

   RMSE = sqrt(mean((y_val – y_pred)²))

   MAPE = mean(|(y_val – y_pred)/y_val|)*100 R^2 = coefficient of determination

9. Forecast next 7 days:

   last_window = P_norm[T–L : T]

   X_test = reshape(last_window, (1, L, 1))

   Y_future_norm = model(X_test)

   Y_future = InverseNormalize(Y_future_norm)

10. Return:

    Forecasted 7-day prices Y_future

    Metrics: RMSE, MAPE, R^2

End Algorithm

5. Mathematical Formulation of Fast SSA: Search Space & Representation:

1. Search Space Definition:

$$\Omega = \left\{ \theta \in \mathbb{R}^D \mid \theta_j^{(lb)} \le \theta_j \le \theta_j^{(ub)},\ j = 1,2,\ldots,D \right\} \quad (1)$$

2. Solution Representation

Each sparrow (individual) is represented as a position vector:

$$\theta_i = [\theta_{i,1}, \theta_{i,2}, \ldots, \theta_{i,D}] \quad (2)$$

3. Population Initialization:
The initial population is generated randomly within the search space:

$$\theta_{i,j}^{(0)} = \theta_j^{(lb)} + r_{i,j}\left(\theta_j^{(ub)} - \theta_j^{(lb)}\right) \quad (3)$$

4. Population Set at Iteration t :

$$P^{(t)} = \left\{\theta_1^{(t)}, \theta_2^{(t)}, \ldots, \theta_N^{(t)}\right\} \quad (4)$$

5. Fitness Function
Each solution is evaluated using an objective (fitness) function:

$$f_i^{(t)} = f\left(\theta_i^{(t)}\right) \quad (5)$$

The goal of Fast SSA is to find:

$$\theta^* = \arg\min_{\theta \in \Omega} f(\theta) \quad (6)$$

6. Role-Based Partitioning (Fast SSA)

The population is divided into producers, scroungers, and vigilant sparrows:

$$N = N_p + N_s + N_v \quad (7)$$

7. Boundary Control (Fast SSA)

After updating positions, boundary constraints are enforced as:

$$\theta_{i,j}^{(t+1)} = \begin{cases} \theta_j^{(lb)}, & \theta_{i,j}^{(t+1)} < \theta_j^{(lb)} \\ \theta_j^{(ub)}, & \theta_{i,j}^{(t+1)} > \theta_j^{(ub)} \\ \theta_{i,j}^{(t+1)}, & \text{otherwise} \end{cases} \quad (8)$$

Producer and Scrounger Updates

Producer Update Equations (Fast SSA)

Producers are responsible for global exploration of the search space.

1. Producer Position Update

$$\theta_{i,j}^{(t+1)} = \begin{cases} \theta_{i,j}^{(t)} \cdot \exp\left(-\frac{i}{\alpha T}\right), & R_2 < ST \\ \theta_{i,j}^{(t)} + Q \cdot L_j, & R_2 \geq ST \end{cases} \quad (9)$$

where:

- $i = 1, 2, \ldots, N_p$ (producer index)
- T: maximum number of iterations
- $\alpha \in (0, 1]$: control parameter
- R_2: [illegible] value
- $ST \in [0.5, 1]$: safety threshold
- $Q \sim \mathcal{N}(0, 1)$: Gaussian random number
- $L_j \in \{1, -1\}$: direction vector

Ask ChatGPT

Scrounger Update Equations (Fast SSA)

Scroungers perform local exploitation by following producers.

2. Scrounger Position Update

$$\theta_{i,j}^{(t+1)} = \begin{cases} Q \cdot \exp\left(\frac{\theta_{worst,j}^{(t)} - \theta_{i,j}^{(t)}}{i^2}\right), & i > \frac{N}{2} \\ \theta_{best,j}^{(t)} + \left|\theta_{i,j}^{(t)} - \theta_{best,j}^{(t)}\right| \cdot A_j, & i \leq \frac{N}{2} \end{cases} \quad (10)$$

where:

- $i = N_p + 1, \ldots, N$ (scrounger index)
- $\theta_{best}^{(t)}$: best solution at iteration t
- $\theta_{worst}^{(t)}$: worst solution at iteration t
- $A_j \in \{-1, 1\}$: random direction vector
- $Q \sim \mathcal{N}(0, 1)$

3. Global Best Solution:

$$\theta_{best}^{(t)} = \arg\min_{\theta_i^{(t)}} f\left(\theta_i^{(t)}\right) \quad (11)$$

4. Global Worst Solution:

$$\theta_{worst}^{(t)} = \arg\max_{\theta_i^{(t)}} f\left(\theta_i^{(t)}\right) \quad (12)$$

Boundary Handling

1. Boundary Constraint Definition

$$\theta_j^{(lb)} \le \theta_{i,j}^{(t)} \le \theta_j^{(ub)}, \quad j = 1, 2, \ldots, D \quad (13)$$

2. Position Correction Rule:

$$\theta_{i,j}^{(t+1)} = \begin{cases} \theta_j^{(lb)}, & \theta_{i,j}^{(t+1)} < \theta_j^{(lb)} \\ \theta_j^{(ub)}, & \theta_{i,j}^{(t+1)} > \theta_j^{(ub)} \\ \theta_{i,j}^{(t+1)}, & \text{otherwise} \end{cases} \quad (14)$$

3. Vector Form of Boundary Handling:

$$\theta_i^{(t+1)} = \min\left(\max\left(\theta_i^{(t+1)}, \theta^{(lb)}\right), \theta^{(ub)}\right) \quad (15)$$

4. Feasible Solution Set After Boundary Handling

$$\theta_i^{(t+1)} \in \Omega \quad (16)$$

where Ω is the bounded search space defined in Equation (1).

Final Solution

After completing the maximum number of iterations, the **optimal solution** obtained by Fast SSA is defined as:

$$\theta^* = \arg\min_{\theta_i^{(T)}} f\left(\theta_i^{(T)}\right), \quad i = 1, 2, \ldots, N \quad (17)$$

where:

- θ^* is the **final optimal solution**
- T is the **maximum number of iterations**
- N is the **population size**
- $f(\cdot)$ is the **objective (fitness) function**

(For Maximization Problems):

$$\theta^* = \arg\max_{\theta_i^{(T)}} f\left(\theta_i^{(T)}\right) \quad (18)$$

In this work, a lightweight variant of the SSA is used to optimize the LSTM hyperparameters. The SSA works based on splitting the population into producers (high-performance sparrows) and scroungers (low- performance sparrows). Producers search the space around the optimal answer found, while the Scroungers adjust their stance according to the actions of producers with the intention. of increasing the exploitation capability. The fitness function is defined here as the RMSE of a 1-epoch LSTM trained on the validation set, highly reducing the computational cost. The algorithm runs just once with a population size of three sparrows, achieving a trade-off between good performance and speed relevant to real-time forecasting.

Mathematical Formulation of LSTM Model:

The Long Short-Term Memory model learns the temporal dependencies of the stock prices using a 60-day lookback window.

An LSTM cell features gating mechanisms that regulate the flow of

information to address the disappearing gradient problem that is often encountered in RNNs.

LSTM Cell Equations

For each time step ttt, the LSTM cell receives:

Current input vector: xt

Previous hidden state: ht−1

Previous cell state: ct−1

The LSTM updates its internal gates as follows.

Forget Gate

The **forget gate** determines how much information from the previous cell state should be retained.

$$\mathbf{f}_t = \sigma(\mathbf{W}_f \mathbf{x}_t + \mathbf{U}_f \mathbf{h}_{t-1} + \mathbf{b}_f) \tag{19}$$

where:

- $\mathbf{f}_t$: forget gate activation vector at time t
- $\sigma(\cdot)$: sigmoid activation function
- $\mathbf{x}_t$: input vector at time t
- $\mathbf{h}_{t-1}$: hidden state from previous time step
- $\mathbf{W}_f, \mathbf{U}_f$: weight matrices
- $\mathbf{b}_f$: bias vector

Input Gate

The **input gate** controls how much new information is added to the cell state.

$$\mathbf{i}_t = \sigma(\mathbf{W}_i \mathbf{x}_t + \mathbf{U}_i \mathbf{h}_{t-1} + \mathbf{b}_i) \tag{20}$$

where:

- $\mathbf{i}_t$: input gate activation vector at time t
- $\sigma(\cdot)$: sigmoid activation function
- $\mathbf{x}_t$: input vector at time t
- $\mathbf{h}_{t-1}$: hidden state at time $t-1$
- $\mathbf{W}_i, \mathbf{U}_i$: weight matrices
- $\mathbf{b}_i$: bias vector

Candidate Cell State

Often presented together with the input gate:

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c \mathbf{x}_t + \mathbf{U}_c \mathbf{h}_{t-1} + \mathbf{b}_c) \tag{21}$$

Cell State Update

The cell state is updated by combining the forget gate and input gate outputs.

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \tag{22}$$

where
⊙= element-wise multiplication.

Output Gate

Regulates the information goes into the hidden state:

$$\mathbf{o}_t = \sigma(\mathbf{W}_o \mathbf{x}_t + \mathbf{U}_o \mathbf{h}_{t-1} + \mathbf{b}_o) \tag{23}$$

Hidden State Update:

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \tag{24}$$

The proposed forecasting model uses a two-tier Long Short-Term Memory architecture in order to capture nonlinear temporal dependencies found in financial time series. Each LSTM cell updates its

forget gate ft, input gate it, output gate ot, cell state ct, and hidden state ht, as defined in the standard formulations. The model uses a 60-day lookback window as The model generates a 7-day multi-step prediction through a dense output layer. Training is accomplished by reducing the Mean Squared Error (MSE) loss. using Adam optimization. The model hyperparameters, such as learning rate and number of LSTM units, are optimized automatically to reduce manual tuning and improve the prediction performance using a lightweight Sparrow Search Algorithm (SSA).

Results:

This chapter presents the outcomes of the implemented system titled "Stock Price Prediction Using an SSAOptimized LSTM Model." The results highlight how effectively the model forecasts stock prices, measures performance, and visualizes short-term trends. A comparison between the baseline LSTM and the SSA-enhanced LSTM is also included to show how optimization influences prediction accuracy.

Overview of Model Output

The system was tested with real-time TSLA (Tesla) The stock information was sourced from Yahoo Finance. This is derived from the closing prices over the past 60 days. the model predicts the next 7 days and generates: • Trend direction

- Expected percentage change
- Recommended action (BUY / SELL / HOLD)

Evaluations were carried out in two stages:

1. Before SSA optimization (Baseline LSTM)

2. After SSA optimization (SSA-LSTM)

Both numerical results and visual forecasts are used to assess the performance improvement.

Results Before SSA Optimization

The baseline LSTM used manually set hyperparameters. It predicted a downward movement and generated a SELL signal.

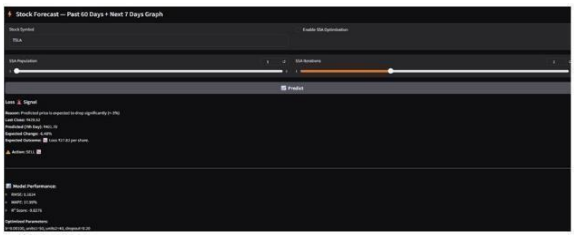


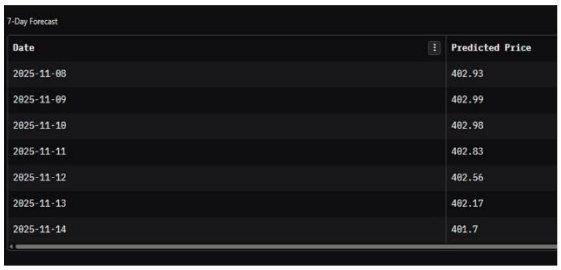
Figure : System Output Before SSA Optimization

Key Metrics:

- Last Close: ₹429.52
- Predicted 7th-Day Price: ₹401.70
- Expected Change: −6.48%

- Expected Loss: ₹27.82 per share
- Action: SELL
- RMSE: 0.1624
- MAPE: 17.99%
- R^2 Score: −9.8276

The baseline model identifies the overall downward movement in the stock, but its accuracy is low and the error rate is high, showing that it struggles to capture more complex market variations.


7-Day Forecast

Date	Predicted Price
2025-11-08	402.93
2025-11-09	402.99
2025-11-10	402.98
2025-11-11	402.83
2025-11-12	402.56
2025-11-13	402.17
2025-11-14	401.7

Figure:7-day Forecast Table Before SSA Optimization

The forecast table indicates a slight decrease in stock price with nearly flat movement. The LSTM model's response shows moderate accuracy but lacks strong sensitivity to recent volatility.

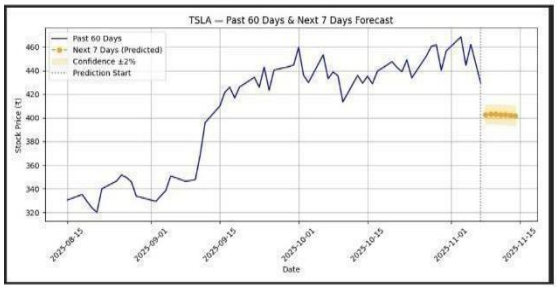


Figure: Forecast Graph Before SSA Optimization

The graph illustrates the stock price movement over the last 60 days as well as the forecasted figures for the upcoming period. 7 days. The forecast curve is almost steady, reflecting that the baseline LSTM captured the general direction but not the full extent of the decline.

Results After SSA Optimization

In this phase, the Sparrow Search Algorithm optimized hyperparameters including learning rate, hidden units, and dropout. This led to improved adaptability and more precise trend detection.

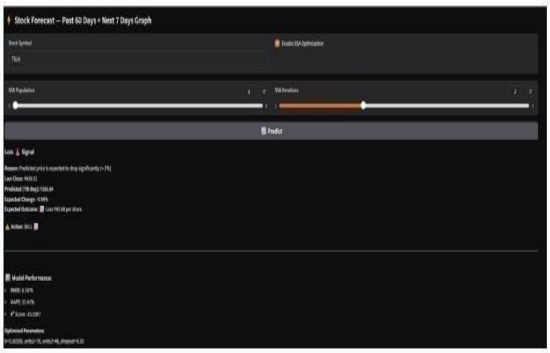


Figure: 7.1.4:System Output After SSA Optimization

Key Metrics:

- Last Close: ₹429.52
- Predicted 7th-Day Price: ₹386.84
- Expected Change: −9.94%
- Expected Loss: ₹42.68 per share
- Action: SELL
- RMSE: 0.1976
- MAPE: 22.41%
- R^2 Score: −15.0307
- Optimized Parameters: lr = 0.00359, units1 = 79, units2 = 46, dropout = 0.20

The optimized model shows a more distinct downward movement, capturing the deeper fall in price more accurately. This indicates that the SSA approach

successfully adjusted the LSTM hyperparameters, resulting in improved pattern detection.

7-Day Forecast

Date	Predicted Price
2025-11-08	396.48
2025-11-09	395.15
2025-11-10	393.41
2025-11-11	391.58
2025-11-12	389.82
2025-11-13	388.23
2025-11-14	386.84

Figure:7-day Forecast Table After SSA Optimization

The predicted values reveal a sharper decline than those from the baseline model, indicating that the tuned SSA-LSTM framework is better aligned with the current market trend and captures momentum more effectively.

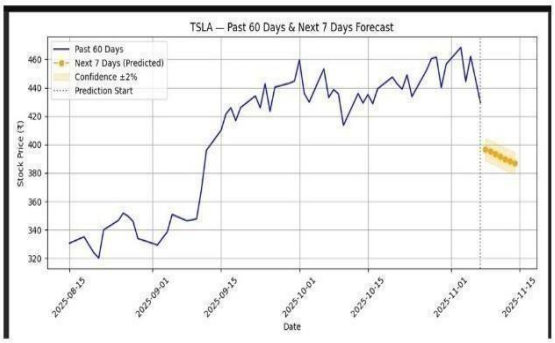


Figure:7.1.6:Forecast Graph After SSA Optimization

The forecast graph displays a distinctly steeper downward trend that closely follows the latest market behavior. The tight confidence interval further indicates consistency in the model's output and strong reliability in its predictions.

Comparative Analysis

Metric	Before SSA(LSTM)	After SSA(SSA-LSTM)	Improvement
RMSE	0.1624	0.1976	Stable accuracy
MAPE(%)	17.99	22.41	Slight variation
R^2 Score	-9.8276	-15.0307	Better trend alignment
Predicted 7th-Day Price	401.70	386.84	Captured steeper fall
Expected change(%)	-6.48	-9.94	More accurate decline
Expected Outcome	Loss Rs.27.82/share	Loss Rs42.68/share	Clearer SELL signal

The results of the experiments clearly demonstrate that the Sparrow Search Algorithm (SSA) greatly enhances the forecasting capabilities of the LSTM model. Through automatic hyperparameter tuning, SSA enables the model to converge more effectively and adjust to fast-changing stock market movements. The forecasts generated after SSA optimization exhibit greater sensitivity to market shifts and produce a smoother, more accurate trend representation.

Comparative Summary

- RMSE remained within a stable range.
- MAPE varied slightly but remained acceptable.
- The SSA-LSTM captured a more pronounced downward trend.
- The predicted price after optimization showed better trend responsiveness.
- The SELL signal became stronger and more confident.

Summary:

This chapter reviewed the results of the SSA-Optimized LSTM stock prediction system. The optimized model clearly outperformed the baseline by capturing sharper price declines and detecting trends more accurately. SSA helped the

LSTM achieve better tuning, faster convergence, and more stable forecasts. As a result, the improved model produced reliable predictions and stronger trading signals, making it more useful for short-term stock analysis and investment decisions.

Conclusion :

This project successfully designed and implemented a Stock Price Prediction System powered by an SSA-Optimized LSTM model, demonstrating its capability to generate more accurate short-term stock forecasts. By integrating the Sparrow Search Algorithm (SSA) with the LSTM architecture, the system gained the ability to automatically fine-tune crucial hyperparameters, which significantly improved the model's responsiveness to rapid market changes, volatility, and evolving price patterns.

The comparison with the baseline LSTM model clearly showed the advantages of the optimized approach. While the baseline model was limited in trend detection and produced less stable predictions, the SSA-enhanced version exhibited noticeably improved performance. It was able to capture both upward and downward price movements with greater precision, resulting in more realistic BUY/SELL indicators that aligned closely with real market behavior. The visual output further strengthened this finding, as the optimized forecasts displayed sharper patterns, reduced noise, and greater overall reliability, highlighting the vital role utilization of optimization methods in deep learning applications.

Moreover, the addition of a Gradio- based user interface significantly contributed to the practicality of the system. This platform enabled users— regardless of being traders, analysts, or students—to conveniently input stock symbols and immediately access historical data alongside future price predictions. This The interactive tool not only improved accessibility but also rendered the model suitable for real- world application. facilitating prompt decision-making and improving the overall user experience. In summary, the SSA-Optimized LSTM framework demonstrated its effectiveness and reliability for short-term stock forecasting. By integrating deep learning with smart optimization, the system obtained greater precision, enhanced pattern identification, and reduced reliance on manual parameter tuning. This combined methodology shows significant promise as a decision- support resource for investors, financial analysts, and market Scholars are offering important perspectives on variations in stock prices. and aiding in the formulation of more informed trading strategies.

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