Dandelion Optimizer with LSTM Model (DO-LSTM) for Stock Input Feature Selection for Price Forecasting

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***Abstract*— Stock price prediction is a critical decision-making function in finance, which offers investors valuable information regarding future market trends. This paper presents a novel hybrid model that combines the Dandelion Optimizer (DO) and Long Short-Term Memory (LSTM) networks for forecasting the stock market close price. Dandelion Optimizer is employed as a feature selection method to identify the most significant technical indicators, e.g., Simple Moving Average (SMA), Exponential Moving Average (EMA), Momentum, and Volatility, which have a direct influence on the stock price movements. Two feature selection approaches are explored: DO with Linear Regression-based Feature Selection and DO with LSTM-Based Feature Selection. Experimental results indicate that the DO with Linear Regression Feature Selection + LSTM Prediction Model outperforms the LSTM-based feature selection model in terms of prediction accuracy and reliability with the lowest Mean Squared Error (MSE) of 14.4632 and the highest R^2 Score of 0.93. The findings validate the importance of technical indicators in enhancing model performance and the promise of hybrid optimization-based deep learning models for financial time series forecasting. By offering a reliable and computationally effective framework, this study positively impacts the advancement of intelligent forecasting of stocks systems.**

***Keywords* — Stock Market, Long short-term memory (LSTM), Dandelion Optimizer(DO), Technical Indicator, Machine learning techniques**

I. INTRODUCTION

Stock market forecasting is an important field of study because of its impact on investment choices, risk management, and financial stability. The stock market is inherently unstable, subject to economic conditions, investor psychology, and extraneous events, and hence precise forecasting is a difficult task. Several optimization techniques, such as Genetic Algorithm (GA)[1], Rat Swarm Optimization (RSO)[2], teaching-learning based optimization(TLBO)[3] and Artificial Bee Colony (ABC)[4], have been used to enhance prediction accuracy of stock market by optimizing model parameters and feature selection. These conventional methods tend to suffer from premature convergence, low computational efficiency, and difficulty in dealing with high-dimensional datasets. Recent developments have brought forth the Dandelion Optimizer (DO), which has shown better performance in exploration-exploitation balance, prediction accuracy improvement, and optimization of complex search spaces more effectively than its earlier versions [5]. Apart from optimization methods, technical indicators are also important in stock market analysis. Simple Moving Average (SMA) and Exponential Moving Average (EMA) both smooth out the price movements in order to reveal trends, whereas SMA_10 and SMA_50 pick up short- and long-term trends, respectively, and EMA_10 and EMA_50 offer more sensitive means to recent price variations. Momentum indicators quantify the extent of price motion, which specifies trend strength, while volatility measures the size of price variations to help in judging risk. This research combines these technical metrics with new optimization methods to maximize stock price forecasting accuracy. By comparing and assessing GA, RSO, TCBO, ABC, and the Dandelion Optimizer, this paper will offer insight into the best optimization method for forecasting stock markets.

II. RELATED WORK

Several research papers use various nature-based meta heuristic methods for stock forecasting as provided in Table I.

TABLE I. RELATED WORK ON STOCK FORECASTING USING OPTIMIZATION TECHNIQUES STOCK

Related Work on stock forecasting using optimization techniques	Summary of Work
1. **Genetic Algorithm (GA)** [6]	In this paper, the author first describes the Chinese news-based stock trend prediction model. Based on the model, we then introduce the stock trend prediction (STP) algorithm with consideration of Chinese news and technical indicator for predicting stock trends. Since parameters setting is an optimization issue, we then adjust the model and develop the second stock trend prediction algorithm to obtain the optimal trading scenario by genetic algorithms, i.e., GATSP.
2. **Particle Swarm Optimization (PSO)** [7]	Along with discussing the ramifications of PSO, it examines its superiority for stock portfolio optimization, stock price and trend prediction, and other associated stock market elements.
1. **Ant Colony Optimization (ACO)** [8]	According to experimental data, the ACO-SPP predicts stock prices more accurately than the approaches that were examined in terms of accuracy, F-score, AUC, discriminant power, and Youden's index.
2. **Simulated Annealing (SA)** [9]	The prediction performance of stock price rise and fall is verified, and the hybrid model based on LSTM neural network proposed in this paper has certain feasibility and stability in the prediction of stock price rise and fall.
3. **Grey Wolf Optimization (GWO)** [10]	This paper uses grey wolf optimizer MOGWO and NSGA II.to offers accurate predictions for one day in advance.
4. **Harmony Search Algorithm (HSA)** [11]	This work proposes a novel two-stage ensemble models for stock price prediction that combine the extreme learning machine (ELM), improved harmony search (IHS), and empirical mode decomposition (EMD) (or variation mode decomposition, or VMD) algorithms. These models are called EMD–ELM–IHS and VMD–ELM–IHS, respectively.

Nature-inspired algorithms as shown below in the Fig.1. are optimization methods that emulate biological, ecological, or physical phenomena in nature to address difficult computational problems. They are broadly applied for feature selection, parameter tuning, and predictive modeling because they can effectively search large solution spaces. Typical examples are Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Dandelion Optimizer (DO). These algorithms use natural occurrences like evolution, swarm intelligence, and seed dispersal in plants to arrive at optimal or close-to-optimal solutions. Stock market prediction through nature-inspired algorithms has a number of benefits. They are able to automatically choose the most appropriate technical indicators and attributes, enhancing the accuracy of models. These algorithms avoid local minima, ensuring better exploration of the solution space. They adjust hyper parameters of machine learning models to improve prediction performance. They are also very flexible and can handle dynamic and non-linear patterns in share data. They tend to converge quicker to optimal solutions than classical optimization techniques. Stock prediction systems may attain improved accuracy and stability in unstable markets by merging deep learning models such as LSTM or CNN with nature-inspired algorithms

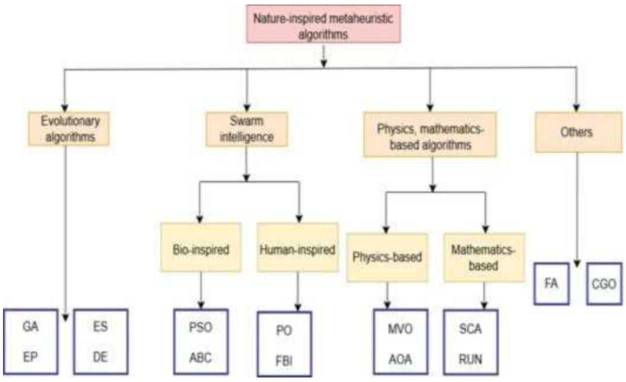

Fig.1. Classification of Meta heuristic algorithms influenced by nature.

This picture in Fig.1 depicts a taxonomy of nature-inspired metaheuristic algorithms, which are frequently employed in optimization problems. These are natural process- and behavior-based algorithms, typically employed to optimize feature selection, model parameters, and hyper parameters in intricate problems such as stock price prediction.DO belongs to the "Bio-inspired" category of Swarm Intelligence in this taxonomy. It imitates the seed dispersal mechanism of dandelions, maximizing solutions by effectively exploring and exploiting the search space. DO can be employed to choose the most appropriate technical indicators and LSTM hyper parameters to enhance prediction performance.

III. DATA SET AND TECHNICAL INDICATORS

The data has 2035 rows of Tata Global stock market observations with 8 columns corresponding to different stock characteristics as shown in Table II. Similarly, The dataset contains historical stock price data for Tesla over the past 10 years, enriched with several technical indicators to analyze market trends and stock performance. The data includes the date, as well as the opening, highest, lowest, and closing prices for each trading day. It also details the volume of shares traded.

TABLE II. DESCRIPTION OF DATA SET OF TATA GLOBAL STOCK

Attributes	Description
Date	Date of trade (string format).
Open	Price at opening of trading day.
High	Highest price within the session.
Low	Low price within the session.
Last	Price upon last trade preceding the end of the session.
Close	Ultimate closing price on the stock (target variable to predict).
Total Trade	Total shares traded in the session.

Turnover (Lacs)	Total value of transactions in lakhs.

The data range is from ₹80.95 to ₹325.75, with the average closing price being around ₹149.45. The volumes of trades range widely, with a high of about 2.9 crores shares traded in a session. This data set is appropriate for deep learning-based time series stock price prediction models and optimization methods. Following Technical Indicators are developed from this data using Equations 1 to 6 as shown in Table III.

TABLE III. TECHNICAL INDICATORS USED IN THE MODEL

Technical Indicators	Formula
SMA_10	$\frac{\sum_{i=1}^{10} P_i}{10}$ (Eq.1)
SMA_50	$\frac{\sum_{i=1}^{50} P_i}{50}$ (Eq.2)
EMA_10	$\left(P_t \times \frac{2}{11}\right) + \left(EMA_{t-1} \times \left(1 - \frac{2}{11}\right)\right)$ (Eq.3)
EMA_50	$\left(P_t \times \frac{2}{51}\right) + \left(EMA_{t-1} \times \left(1 - \frac{2}{51}\right)\right)$ (Eq.4)
Momentum	$P_t - P_{t-n}$ (Eq.5)
Volatility	$\sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_i - \mu)^2}$ (Eq.6)

IV. SIMULATION OF PROPOSED MODEL

A. Dandelion Optimizer as Optimizer

The Dandelion Optimizer (DO) as stated in this paper [12] is inspired by the seed dispersal mechanism of dandelion flowers, utilizing exploration and exploitation strategies to find optimal solutions. Here the optimizer is used to select the best input features for prediction of closing prices. It works through the following stages:

a) Seed Dispersal (Exploration Phase): Similar to how dandelion seeds spread over vast distances by wind, the algorithm randomly initializes potential solutions across the search space. This ensures a diverse set of candidates, preventing premature convergence to suboptimal results.

b) Adaptive Movement (Search Adjustment): Seeds that land in more favorable environments (better solutions) have a higher chance of growing. The algorithm refines the search by adjusting positions based on fitness evaluation, gradually moving towards promising areas.

c) Resource Competition (Exploitation Phase): Just like only the strongest dandelion seeds survive in a competitive environment, the algorithm prioritizes the best-performing solutions. Poor candidates are replaced, and strong ones continue evolving to refine the optimal answer.

d) Convergence to Optimal Solution: The process repeats until a stopping criterion is met, ensuring that the best possible solution is identified efficiently while balancing exploration and exploitation.

This approach makes the Dandelion Optimizer highly effective in handling complex optimization problems, outperforming traditional algorithms in adaptability and precision. The flowchart below in Fig.2. Provides a glimpse of how dandelion optimizer perform in selecting the best solution for the model. Here the dandelion optimizer produces the best feature set based on LSTM-Based Feature Selection as well as Linear Regression-Based Feature Selection based on their individual predictive performance. Then these best set are fed as input parameters to the predictive model LSTM to predict the closing price.

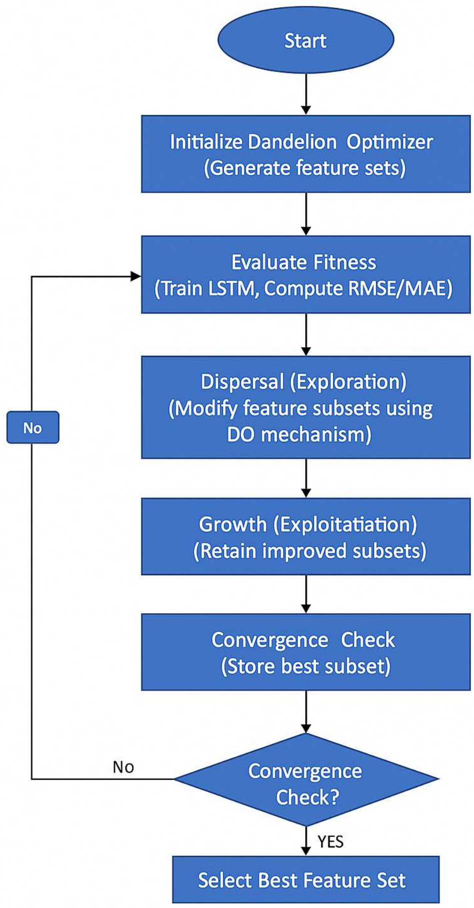

Fig.2. Flowchart of Dandelion Optimizer For Selection of Inputs.

B. Proposed Model as DO-LSTM (Dandelion Optimizer-LSTM)

The flowchart in figure Fig.3. illustrates the designed Dandelion Optimizer-Long Short-Term Memory (DO-LSTM) framework to forecast the stock price. To increase stock forecast accuracy, the model integrates the LSTM neural network [13] with the Dandelion Optimizer (DO). The process starts with the inputting of stock parameter data, such as historical prices and technical indicators. The DO algorithm initializes its population and optimizes the input features of the LSTM network by simulating the natural growth and dispersal of dandelion seeds. The objective function computes the fitness of each solution, choosing the optimal features that reduce prediction error. The optimized features are then passed to the LSTM model as input, which learns the training data. The process is repeated until the specified number of epochs is completed. Lastly, the model provides an estimated closing price of the stock. The proposed hybrid method enhances convergence rate, accuracy, and overall performance in volatile stock markets.

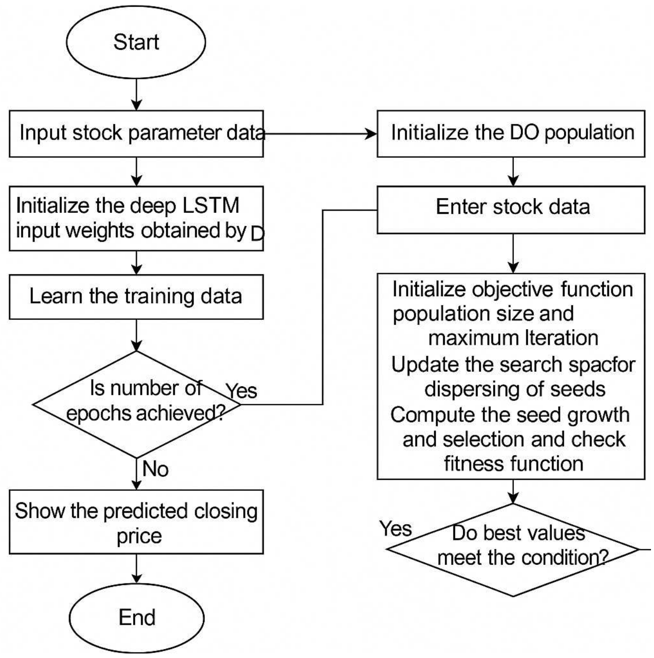

Fig.3. Proposed Model Dandelion Optimizer –LSTM Flowchart

V. RESULTS AND DISCUSSION

The table Table IV shows the performance comparison of various combinations of feature selection for predicting stock prices with the Dandelion Optimizer (DO) and Linear Regression. The binary feature selection vector shows the presence (1) or absence (0) of certain stock parameters. The efficacy of the model is measured by Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) metrics.The following observations are as follows:

a) The optimum combination of features is [0 1 1 0 1 0], exhibiting the minimum MSE (14.4632), RMSE (3.8030), and MAE (3.1887), but with the highest R^2 (0.93) value, reflecting high predictive accuracy between the predicted and actual values.
b) The mixture [0 1 1 0 1 1] works reasonably well with MSE (55.8379) and R^2 (0.70), which indicates below-average predictive ability.
c) The combination of features [1 1 1 0 1 0] results in higher errors with MSE (62.5986) and R^2 (0.66), suggesting lower prediction accuracy.
d) The poorest performance is seen with the same combination repeated using MSE (105.4397) and R^2 (0.42), showing poor model performance.the worst, with the highest error rates on all measures. Adam, with the lowest MAE (8.07), MSE (118.56), and RMSE (10.88), is the best option for the CNN-LSTM model.

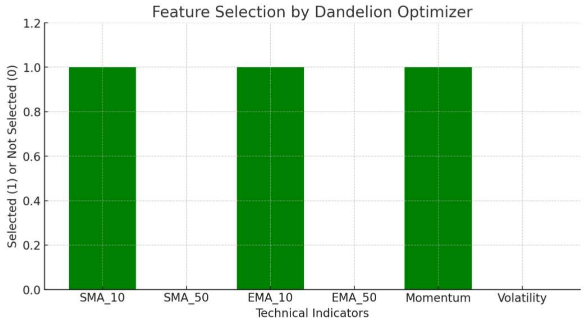

Fig.4. Feature Selection by Dandelion Optimizer

The green bars represent the input selected features (1) and the (0)s represent the discarded features. The following selected features in this Fig.4. for example are SMA_10,EMA_10 and Momentum.

Stock market information is high-dimensional and noisy.Feature selection must be done properly to prevent confusing the model. The Dandelion Optimizer does this automatically and better, adapting the input to the LSTM for more accurate forecasting.The bars at height 1 (SMA_10, SMA_50, EMA_10, EMA_50, Momentum) mean that the Dandelion Optimizer chose these features as the most significant inputs for training the LSTM model.They are probably contributing highly towards enhancing the accuracy of the model.Through picking the most applicable indicators only, DO helps prevent overfitting, lowers the dimension, and improves generalization of LSTM models.

It produces a model faster and mostly with better precision through eliminating non applicable features or redundancy.

TABLE IV. PREDICTIONS OF DANDELION OPTIMIZER WITH LINEAR REGRESSION-BASED FEATURE SELECTION INPUTS WITH LSTM AS PREDICTIVE MODEL

Best Feature Selection	MSE	RMSE	MAE	R2
[0 1 1 0 1 0]	14.4632	3.8030	3.1887	0.93
[0 1 1 0 1 1]	55.8379	7.4724	6.5456	0.70
[1 1 1 0 1 0]	62.5986	7.9119	7.04556	0.66
[1 1 1 0 1 0]	105.4397	10.2683	9.2874	0.42

Table V displays the performance results of various combinations of feature selection optimized using the Dandelion Optimizer (DO) with the LSTM-based prediction model. The binary feature selection vectors indicate the inclusion (1) or absence (0) of particular stock parameters. R-squared (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) metrics are used to gauge the accuracy of the

model in predicting outcomes. The optimal combination is [1 0 0 0 1 1], which has the lowest MSE (22.2581), RMSE (4.7178), and MAE (3.9445), and the highest R² value (0.88), reflecting high prediction accuracy.
The blend [0 0 1 0 1 1] is moderately well performing with MSE (51.3058) and R² (0.72), proposing satisfactory predictive capability.
Two runs of the combination [0 0 0 1 1 1] produce similar performance, with MSE values of 82.1542 and 52.5387, and R² values of 0.55 and 0.72, indicating inconsistent performance across trials. Figures 5-12 shows the graph of actual verses predicted stock prices using the DO-LSTM models based on Linear Feature Selection and LSTM-based feature selection inputs.

TABLE V. Predictions of Dandelion Optimizer with LSTM-Based Feature Selection Inputs with LSTM as Predictive Model

Best Feature Selection	MSE	RMSE	MAE	R2
[0 0 0 1 1 1]	82.1542	9.0638	7.75143	0.55
[1 0 0 0 1 1]	22.2581	4.7178	3.9445	0.88
[0 0 1 0 1 1]	51.3058	7.1628	6.0747	0.72
[0 0 0 1 1 1]	52.5387	7.2483	6.0472	0.72

The comparison of Predictions of Dandelion Optimizer with Linear Regression-Based Feature Selection Inputs using LSTM and Predictions of Dandelion Optimizer with LSTM-Based Feature Selection Inputs using LSTM points out the differences in performance on the basis of feature selection approaches coupled with the LSTM predictive model as given in the Table VI.Fig 13 and Fig 14 provides the prediction of a new stock market data of TESLA as testing for the proposed model.This also shows an R-square value of 0.91 which proves the efficiency of the model.

TABLE VI. Comparison of Dandelion Optimizer-Based Stock Prediction Models

Criteria	DO with Linear Regression Feature Selection + LSTM Prediction Model	DO with LSTM-Based Feature Selection + LSTM Prediction Model
Best MSE	14.4632	22.2581
Best RMSE	3.8030	4.7178
Best MAE	3.1887	3.9445
Best R² Value	0.93	0.88
Feature Selection Influence	Linear Regression selects more relevant input features, enhancing prediction accuracy.	LSTM-based feature selection relies on internal learning but provides slightly lower accuracy.
Consistency of Results	More consistent with smaller error variations	Less consistent with fluctuating errors
Computational Complexity	Lower computational time due to linear regression	Higher computational time due to LSTM feature selection
Overall Performance	Higher accuracy and efficiency	Good performance but slightly lower accuracy

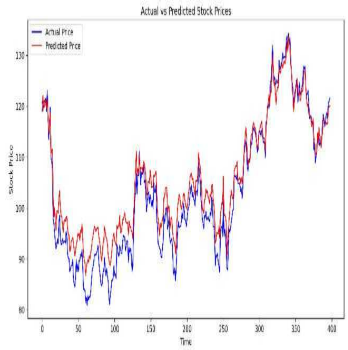

Fig.5. Stock prediction of Actual vs Predicted for DO-LR-1

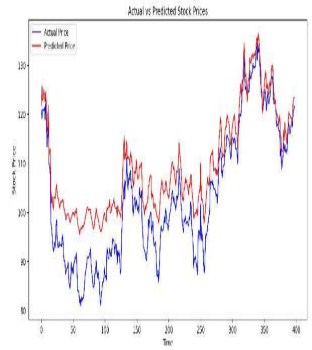

Fig.6. Stock prediction of Actual vs Predicted for DO-LR-2

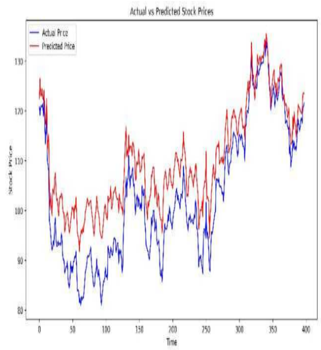

Fig.7. Stock prediction of Actual vs Predicted for DO-LR-3

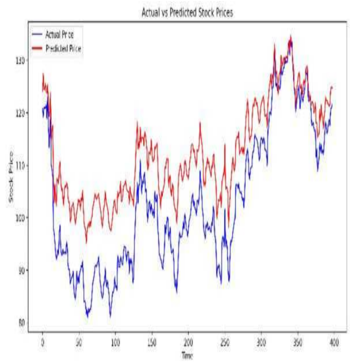

Fig.8. Stock prediction of Actual vs Predicted for DO-LR-4

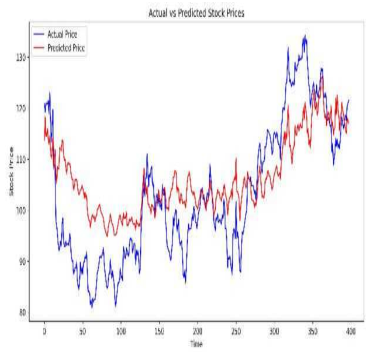

Fig.9. Stock prediction of Actual vs Predicted for DO-LSTM-1

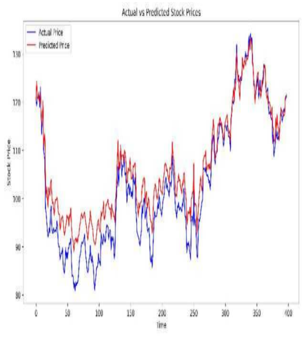

Fig.10. Stock prediction of Actual vs Predicted for DO-LSTM-2

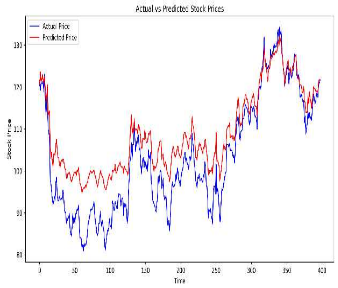

Fig.11. Stock prediction of Actual vs Predicted for DO-LSTM-3

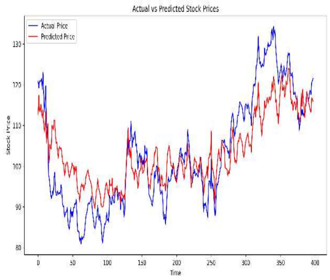

Fig.12. Stock prediction of Actual vs Predicted for DO-LSTM-4

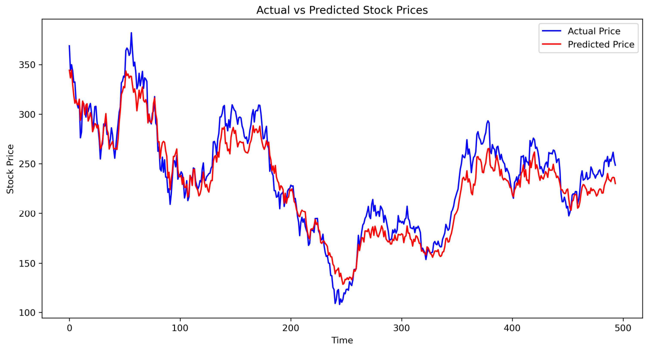

Fig.13.Stock Prediction of TESLA Actual vs Predicted Price For DO-LR Model(**Testing**)

Statistics Measures:

MSE: 236.44677888988662, RMSE: 15.376826034324724, MAE: 13.07482755362791, R2: 0.917865807289321

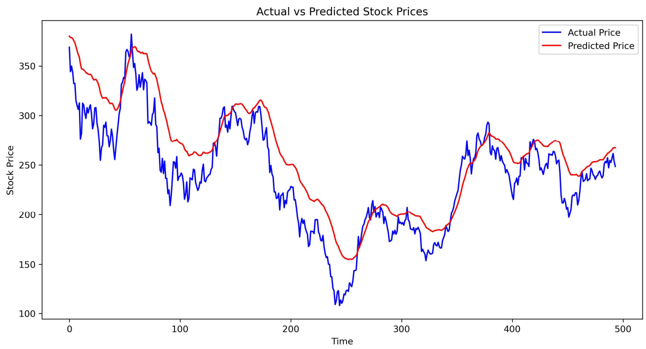

Fig.14.Stock Prediction of TESLA Actual vs Predicted Price For DO-LSTM Model(**Testing**)

Statistics Measures:

MSE: 855.9403697719728, RMSE: 29.256458599290053, MAE: 24.413525622533886, R2: 0.8926731697942026

VI. CONCLUSION

The comparative evaluation of Dandelion Optimizer (DO) with Linear Regression Feature Selection + LSTM Prediction Model and DO with LSTM-Based Feature Selection + LSTM Prediction Model serves to accentuate the importance of combining feature selection methods with deep learning algorithms to predict stock price.DO with Linear Regression Feature Selection + LSTM Prediction Model surpasses the model based on feature selection using LSTM in accuracy and stability. The main reason lies in the fact that feature selection based on Linear Regression selects the most significant technical indicators prior to model training, which eliminates noise and enhances predictive performance. Best MSE (14.4632) and Best R^2 Value (0.93) of this model clearly indicate that it is more precise and stable predictions by choosing the most significant features only. In contrast, the DO with LSTM-Based Feature Selection utilizes the internal learning capability of LSTM layers, resulting in a lower accuracy since the model cannot remove the less important features to any significant extent. Also, its increased computational expense makes it inefficient to use when working with large datasets. Another data set TESLA is tested with the proposed models and the actual verses predicted prices are visualized in Fig.13 and Fig.14 which shows the scalability for larger datasets.

Technical indicators like Simple Moving Average (SMA), Exponential Moving Average (EMA), Momentum, and Volatility are of great significance when forecasting stock prices. Technical indicators provide information on the trend in the market, price momentum, and price movement, which aid the model in comprehending the historical behaviour of the stock. With DO-based feature selection including only the most fundamental indicators, the model can focus on vital patterns while minimizing the influence of irrelevant information, leading to better predictive performance.

In conclusion, the Dandelion Optimizer with Linear Regression Feature Selection and LSTM Prediction provides a more accurate, trusty, and computationally efficient approach towards forecasting stock prices and is a suitable strategy for financial time series prediction.

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