APCI 0776

Dandelion Optimiser with LSTM Model for Stock Input Feature Selection for Price Forecasting

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Outline

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- ❑ Literature Review
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Introduction

- The stock market allows investors to analyze a company's current and future financial value, offering better returns than savings or bonds.
- Artificial intelligence (AI) and machine learning (ML) analyze large datasets, identify trends, and improve stock market forecasting.
- Techniques like neural networks, natural language processing (NLP), and sentiment analysis are applied to news, social media, and stock prices for better predictions.
- This paper introduces a hybrid model that integrates the Dandelion Optimizer (DO) and Long Short-Term Memory (LSTM) networks for stock price prediction.This paper uses a BiLSTM (Bidirectional Long Short-Term Memory) model to predict closing prices for Meta, Amazon, Apple, and Tesla using Yahoo Finance data.
- DO is used for feature selection, identifying crucial technical indicators such as Simple Moving Average (SMA), Exponential Moving Average (EMA), Momentum, and Volatility to improve forecasting accuracy.

Motivation

- Traditional optimization methods like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are widely used to fine-tune model parameters for better stock price prediction.

- Artificial Bee Colony (ABC) and Grey Wolf Optimizer (GWO) are gaining popularity for their ability to balance exploration and exploitation in feature selection.

- Dandelion Optimizer (DO) has shown improved efficiency in selecting key technical indicators for financial forecasting.

- Combining LSTM with optimization techniques like DO, GA, or PSO helps in refining feature selection and improving accuracy.

- Hybrid models integrating deep learning with metaheuristic algorithms are proving to be more effective in stock market predictions compared to standalone models.

Literature Review

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.
1. 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.
1. 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.
1. Grey Wolf Optimization (GWO) [10]	This paper uses grey wolf optimizer MOGWO and NSGA II.to offers accurate predictions for one day in advance.
1. 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.

Models/Methods

- **Start**: Begin the optimization and prediction process.
- **Input stock parameters**: Load historical stock data and technical indicators.
- **Initialize DO and LSTM**:
- Dandelion Optimizer (DO) initializes a random population.
- LSTM input weights are set based on DO-selected features.
- **Optimization process**:
- Set objective function, population size, and maximum iterations.
- Simulate seed dispersal to explore and adjust potential solutions.
- Evaluate fitness and select the best solutions.
- **Feature Selection**:
- If optimal features are found, pass them to LSTM for training.
- Otherwise, continue DO iterations.
- **Train LSTM**: Learn from the optimized input features.
- **Check training completion**: If required epochs are achieved, move to prediction.
- **Prediction**: Output the stock's predicted closing price.
- **End**: Conclude the model's prediction cycle.

Block Diagram/Algorithm

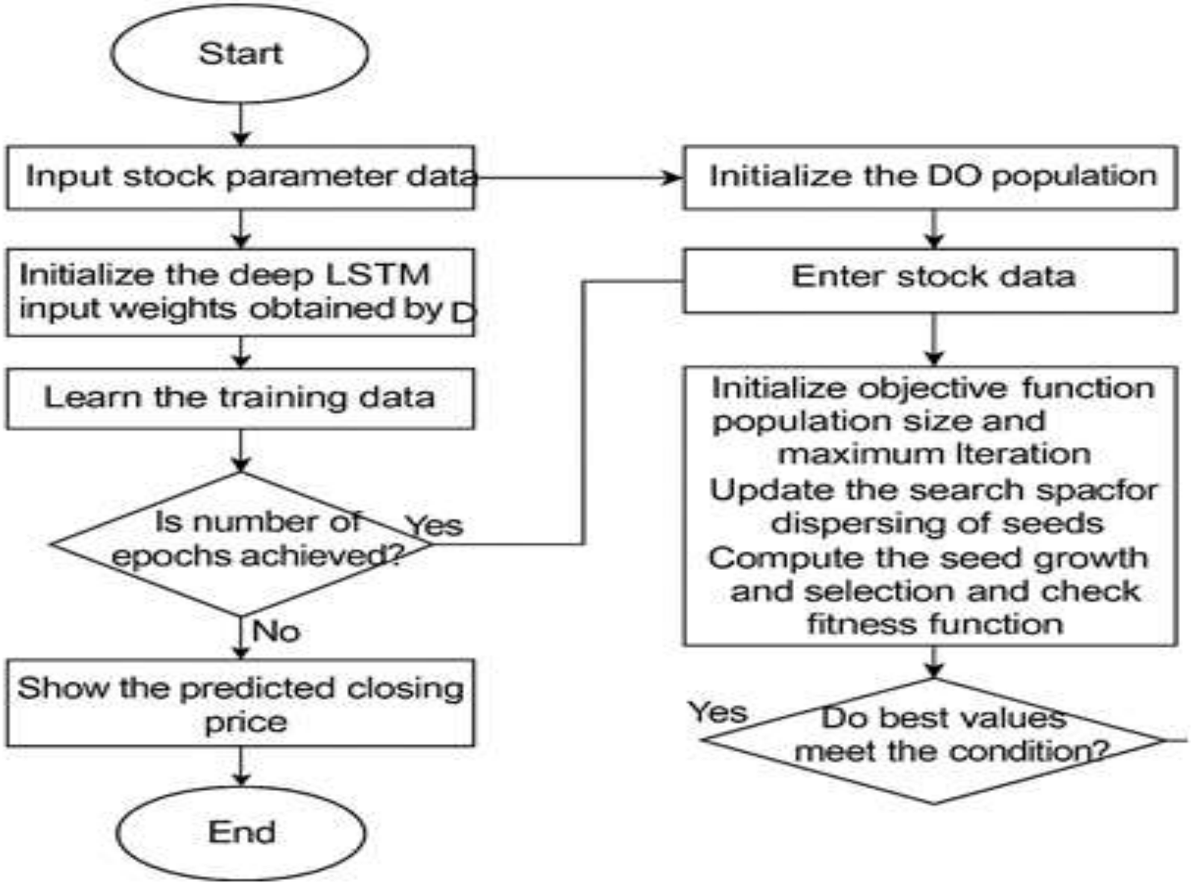


Fig.1. Proposed Model Dandelion Optimizer –LSTM Flowchart

Results

TABLE II. 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 III. PREDICTIONS OF DANDELION OPTIMIZER WITH LSTM-BASED FEATURE SELECTION INPUTS WITH LSTM AS PREDICTIVE MODEL

Best Feature Selection	MSE	RMSE	MAE	R2
[000111]	82.1542	9.0638	7.75143	0.55
[100011]	22.2581	4.7178	3.9445	0.88
[001011]	51.3058	7.1628	6.0747	0.72
[000111]	52.5387	7.2483	6.0472	0.72

Results

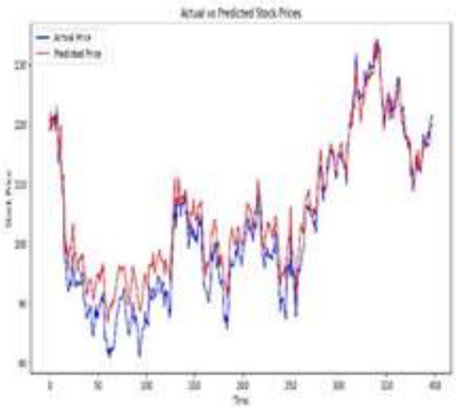


Fig.2. Stock prediction of Actual vs Predicted for DO-LR-1

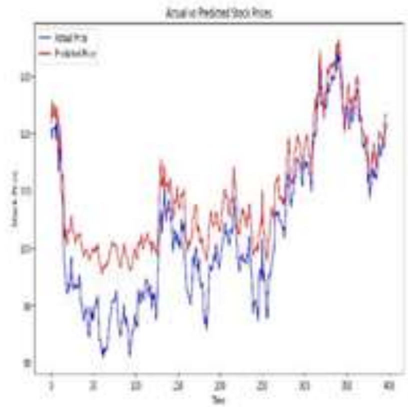


Fig.3. Stock prediction of Actual vs Predicted for DO-LR-2

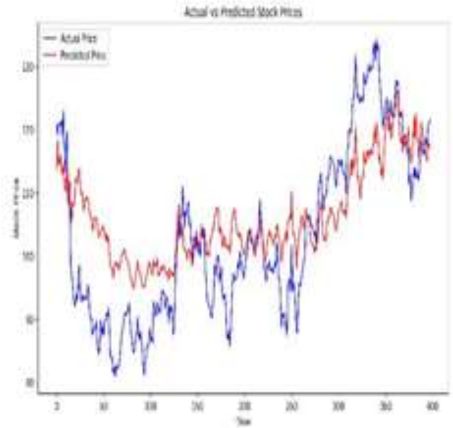


Fig.6. Stock prediction of Actual vs Predicted for DO-LSTM-1

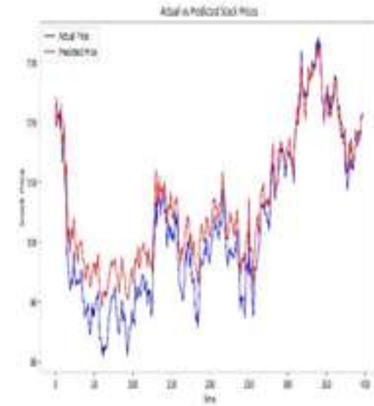


Fig.7. Stock prediction of Actual vs Predicted for DO-LSTM-2

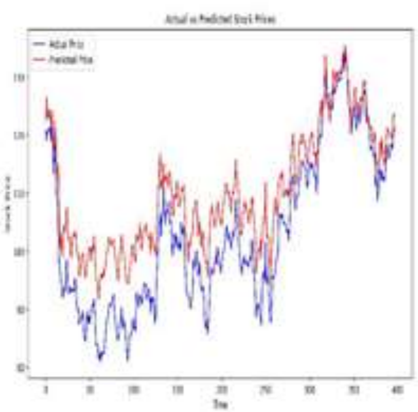


Fig.4. Stock prediction of Actual vs Predicted for DO-LR-3

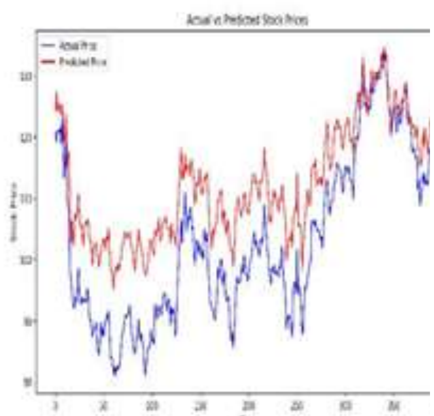


Fig.5. Stock prediction of Actual Predicted for DO-LR-4

Fig.8. Stock prediction of Actual vs Predicted for DO-LSTM-3

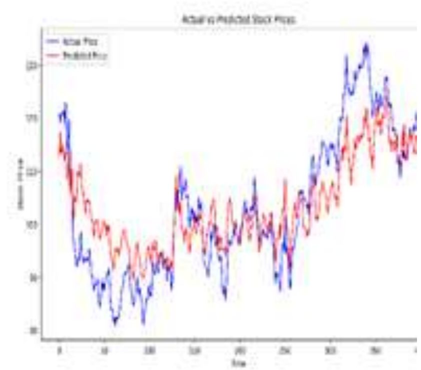
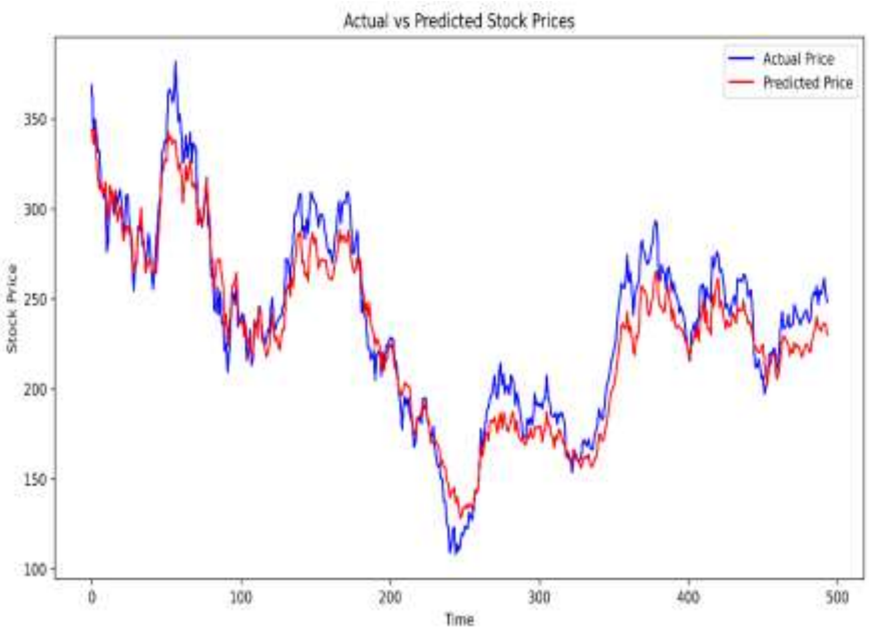


Fig.9. Stock prediction of Actual Predicted for DO-LSTM-4

Results



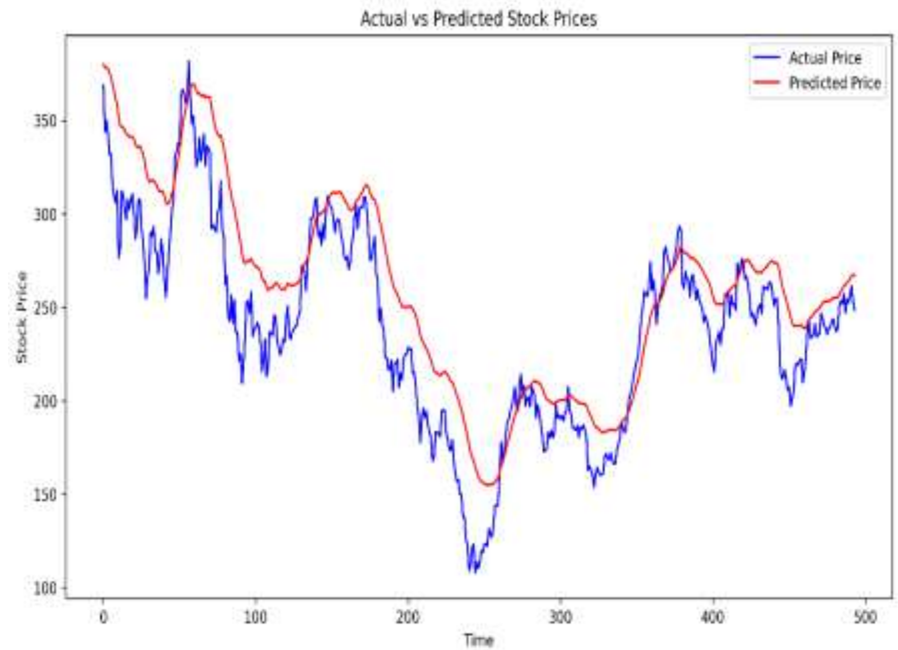


Fig.10.Stock Prediction of TESLA Actual vs Predicted Price For DO-LR Model(Testing)

Statistics Measures:

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

Fig.11.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

Discussion

- 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.

Conclusion

Strengths:

•Combines **feature optimization (DO)** with **deep learning (LSTM)** for superior stock forecasting.

•Achieves **high prediction accuracy** (R^2 = 0.93) by selecting only the most important technical indicators.

•**Reduces model complexity** by eliminating irrelevant features.

•**Adapts well** to different stock datasets (tested on Tata Global and Tesla stocks).

Limitations:

•**Computational cost**: Optimization and LSTM training are resource-intensive for very large datasets.

•**Market volatility sensitivity**: Extreme and sudden market shifts may still challenge model predictions.

•**Overfitting risk**: If too many features are selected or insufficient data is used.

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