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An integrated mathematical cognitive system employing swarm computing for convergence of artificial intelligence and knowledge representation

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Abstract

This research introduces an enhanced LSTM framework utilizing PSO for forecasting the opening value of the NSE index. This study introduces the LSTM and augmented PSO-LSTM framework for stock price prediction, utilizing the notion of time series. The enhanced PSO-LSTM technique utilizing PSO to enhance the weights of Long Short Term Memory framework, thereby enhancing prediction accuracy. PSO is employed to adjust weights of the LSTM framework, thereby diminishing forecasting error. Following the preliminary processing of past stock data, which encompasses starting price, closing cost, highest cost, lowest rate, as well as regular volume, we develop the LSTM utilizing time series derived from this past dataset. Ultimately, we implement the suggested LSTM to forecast opening value of NSE index. The PSO optimization algorithm, applied to the LSTM model through empirical study, efficiently identifies the best neural network weights, minimizes the loss function, facilitates speedy fitting, and yields more accurate predictions.

Subject Classification: *26A33, 35C05, 39B72.*

Keywords: *Mathematical framework, Cognitive computing, Mathematical decision making, Expert systems, Machine learning, Artificial neural network, Long short term memory, Convergence accuracy, Computational intelligence.*

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1. Introduction

Basically success of stock market transactions reflects a nation's economic condition. In 2016, overall business capitalization of China's equity market constituted 146% of GDP, ranking highest among emerging nations. The USA represented 174%, ranking on top among industrialized nations. Rewards as well as risk associated with the share market are comparatively elevated. Stock business in numerous nations generate substantial volumes of data daily. Trading organizations are progressively utilizing statistics as principal orientation for their investment decisions. Short- term changes in stock prices have been shown to be predictable. To forecast stock price trends, Investigators both nationally and globally, have utilized diverse analytical and econometric methodologies, including the exponential smoothing technique [1], regression technique [2], ARIMA framework [3], and GARCH framework (generalized autoregressive conditional heteroskedasticity) [4]. Nonetheless, since the multiplicity of factors affecting stock prices and the intricacy of their effect processes, it is challenging to elucidate them through a mathematical model.

2. Literature Survey

In recent years, machine learning has been employed across different domains, including banking, transportation, and medical. The stock, as a significant component of monetary instruments, not just merely reflect individuals' living standards, also signifies the marketplace budget; hence, forecasting stock trends is more favored by academics [5]. While the extensive historical stock data offers resources for investors and analysts, relying just on personal experience and intuition for analysis is evidently erroneous and inefficient. Consequently, individuals require a smart, technical, and proficient study methodology to assist and direct stock trading [6]. Historically, scientists predominantly utilized several conventional statistical techniques for time series modeling, including GARCH, ARMA [7], and Regression Model [8]. Conversely, such frameworks often include just the linear connection among the price of stocks and it's affecting elements. Consequently, due to the great complexity of stock price predictions, achieving convincing accuracy is challenging. In recent years, soft computing techniques such as decision trees [9], SVM [10], enhanced clustering algorithms [11], and advanced neural networks [12] have been utilized for stock prediction [13], yielding commendable outcomes. While neural networks have demonstrated commendable performance during trade estimation, stronger neural networks may be better suitable for these nonlinear complex environments [14]. RNNs are commonly utilized for the study of predictive stock market data; yet, they encounter issue of gradient vanishing when addressing long-term time series challenges [15]. The temporal memory unit of the LSTM framework can assimilate temporary data from historical data, making it appropriate for forecasting time series issues involving breaks and delayed occurrences [16-18]. This article employs an LSTM neural network to forecast the highest price for shares, with optimization achieved by PSO. In our study, however, PSO is employed to improve internal weight updates of the neural framework, specifically seeking the inclusive optimum rather than refining conventional exterior features. This approach enables neural framework to efficiently adapt to aimed data and establish the finest framework architecture. Additionally, the LSTM optimized using Particle Swarm Optimization is compared with the standard LSTM neural network. in terms of prediction results and variations in the loss function.

3. Principles of LSTM Framework

For the LSTM framework, hidden-layer neurons in the recurrent neural framework are substituted with neurons of LSTM framework to provide long-term retention capabilities [19-20]. Long-term dependencies are captured by LSTM, which performs exceptionally well in sequence forecasting tasks perfect for machine translators and time series. The system's temporary memory is maintained by the LSTM in a concealed state. The input, the preceding concealed state, and the present state of the memory cell are used to update the hidden state. Basic gate structure of LSTM enables selective information influence on the state of apiece instant in the recurrent neural network. The significance ranges from 0 to 1, it is possible to quantify the amount of information currently being processed using this framework. Forget gate identifies which elements of preceding state can be discarded, and input gate specifies which elements can be included into present state. Output gate establishes present result by considering most recent position, prior outcome, as well as current input. The LSTM neural framework incorporates temporal dynamics into its architecture, enhancing its adaptability for time-series statistics interpretation. It comprises 3 levels of system arrangement: input layer, concealed layer, and outcome layer. We present an enhanced LSTM forecasting framework with PSO to reduce forecast inaccuracy. The system preparation mostly focuses on concealed layer as the subject of investigation. Initially, in the input layer, we specify that the LSTM model will substitute hidden layer of RNN cells utilizing LSTM cells, therefore endowing them with capability for long-term memory.

The forward formulas are as follows:

$$i_t = \sigma(\omega_{xi}\, x_t + \omega_{hi} h_{t-1} + \omega_{ci} c_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(\omega_{xf}\, x_t + \omega_{hf}\, h_{t-1} + \omega_{cf}\, c_{t-1} + b_f) \tag{2}$$

$$c_t = f_t\, c_{t-1} + i_t \tanh(\omega_{xc} x_t + \omega_{hc} h_{t-1} + b_c) \tag{3}$$

$$o_t = \sigma(\omega_{xo}\, x_t + \omega_{ho}\, h_{t-1} + \omega_{co}\, c_t + b_o) \tag{4}$$

$$h_t = o_t \tanh(c_t) \tag{5}$$

In aforementioned formulas, i symbolizes the source gate, f identifies the forget gate, c represents the cell state, o means the output gate, W relates to the corresponding weight coefficient matrices, and b is the bias term. The signs σ and tanh represent the sigmoid and hyperbolic tangent activation functions, respectively. Long Short Term Memory can incorporate or eliminate data in a cell via a gate control mechanism. Here valves can choice fully ascertain if information is transmitted. Since prior state of the framework serves as input for the sigmoid function; if outcome meets valve's threshold, it will be multiplied element- wise with the current layer's calculations. This will function as latest input for subsequent layer, if not, disregard the output [21].

4. Artificial Neural Network with Particle Swarm Optimization

PSO is a method based on swarm intelligence, modeled after the foraging behavior of avian species. If an ideal solution exists for the problem concerning the mapping of edibles that birds seek, a sort of particle is employed to mimic aforementioned bird individuals, characterized by two parameters: velocity and location. Particle's present place may be considered a potential resolution to the ideal resolution. Each element autonomously explores solution space. By constantly apprising speed and location and recapitulating, the globally best result that meets criteria is ultimately obtained. we employ the PSO approach to refine these constraints. PSO may inhibit convergence of networks from becoming trapped in a local optimum. The weighing coefficients of the LSTM concealed layer function as feed for the particle swarm.

5. PSO – LSTM Framework

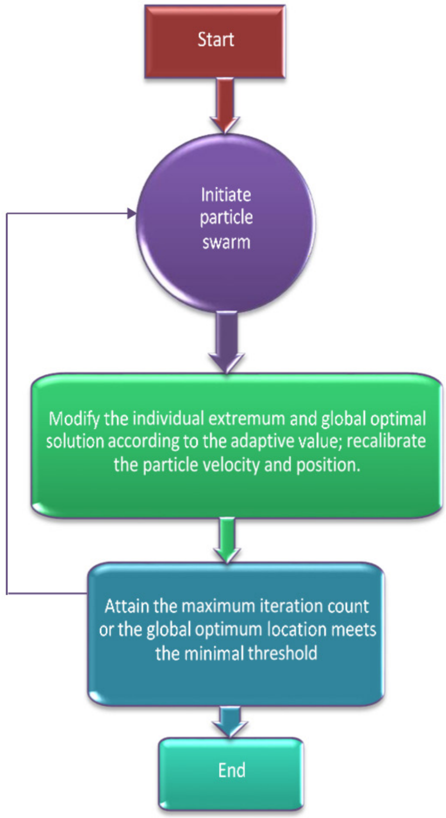

Figure 1

PSO Optimization for LSTM Neural Network Algorithm

LSTM-PSO model incorporates PSO to enhance internal parameters of the classic LSTM framework. Conventional PSO typically performs improvement of the network model parameters by adjusting the epochs count and learning rate demonstrate in Figure 1. This research presents a PSO method designed to facilitate swift adaptation of the neural framework aims to optimize data by effectively seeking the global optimum to improve inside weight adjustment procedure for neural framework. The construction of the LSTM prediction model entails numerous factors, among which the weights are crucial. To enhance predictive outcomes, since beginning outcome inaccuracy of the LSTM functions as the fitness measure for particle swarm, thereafter evaluating the performance of each particle based on specific criteria. The stochastic starting particle swarm modifies its parameters based on individual and global extrema.

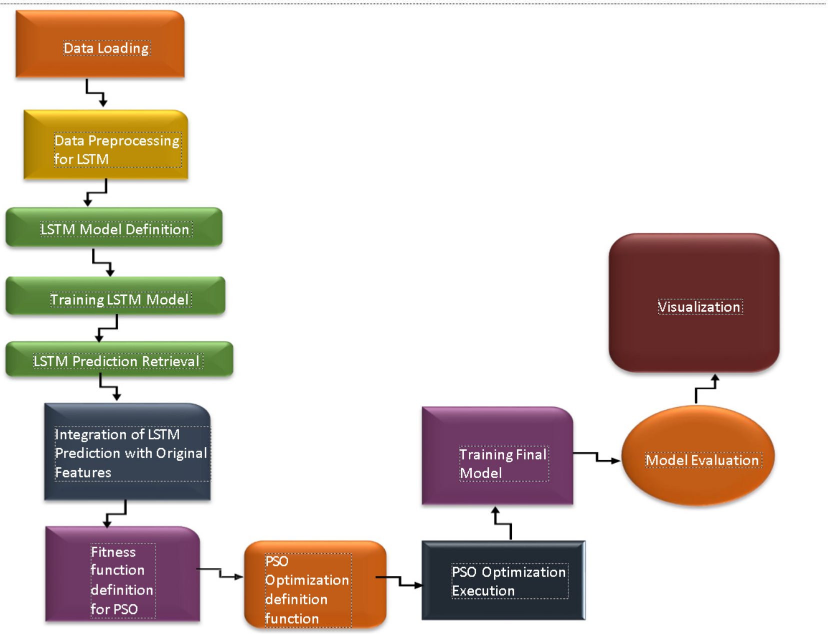

Figure 2

Proposed Methodology

Figure 2 demonstrate the optimization of Long Short-Term Memory algorithm by PSO algorithm, the optimal particle location vector value within particle swarm is sequentially employed as the preliminary value for every weight within the LSTM framework. The dimensions of each particle may be determined based on architecture of neural framework, with the MSE of each node's output from specified training set serving like fitness value for the particle swarm. Subsequently, we assess fitness value metric of every element based on the fitness function; a lower rate indicates a reduced inaccuracy in output of the framework. It signifies enhanced efficacy of the respective granules. Location of the particle is constantly adjusted to progressively minimize inaccuracy within framework's outcome layer. For every iteration, particle exhibiting minimal inaccuracy is designated as the existing optimal particle.

The steps are as follows:

1. **Information Loading:** Data is imported using a CSV file titled 'MSFT.csv' into a Pandas DataFrame.
2. **Dataset Pre-processing for LSTM:** This encompasses reshaping the data, scaling features via Min- Max scaling, and splitting data into learning and testing subsets.
3. **LSTM Framework:** The LSTM framework is established via Keras, assembled with the Adam optimizer, and use MSE as the loss function.
4. **Training LSTM Model:** Specified LSTM framework is trained with learning dataset.
5. **LSTM Predictions Retrieval:** Predictions are made employing trained LSTM framework on both training and evaluation datasets.
6. **Integration of LSTM Predictions with Original Features:** The LSTM predictions are concatenated with the original features.
7. **Fitness Function Definition for PSO:** A fitness function is defined for Particle Swarm Optimization (PSO) algorithm utilizing linear regression. This function calculates mean squared error between actual and predicted values.
8. **PSO Optimization Function Definition:** A function for PSO optimization is defined using the PySwarms library.
9. **PSO Optimization Execution:** PSO optimization is executed to discover the best parameters for linear regression.
10. **Training Final Model with Optimal Parameters:** A final linear regression framework is trained with the optimal parameters obtained from PSO optimization.
11. **Framework Assessment:** The evaluation of final framework is assessed on the testing dataset by computing metrics like MSE, RMSE, MAE, and R-squared (R^2) score.
12. **Visualization of Actual Vs Predicted Values:** Matplotlib is utilized to visualize the actual vs predicted opening prices.

The primary integration procedures of the two methods are outlined: (1) The constraints of Particle Swarm Optimization establish pertinent constraints of the Long Short-Term Memory framework; (2) The output inaccuracy of LSTM is used as the evaluation metric for PSO; (3)

Ideal result derived from Particle Swarm Optimization is designated as learning parameters for the neural framework. The PSO-LSTM framework integrates the strengths of both processes, enhancing its global search capability as well as its local search proficiency. Based on empirical evidence and practical analysis, we established element dimension at 60, extreme iteration counts at 200, inertia weight at 0.6, acceleration coefficients c1 and c2 at 1.5, location constraint ranges at [-5, 5], as well as velocity constraint range at [-1, 1]. The outcome inaccuracy of LSTM framework model functions as fitness criterion for PSO; as quantity of epoch's increases, function score decreases resulting in enhanced individual fitness.

6. Evaluation Matrices

6.1 *RMSE*

The word "square root" denotes the mathematical procedure that determines the value corresponding to the real and projected averages of squared distances. The variable N represents the quantity of value points.

6.2 *Mean Absolute Error*

The phrase "average difference" denotes the mean divergence between actual data and predicted data. It measures the degree to which forecasts diverge from the actual output. This elucidates the flaws in the forecasts.

6.3 *Mean Square Error*

It is a statistical technique that calculates the difference of the squared means between observed and forecasted data. The computation presented denotes the scientific formula employed for quantifying Mean Squared Error.

6.4 *Coefficient of Determination (R^2)*

R^2 illustrates the efficacy of our regression model by juxtaposing it with a rudimentary framework that solely predicts average projected data based on the training dataset.

7. Experimental Analysis and Results

Table 1

LSTM Testing Model – Error Data

Epoch	RMSE	MSE	MAE	R^2
10	0.0186	0.0003	0.0151	0.9935
50	0.0138	0.0001	0.0108	0.9964
100	0.0123	0.0001	0.0092	0.9972
200	0.0100	0.0001	0.0073	0.9981
500	0.0104	0.0001	0.0079	0.9979
1000	0.0098	0.0097	0.0072	0.9982

Table 2

PSO-LSTM testing model – Error data

Epoch	RMSE	MSE	MAE	R^2
10	0.0191	0.0033	0.0155	0.9935
50	0.0095	0.0022	0.0075	0.9984
100	0.0083	0.0019	0.0062	0.9988
200	0.0061	0.0012	0.0042	0.9994
500	0.0056	0.0006	0.0039	0.9993
1000	0.0053	0.0004	0.0033	0.9996

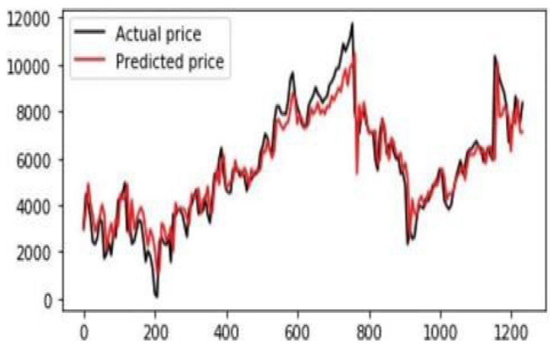

Figure 3

Forecasted NSE index using LSTM

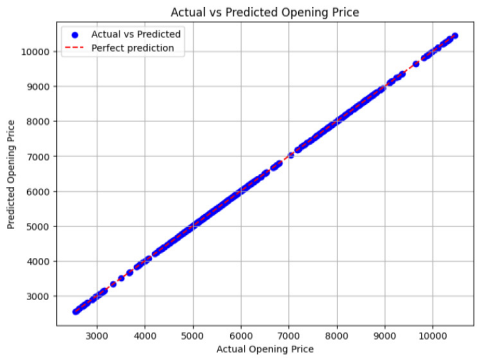

Figure 4

Forecasted NSE index using by PSO-LSTM

Table 1 and Table 2 demonstrate that RMSE value for the LSTM prediction is 0.0098, whereas the RMSE for the PSO-LSTM is 0.0053. R^2 value for LSTM framework is 0.9982, and for the PSO-LSTM model, it is 0.9996. Consequently Figure 3 shows Forecasted NSE index using LSTM, while Figure 4 shows enhanced PSO-LSTM algorithm result which demonstrates superior accuracy.

8. Conclusion

This study suggested a hybrid deep learning strategy based on optimization by putting forward a technique for adaptive PSO. This research presents an enhanced LSTM neural network technique that employs PSO to optimize LSTM parameters. The outcome inaccuracy of the neural framework serves as fitness criterion for PSO to determine ideal weights for LSTM framework. Subsequently, we designate global optimum value as the initial parameter to facilitate optimization of LSTM framework through the PSO method, thereby constructing a neural framework predicated on PSO-LSTM technique. This paper introduces a deep learning framework for share market prediction. The study demonstrates that PSO-LSTM model exhibits superior performance and improved precision.

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