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Deep Learning Analysis of Impact of Arctic Sea Extent Over Indian Ocean Sea Surface Temperature

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Abstract: Increasing global warming is creating lot of dynamics in polar sea ice extent and concentration. Many works have explored the impact of Arctic sea ice extent over temperature, rainfall in global context. In India specific context, analyzing the impact of Arctic sea ice over Indian Ocean sea surface temperature is critical as the study is important for understanding the monsoon behaviour, aquatic life conditions and effect of storms over Indian coast. This work proposes a novel optimized multivariate long short term memory model for predicting the Indian Ocean sea surface temperature at a fine grained level using the Arctic sea ice extent data. The hyperparameters for optimizing the deep learning model were identified and optimized using Grass hopper swarm optimization algorithm. The model training was itself optimized using hinge loss error minimization. The prediction error is measured in term of root mean square and it was atleast 32% lower in proposed solution compared to artificial neural network and 18% lower compared to convolutional neural network techniques.

Keywords: Arctic sea ice, Indian ocean, Sea surface temperature, Predictability.

1 Introduction

Energy exchange between the polar and tropic regions is strongly influenced by the polar ice dynamics. It also influences the total solar energy absorbed by earth [1] by causing variance in the heat/momentum exchange to atmosphere and insulating effect of ocean surfaces [2]. The average temperature of land and sea has increased by 0.85 ◦C [3] since 1970 and mean sea level has increased by 0.2 m. For every decade, Arctic sea area decreased by almost 3.5 to 4%. This rapid change in Arctic sea extent affects climate, biology and indirectly influences the socio economic activities negatively. Arctic sea ice extent influences the climate by preventing heat exchange between atmosphere and ocean thereby reducing the insulation of sea ice cover. The effect of Arctic sea ice is not only local but also remote. Compared to local, remote effects are complex and difficult to comprehend. Various attempts have been made to analyze the impact of polar ice over various parameters like rainfall, temperature over various regions of the world etc. Sea ice dynamics in Arctic affects the southern ocean which in turn affects the circulation in linked oceans of Atlantic, Pacific and Indian Oceans. Indian Ocean circulation impacts the ocean sea surface temperature and the monsoon rainfalls at Indian Ocean. Thus Arctic sea ice extent is an important climate indicator which affects Indian Ocean and Indian climate.

Many works have analyzed the impact of polar sea cover over climate in various reasons using various techniques like linear regression, partial correlation, temporal cross correlation and statistical approaches. Detailed discussion on these approaches is presented in section 2. Most of these approaches are short term and they use statistical techniques. They were not designed to model the intricate dependences between observations and various short /long term trends in the data. In a work, close to the scope of this research scope, South Indian ocean surface temperature was predicted based on

Antarctica sea ice concentration by Tripathi et al [19]. Different from statistical approach, machine learning was used for prediction of ocean temperature in this work. Sea ice concentration was averaged over the Antarctic region (600 S - 890 S and 10 E - 890 E) and used as input for Artificial neural network (ANN) to predict sea surface temperature. Compared to statistical methods, ANN based regression provided better performance. Motivated by this observation, this work brings the realm of deep learning techniques into prediction of sea surface temperature which has superior performance compared to ANN. Deep learning regression provide superior performance due to their more intricate feature learning ability and capability to incorporate more spatial and temporal correlation into regression fit.

This work applies multivariate LSTM fine tuned using meta-heuristics for predicting the Indian Ocean surface temperature from Arctic sea ice extent. Though LSTM provides better results compared to ANN, the performance of it is further enhanced by fine tuning the hyper parameters of LSTM using meta- heuristics optimization. This makes the LSTM fine tuned to predict sea surface temperature (SST) with higher prediction accuracy and lower root mean square error. Following are the novel contributions of the work.

(i) A novel multivariate LSTM model correlating the Arctic sea ice extent to Indian Ocean sea surface temperature at a fine grained level is proposed and Indian Ocean sea surface temperature was predicted with higher accuracy with longer temporal correlation. To the best of our knowledge, there are no earlier works correlating the Arctic sea ice extent to Indian Ocean sea surface temperature at a fine grained level.

(ii) The hyperparameters for optimizing the multivariable LSTM model were identified and optimized using Grass hopper swarm optimization (GSO) algorithm. The fitness function was designed to reduce the root mean square error in prediction. Experimentation was conducted with different hinge error minimizations to identify the optimal value for hyperparameters without getting into local minima problem.

(iii) Compared to existing works, long term temporal correlation was tested in proposed solution for data sequence of different windows and the optimal window with higher prediction performance was selected.

The paper is organized as follows: Section 2 provides a detailed survey on polar sea extent based predictability. Section 3 details the proposed methodology and data used for experimentation. Section 4 presents the results and analysis over the results. Section 5 presents the concluding remarks and scope for future work.

2 Survey

Oza et al [4] analyzed the monthly fractional sea ice over in the Antarctic (1999-2009) and its influence on climate in local regions. Author fitted a linear regression model and found sea ice cover has strong correlation to cooling trends locally. Kennel et al [5] analyzed the influence of sea ice extent in Arctic region on pacific area climate. Regression models was used for correlation analysis in this work. Syairah et al [6] made a study correlating Indian ocean sea ice extent to average Indian rainfall. Various correlation techniques like partial, composite etc were explored in this work. Works [7-9] analyzed the teleconnection between Antarctic sea ice extent to climate variability indexes. Linear correlation were used in these studies. Prabhu et al [10] analyzed the influence of Antarctic sea extent on south west monsoon rainfall through correlation tests. Though the study found strong correlation, the study is only short range. The influences of Arctic sea ice on earth's climate were investigated using observations and simulations in studies [11-17]. Among them statistical correlation with singular value decomposition was used in [17] to analyze the relationship between sea ice concentration in Arctic region to Chinese rainfall. Xue et al [18] used composite analysis to analyze the influence of sea ice oscillation in Antarctic region on monsoon over east Asian countries. Most of above works are based on deterministic coupled circulation models based on atmospheric air data. The works are statistical techniques at seasonal lead times of two months and beyond. Tripathi et al [19] analyzed the influence of sea ice concentration in Antarctic region on ocean surface temperature. Southern (400 S - 410 S and 820 E - 850 E) and the Central (220 S - 240 S and 790 E - 810 E) regions of Indian ocean was considered in this work. The sea ice concentration averaged over the Antarctic region (600 S - 890 S and 10 E - 890 E) has been used for identifying any relationship that may be present with the SST of these areas using artificial neural networks (ANN). Authors inferred that compared to these statistical techniques, machine learning based regression with ANN were found to better systems for analyzing impact of polar ice effects on climate over a long range. Recently deep learning techniques which are advancement of ANN have been used in many

Table 1. Survey summary

Author	Technique used	Remark	Difference to proposed work
Oza et al [4]	Linear regression	Analysed short term impact on Antarctic sea ice on climate in local regions. But the study did not consider global impact.	Proposed work analyzed influence of Antarctic sea extent at global context in far way Indian ocean region and used more advanced LSTM predictor compared to Linear regression
Kennel et al [5]	Regression	Analyzed the impact of Arctic sea ice extent on pacific climate. But the scope of this paper work is on Indian ocean.	Proposed work analyzed influence of Arctic at far away region with more advanced LSTM predictor compared to Regression
Syairah et al [6]	Partial correlation	Analyzed Antarctic ocean sea extent on Indian monsoon rainfall. But the study did not consider impact at fine grained level.	Proposed solution analyzed influence at more fine grained level by splitting the region studied.
Wu et al [17]	Singular value decomposition	Analyzed the relationship between sea ice concentrations in Arctic region to Chinese rainfall. But the correlation model has higher error.	Compared to singular value decomposition, multivariate LSTM used in proposed solution learns the correlation between Arctic sea extent and Indian ocean sea surface temperature effectively.
Xue et al [18]	Composite analysis	Analyzed the influence of sea ice oscillation in Antarctic region on monsoon over east Asian countries. But the study lacked fine grained analysis at country specific levels.	The predictor variable in proposed solution is Indian ocean sea surface temperature and it is at fine grained level compared to analysis of influence over large are in existing work.
Tripathi et al [19]	ANN	Analyzed the influence of sea ice concentration in Antarctic region on Indian ocean surface temperature. But the study is short term and did not consider correlation over longer duration.	The proposed solution studied the influence of sea ice extent over different window period and the prediction model's hyperparameter are fine tuned to provide higher accuracy
Andersson et al [22]	Deep learning U-Net model	Predicted sea ice extent from polar climate. But the influence was analyzed only at local context.	The proposed solution provided fine grained analysis at Indian ocean level in specific region. The influence was at studied at remote area far from Arctic sea extent compared to local context in existing work.

Table 2. Notations used in equations

Notation	Detail
f_t	Forget vector of LSTM
i_t	Input vector to LSTM
o_t	Output vector of LSTM
$\emptyset_s$	Transformation function of LSTM
h_{t-1}	Cell activation result
W_c	Weights applied on input vector
U_c	Weights applied on hidden state.
P_i	Grasshopper's position at time t
S_i	Grasshopper's Social interaction force value at time t
G_i	Gravitation force value at time t
A_i	Wind force value at time t
d_{ij}	Euclidean distance between two grasshoppers i and j.
f	Attraction intensity of Grasshopper
r	Range of influence of Grasshopper

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forecasting applications. Andersson et al [22] used a deep learning U-Net model to predict the sea ice extent from climate data collected around polar regions. Wei et al [23] used attention based LSTM network for sea ice extent prediction from past data. Mu et al [23] proposed a temporal fusion transformer (IceTFT) model to solve the problem of short term leads in predictability models. Authors used atmospheric and ocean variables to predict sea ice extent. Liu et al [24] predicted sea ice concentration using convolutional LSTM model. Similar to this work, Kim et al [25] predicted sea ice concentration using convolutional neural networks. Chi et al [26] used two stream convolutional neural networks for prediction of sea ice concentration. The scope of prediction considered in works [22-26] is opposite to the score considered in this paper work. This paper attempts to predict climatic variables using sea ice extent, but works [22-26] predicted sea ice extent from oceanic and climatic variables.

The summary of the survey is presented in Table 1. From the survey, it is observed that deep learning LSTM based models were able to forecast long term trends better than statistical and regression based approaches. To the best of our knowledge, there were no relevant works on predicting Indian ocean sea surface temperature from Arctic sea extent. Most the recent deep learning models predicted sea extent from climatic and oceanic variables which is just opposite of the scope of this paper work. The existing works on prediction of Indian Ocean sea surface temperature from climatic variables and Antarctic sea extent too are short term trend based and they lack fine grained prediction. These problems of fine grained prediction, longer temporal correlation are addressed in this work.

3 Methodology

This work addresses the problem of prediction of Indian Ocean sea surface temperature at a fine grained level over long temporal duration with Arctic sea extent dynamics as the input variable. Satellite records on Arctic sea extent became available since 1979 and since then, it is observed that Arctic sea extent has been consistently declining at rate 4.4% per decade. There have not been any past studies exploring the influence of Arctic sea extent on Indian Ocean surface temperature (IST). Data from US ice data center were collected in monthly average over the years 1978 to 2019. The data collected using microwave radiometer and imaging was used for the experimentation. Sea ice extent was collected for Kara Sea (KS). Kara sea being the region with highest loss of summer ice, it justifies the selection of it for study in this work [21]. The influence of KS sea ice extent is analyzed on SST of Indian ocean in range of 24°S- 24°N and 40°E to 120°E. World meteorological organization have collected SSI data at monthly intervals through voluntary observing ships. The archives' of this data since 1961 is available at meteorological department (IMD) in standardized format. This work uses this data from year 1979 to 2019 for experimentation. The data collected for Indian ocean sector are is split to two portions of Western (WEIO) and eastern (EEIO) equatorial Indian ocean regions with partition for WEIO as 10° S-10° N, 40° -70° E and partition for EEIO as 10° S-10° N, 75° -100° E.The raw SST and sea extent data is organized month wise as in Table 3 for processing.

Table 3. Processed dataset

Field	Parameter
1	Year
2	Month
3	Arctic sea extent
4	SST for WEIO
5	SST for EEIO

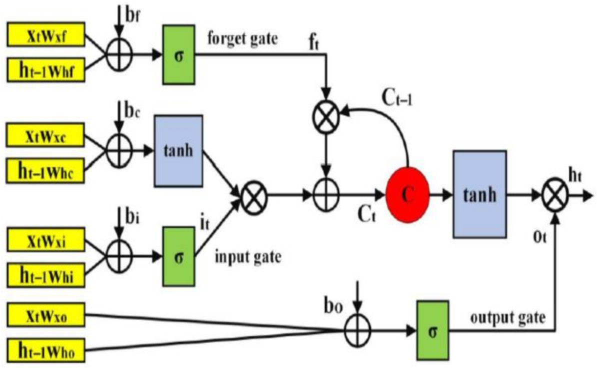

Figure. 1 LSTM structure

The influence of Arctic sea extent on SST of Indian Ocean is analyzed using optimized LSTM. Grasshopper swarm optimization (GSO) algorithm is used for optimizing the LSTM hyper parameters. LSTM is a kind of recurrent neural network with ability to learn long term dependencies in the dataset. It is widely adopted in time series prediction problems due to its non-linear predictability, fast convergence and comparatively lower complexity. Memory cell is the important component of the LSTM whose structure is given in Fig. 1.

The memory cell has three gates: input, output and forget. Each LSTM takes current feature and previous hidden state as input. With this input, it calculates the cell activation as weighted sum of

Table 4. Hyper parameter

Variable	Hyper parameter	Range
x_1	Number of units in dense layer	[5-10]
x_2	Dropout	[0.2 -0.5]
x_3	Decay rate	[0.4 – 0.8]
x_4	Learning rate	[0.0-0.1]
x_5	Momentum	[0.5-0.9]
x_5	Batch size	[32,64,128]

inputs ($W_c x_t$) along with the bias (b_c). The cell activation got as result is then processed with a hyperbolic tangent activation function ($\emptyset_t$) as below

$$c_t = \emptyset_t(W_c x_t + U_c h_{t-1} + b_c) \quad (1)$$

In the above equation, h_{t-1} is the cell activation result of previous LSTM node in the sequence. The values W_c and U_c are the weights for input and the hidden state vector. The level of activation to be retained or forgot is done by controlling the gates.

The hidden state information is calculated at the final state. The level of activation to be retained or lost is controlled by the gates. Level to train is controlled by input gate and level to forget is controlled by the forget gate. Hidden state information to retain in output is controlled by the final gate. The final gate takes two information, forgot vector (f_t) and input vector ((i_t) as input to provide the output vector (o_t).

$$f_t = \emptyset_s(I_{w_f} x_t + I_{U_f} h_{t-1} + bias_f) \quad (2)$$

$$i_t = \emptyset_s(I_{w_i} x_t + I_{U_i} h_{t-1} + bias_i) \quad (3)$$

$$o_t = \emptyset_s(I_{w_o} x_t + I_{U_o} h_{t-1} + bias_o) \quad (4)$$

In the above equation f_t represents the forgot vector, i_t represents the input gate vector and o_t represents the output gate vector and $\emptyset_s$ is the transformation function on inputs.

An important problem in using LSTM for time series prediction is the local minima optimization issue. LSTM cells can get struck at local points which affect their ability to learn non-linearly. This problem can be avoided by fine tuning the hyper parameters of LSTM. Following are the hyper parameters considered for fine tuning the performance of LSTM to avoid the LSTM cells getting struck at local points.

Though there are other important parameters like weights, bias to forget gate, activation functions etc, this work restricts its scope to only 5 parameters in Table 4. The optimal value for these parameters is found using GSO. GSO is selected due to its effectiveness in solving global unconstrained and constrained optimization problems by balancing between exploration and exploitation search strategies [32]. In addition it also offer other benefits like ease of implementation, speed in searching and ease of modifying algorithm components.

GSO is a recent swarm intelligence algorithm proposed in works of Saremi et al [22]. This algorithm is based on the grasshopper's foraging and swarming behaviour. Grasshopper is a pest whose life cycle has two stage nymph and adulthood. In nymph stage, the grasshoppers move in small steps with less movement. In adulthood stage, grasshoppers make long range abrupt movements. GSO algorithm has two phases (i) intensification and (ii) diversification which are based on the movement pattern of grasshoppers in nymph and adulthood stage. Mathematically, GSO represents the swarming behaviour of grasshoppers in terms of their social interaction (S_i), gravitational force (G_i) and wind advection (A_i) as

$$P_i = S_i + G_i + A_I \quad (5)$$

Where P_i is ith grasshopper's position. S_i is calculated for N grasshoppers separated by a Euclidean distance (d_{ij}) with a social force s as

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(d_{ij})\widetilde{d_{ij}} \quad (6)$$

The social force is represented in terms of attraction intensity(f) and attration length (l) as

$$S(r) = f \exp^{\frac{-r}{l}} - \exp^{-r} \quad (7)$$

Attraction and repulsion are the two themes based on which social interaction is measured. For a distance in range of 0 to 15, attraction is felt in range of 2.07 to 4 and repulsion is felt in range of 0 to 2.07. At the distance of 2.07, a comfort zone is realized where there is neither attraction nor distraction.

The gravity force G_i in Eq. (5) is calculated in terms of distance unit vector to center of earth ($\hat{e}_g$) and gravitational constant (g) as

$$G_i = -g\hat{e}_g \quad (8)$$

The wind advection A_i in Eq. (5) is calculated in terms of distance unit vector to wind direction ($\hat{e}_w$) and drift constant (u) is given by

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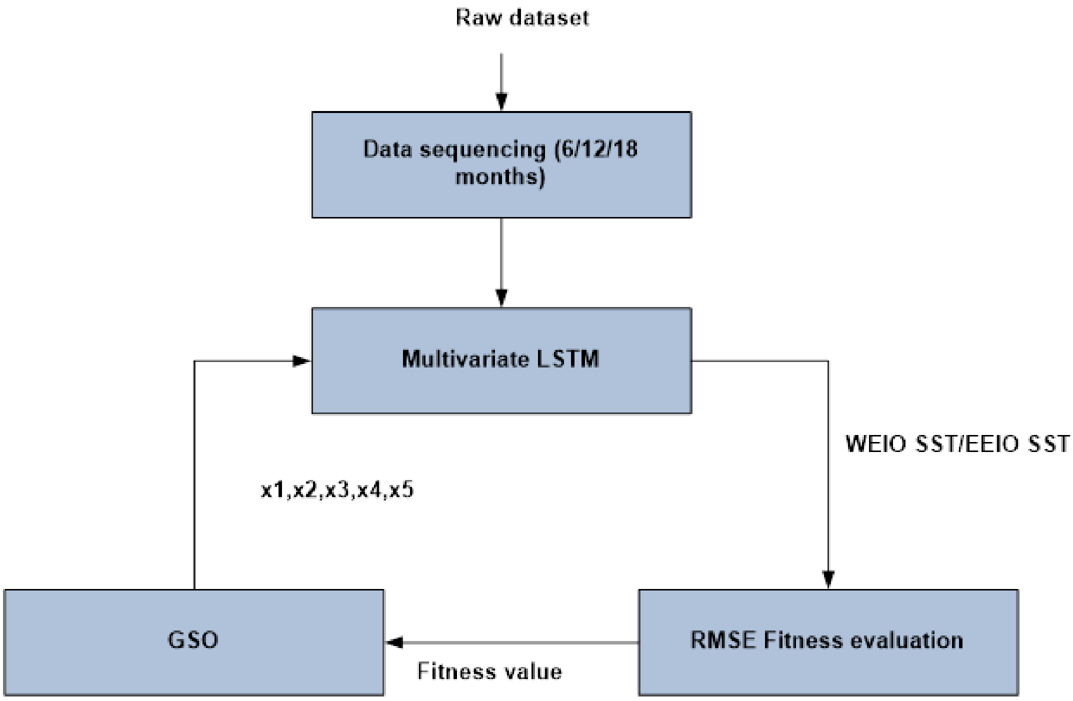

Figure. 2 Methodology

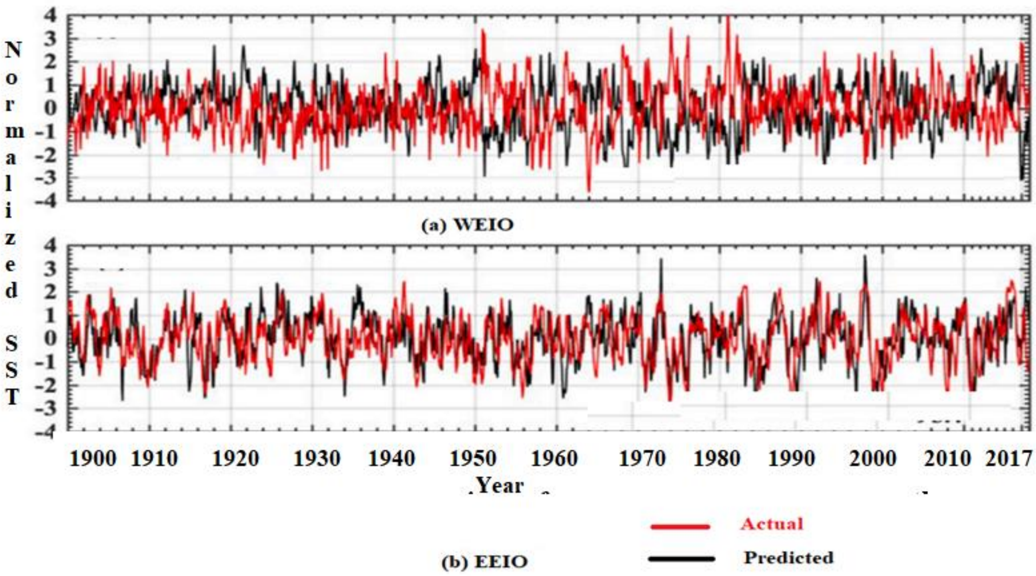

Figure. 3 Comparison of predicted to actual results over the years

$$A_i = u\hat{e}_w \quad (9)$$

Fitting each of the variables , the Eq. (7) is modified with upper bounds(ub_d) and lower bounds(lb_d) in the the d-th dimension and given as Eq. (12).

$$P_i^d = c\left(\sum_{\substack{j=1\\ j\neq i}}^{N} c\frac{ub_d - lb_d}{2}\right) s(|P_j^d - P_i^d|)\frac{P_j - P_i}{d_{ij}}) + \widehat{T}_d \quad (10)$$

In the above equation, the current best solution in d dimension space is represented as $\widehat{T}_d$. The parameter c is similar to inertia weight ω in PSO. This parameter controls the grasshopper's movement around food (target) and provides a fine balance between diversification and intensification. The parameter c is calculated as

$$C = c_{max} - t\frac{c_{max} - c_{min}}{t_{max}} \quad (11)$$

With the maximum value for c represented as c_{max} and minimum value for c represented as c_{min}.

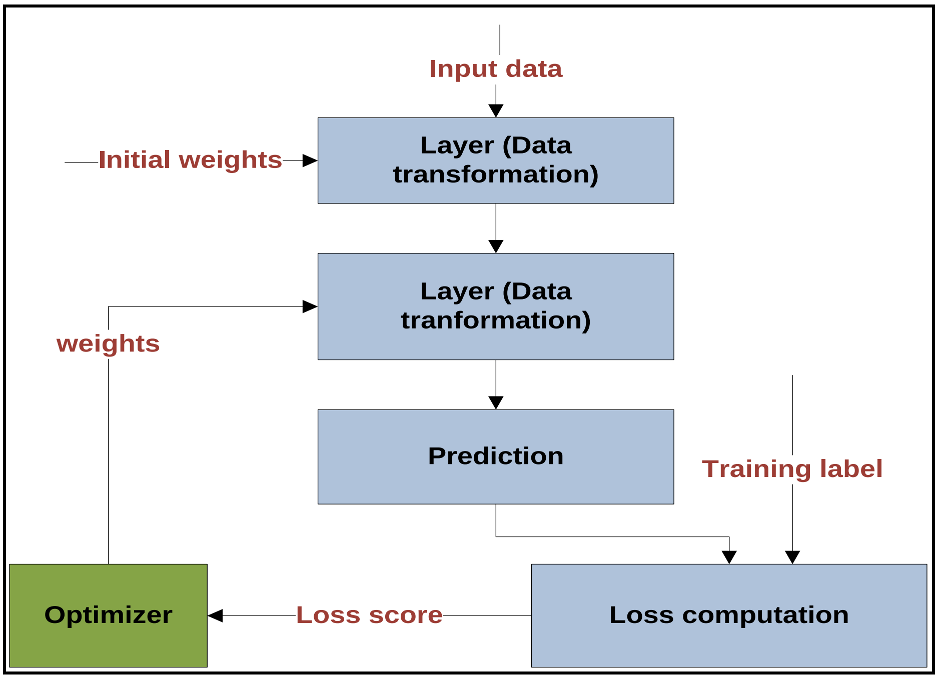

Figure. 4 Optimization flow

The position is updated for every iteration (t) for a maximum number of iterations (t_{max}). Grasshopper position is updated every iteration based on both local and global best solution. The iteration is stopped when they are no change in position of grasshopper. Use of global best position prevents from getting trapped into local optimum.

The pseudo code of grass hopper optimization algorithm is given below

Algorithm 1: GSO

A. Random generation of initial population for n grasshoppers Pi
B. Initialize Cmin, Cmax, and a maximum number of iterationTmax
C. Calculate the fitness function (f(Pi)) for every grasshopper
D. B= Solution of grasshopper with max(f(Pi))
E. **While** (t<tmax) **do**
F. Update c1 and c2
G. **For**i=1 to N grasshopper
H. **do**
I. Distance between grasshoppers normalized in range of 1 to 4.
J. Update position using equation (10)
K. Rectify outlier and normalize grasshoppers position
L. **end for**
M. Update B with best solution so far
N. t=t+1
O. **end while**
P. Return B

The fitness function for parameter optimization is calculated in terms of root mean square error as

$$F = \frac{1}{RMSE} \tag{12}$$

Where RMSE is calculated as the difference between actual and predicted value as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i^{\sim} - y_i)^2} \tag{13}$$

In the above equation N is the number of test samples, y_i is the actual value and $y_i^{\sim}$ is the predicted value.

The best set of hyper parameter values defined in Table 4 is found applying GSO. Initial candidate solutions (solution is a set with values from x_1 to x_5) is generated randomly. GSO is then started. At end of the iteration, the best solution is returned. The notations used in equations are summarized in Table 2.

The overall methodology for analysis is summarized in Fig. 2. The raw dataset is sequenced in form of 6/12/18 months and LSTM is trained to predict the WEIO SST/EEIO SST based on the sequence of Arctic sea extent data. The LSTM hyper parameters are optimized using GSO optimization algorithm with goal of minimization of RMSE. The optimized deep learning model was tested against three different hinge loss error functions of Crammer and Singer, Weston and Watkins and Zhang quadratically smoothed function [28]. The flow of the optimization is as shown in Fig. 4. The parameters of LSTM are fine tuned repeatedly till

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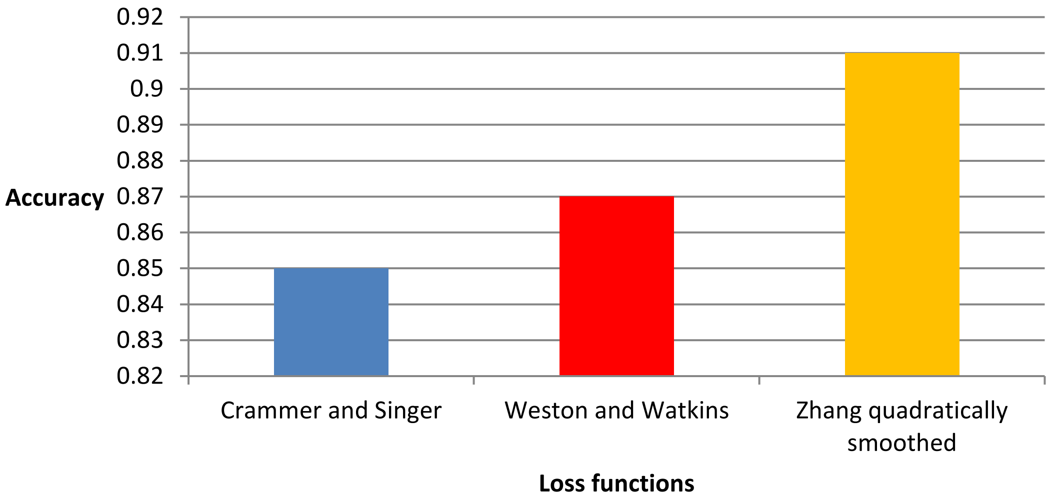

Figure. 5 Accuracy across loss functions

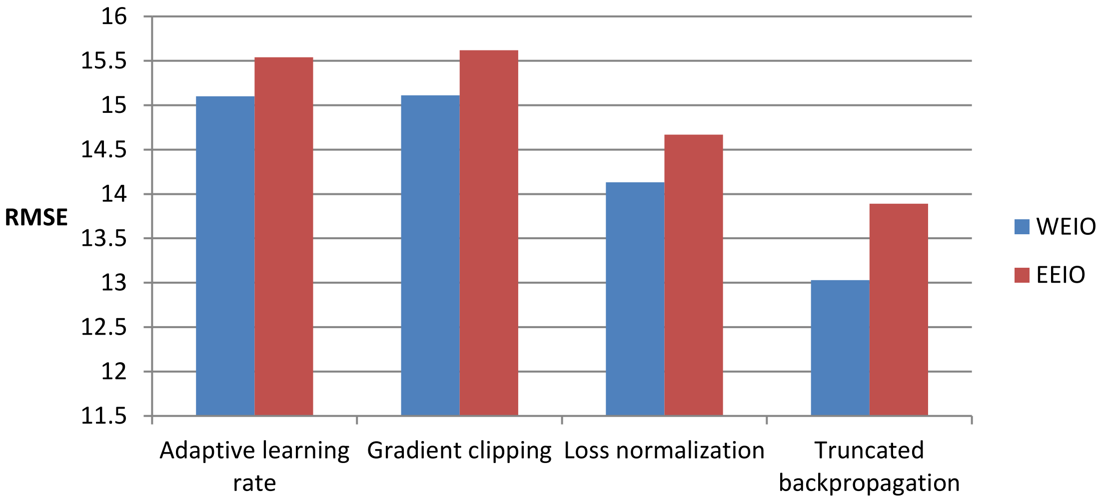

Figure. 6 RMSE across training function

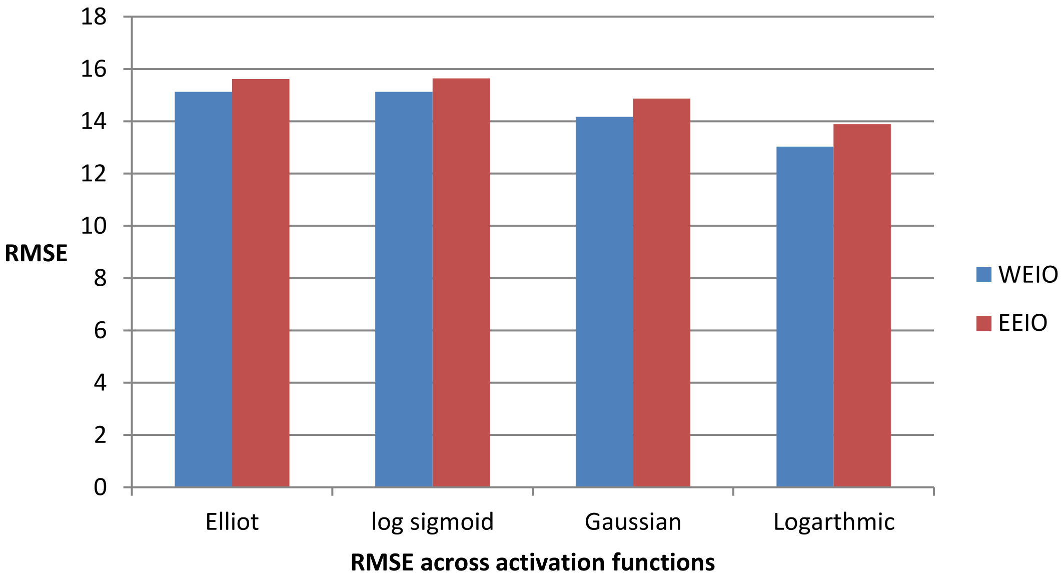

Figure. 7 RMSE across activation functions

the lowest value for loss is obtained. Loss is measured in term of hinge loss function. Experimentation was done with three hinge loss functions of Crammer and Singer, Weston and Walkins and Zhang quadratically smoothed. The accuracy is measured for each of the three loss functions and the result is given in Fig. 5. From the results, it is found that Zhang quadratically smoothed function provides higher accuracy compared to other two loss functions.

4 Results

Arctic sea ice extent data needed for experimentation was collected from portal of National snow and ice data center [30] and the Indian Ocean sea surface temperature data were collected from National center of environmental information [31]. The geo spatial regions where data is extracted are detailed in section 3. The sea extent values are arranged in 6,12,18 past month values as input and WEIO SST in 7,13,19 month/EEIO SST in 7,13,19 as output. Six long range datasets WEIO-S-6,WEIO-S-12,WEIO-S-18, EEIO-S-6, EEIO-S-12,EEIO-S-18 are created. From these datasets, 80% were used for training and 20% were used for testing.

Six different optimized LSTM predictors were trained with 80% data of WEIO-S-6,WEIO-S-12,WEIO-S-18,EEIO-S-6,EEIO-S-12 and EEIO-S-18 dataset.

The prediction performance of the solutions is measured using following metrics: Nash–Sutcliffe model efficiency coefficient (NSE) [23], root mean square error (RMSE) and correlation coefficient (R) The metrics are calculated as follows. The metrics are calculated as below

$$\mathrm{NSE} = 1 - \frac{\sum(\mathrm{P_i} - \mathrm{A_i})^2}{\sum(\bar{\mathrm{A}} - \mathrm{A_i})^2} \tag{14}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{P_i} - \mathrm{A_i})^2} \tag{15}$$

$$\mathrm{R} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\bar{\mathrm{A}} - \mathrm{A_i})((\bar{\mathrm{P}} - \mathrm{P_i})}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\bar{\mathrm{A}} - \mathrm{A_i})^2 \sum_{\mathrm{i}=1}^{\mathrm{n}}(\bar{\mathrm{P}} - \mathrm{P_i})^2}} \tag{16}$$

In the above equation, n represents test observation, A is the actual SST and P is the predicted SST. The proposed methodology was implemented in Python 3.8.2 in Windows OS environment. LSTM from tensorflow module is used.

As identified from survey, there were no existing works on prediction of SST from Arctic sea extent, we could not compare the proposed solution with any recent works on prediction using Arctic sea extent. However, there were related works addressing the prediction of Indian Ocean surface temperature from other climatic variables. Tripathi et al [19] predicted Indian ocean SST from Antarctic sea extent using ANN. Sun et al [29] predicted Indian ocean SST from multimodal air sea data using CNN. The Indian SST predictability performance of proposed solution was compared against ANN solution proposed by Tripathi et al [19] and CNN solution proposed by Sun et al [29].

Table 5. Comparison of RMSE

Solution	RMSE
WEIO	
Proposed	13.78
Tripathi et al [19]	18.35
Sun et al [29]	16.35
EEIO	
Proposed	13.89
Tripathi et al [19]	18.40
Sun et al [29]	16.41

The results for RMSE are given in Table 5.

For WEIO, the proposed solution has 33% lower RMSE compared to ANN [19] and 18.65% lower RMSE compared to CNN [29]. For EEIO, the proposed solution has 32% lower RMSE compared to Tripathi et al [19] and 18.14% lower RMSE compared to Sun et al [29]. The RMSE has reduced in proposed solution due to long term correlation with parameter optimized LSTM based model. In both [19, 29] model parameters were not optimized. Also the approach lacked longer temporal correlation. Compared to Tripathi et al [19], the proposed solution achieved better performance due to use of LSTM model and optimization of hyperparameters using GSO. Sun et al [29] used CNN to learn more intricate features but they were not used for long temporal correlation. Also the solution lacked fine grained classification

The performance results of proposed optimized LSTM classifier for Western Equatorial Indian Ocean are given in Table 6 and for Eastern Equatorial Indian Ocean are given in Table 7.

The RMSE is lower for 12 month based prediction compared to 6 and 18 month based prediction. RMSE is 12.24% lower in 12 month based prediction compared to 6 and 18 month based prediction. The correlation value is also high at 0.66 in 12 month based prediction compared to 6 and 18 month based prediction. The results are consistent in 12 month based prediction for both WEIO and EEIO. The SST for WEIO and EEIO are normalized in the

Table 6. Performance for WEIO

	NSE	RMSE	R
WEIO-S-6	0.55	14.14	0.56
WEIO-S-12	0.49	13.03	0.66
WEIO-S-18	0.57	14.59	0.55

Table 7. Performance for EEIO

	NSE	RMSE	R
EEIO-S-6	0.56	14.17	0.55
EEIO-S-12	0.48	13	0.65
EEIO-S-18	0.57	14.56	0.56

Table 8. Results for WEIO without hyper parameter optimization

	NSE	RMSE	R
WEIO-S-6	0.58	15.49	0.56
WEIO-S-12	0.63	13.78	0.61
WEIO-S-18	0.75	15.74	0.73

Table 9. Results for EEIO without hyper parameter optimization

	NSE	RMSE	R
EEIO-S-6	0.58	15.52	0.56
EEIO-S-12	0.63	13.89	0.61
EEIO-S-18	0.75	15.71	0.73

range of -4 to 4 and plot of actual vs predicted using optimized LSTM for 12 month sequence. Fig. 3 shows the plot of it and from the figure it can be seen that proposed optimized LSTM has comparatively good predictability for both WEIO and EEIO SST.

The results without hyper parameter optimization for Western Equatorial Indian ocean are given in Table 8 and for Eastern Equatorial Indian ocean are given in Table 9.

Comparing LSTM with and without hyper parameter optimization, the NSE has reduced by 28.57%, MAE has reduced by 11.67% and R value has increased by 7.57% due to hyper parameter optimization compared to without optimization.

The RMSE is measured in optimized LSTM for various training functions and the results are given in Fig. 6. Among all the training functions, truncated backpropogation provides lowest RMSE for both WEIO and EEIO.

The RMSE is measured in optimized LSTM for various activation functions and the results are given in Figure 7. Logarithmic activation function has the lowest RMSE compared to other activation functions.

Discussion

The proposed solution predicted the influence of Arctic sea extent on Indian Ocean sea surface temperature at fine grained level of western and eastern regions. To the best of our knowledge, there has been no such works analysing the influence of sea ice extent at a global context in a fine grained manner. The prediction model used in proposed solution is more advanced compared to ANN and CNN models used in the existing works. In addition, the hyperparameters of the predictor model is fined tuned using optimization algorithm. The best set of hyperparameters to optimize was selected and optimized applying GSO without getting into local minima problem in the proposed solution. In addition, the influence was studied at different temporal duration which has not been considered in earlier works.

5 Conclusion

The predictability of Indian Ocean sea surface temperature using Arctic sea ice extent is analyzed using optimized LSTM regressor in this work. The solution solved two problems of fine grained prediction and longer temporal correlation. The study found more than 65% correlation between the Arctic sea ice extend and Indian Ocean sea surface temperature. The study found that LSTM hyper parameter optimization improved the predictability performance by 7.57% compared to default LSTM. The predictability performance was highest when prediction was done based on past 12 month data. Though results were consistent Western Equatorial Indian Ocean region compared to Eastern Equatorial Indian Ocean region. Compared to existing works, the prediction error is atleast 18% lower in the proposed solution. Incorporating Antarctic sea extent and other climatic variables in a fused deep learning model is in scope of future work.

Conflicts of interest

Authors declare no conflict of interest.

Author contributions

Bhupender Singh was the primary author who conceptualized, implemented the concept, collected results and documented the paper. Y.D.S. Arya and

K.C. Tripathi reviewed the work, suggested changes and verified the results.

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