Prediction of Dominant Ocean Parameters for Sustainable Marine Environment

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ABSTRACT Prediction of ocean parameters is the rising interest in ocean-related fields to perceive variations in climatic conditions. Most of the existing methods reveal that predictions involve a single parameter, namely Sea Surface Temperature (SST). This paper proposed a deep learning technique of Multi-Layer Perceptron (MLP) with Multi-Variant Convolutional (MVC) High Speed (HS) Long and short-Term Memory (HM-LSTM) model to predict the four essential parameters - temperature, pressure, salinity and density at three different Oceans - the Bay of Bengal, Arctic Ocean, and the Indian Ocean. The traditional method is limited to time sequence prediction without considering its spatial linkage. The horizontal and vertical parametric variations with spatial and temporal dependencies at 2000 m below the ocean is the observation considerations for the proposed prediction model. The ARGO provides the thermocline, pycnocline, and halocline layers data to perform the parameter prediction. Its results demonstrate the excellent overall accuracy, low Root Mean Square Error (RMSE), and low Mean Absolute Error (MAE) without any overfitting or underfitting compared to the current State-of-the-art. The forecasting of ocean weather helps conserve the ocean environment for human life in food security, developing the global economy, biomedical exploration, medicines, treatments, diagnostic analysis, and producing a significant passenger transport and tourism source.

INDEX TERMS Deep learning, spatial-temporal prediction, high-speed multilayer convolutional LSTM, internet of underwater things, long and short term memory, weather forecasting, sustainable marine environment.

I. INTRODUCTION
Nearly 72 percent of the surface of the planet is surrounded by oceans, which provide 97 percent of water to the earth and roughly 70 percent of the oxygen we breathe [1]. The oceans are a vital part of the Earth’s environment, providing biodiversity, food, and life. As per a study, nearly 40% of the world’s population lives within 100 kilometers of the shore. However, a variety of human practices are putting our oceans at risk. Overfishing is reducing fish stocks, affecting food supplies [2], and altering marine food chains [3]. Marine plastic pollution is also a major problem in the marine environment which causes ingestion, suffocation [4] and entanglement to hundreds of marine species. Marine oil spill [5] causes a high impact on social and economic factors. Around 80% of ocean pollution originates on land, and coastal areas are particularly vulnerable to contaminants. Ocean pollution is a mixture of pollutants and garbage, which originates on land and is poured or thrown into the sea. It harms the climate, the well-being of all animals, and economic systems all over the world. Pollutants are disposed of in the sea. This pollution has an impact on the life of fish and other marine animals. Also, a series of issues such as climate variation, contamination, eutrophication, overfishing, acidification, and sedimentation has a serious effect on our ocean in recent years. We want to preserve, protect, and improve the ocean on a local and global scale.

A regression problem can be used to model the prediction of ocean sensing information. “Linear regression, logistic regression, ridge regression, and support vector regression” are some of the more traditional approaches. For regressive predictive modeling, Jiang et al. make use of SVR [26]. To forecast ocean temperature and salinity, Gou et al. [27] use the KNN regression algorithm. For Single Ocean, the majority of these approaches only consider two variables. HM-LSTM, a specific deep learning algorithm for predicting...
TABLE 1. Literature surveys for ocean parameter prediction using deep learning.

| Model         | Compared model | Location          | Source         | Period               | Metrics               | Predicted parameter                      |
|---------------|----------------|-------------------|----------------|----------------------|-----------------------|------------------------------------------|
| DA-NN         | Ensemble Kalman Filter | Atlantic         | AVISO and GHRSSST  | 2001-2010            | R, MSE                | SSH, SST, Eastward and Northward velocities [6]|
| SVM-PSO       |                 | Brazilian coast  | buoy           | September 2005 to December 2007 | Mean, Median, Standard deviation | SST [7] Spatio-temporal, SST [8] SST [9] |
| CFCC-LSTM     | SVM, SVR, PC-LSTM | Bohai Sea        | AVHRR          | 2007-2012            | RMSE, ACC             | SST [10] Spatio-temporal, SST [8] SST [9] |
| LSTM RNN      | MLP, SVR        | Deep China       | NOAA           | 1981-1996 to 2018    | RMSE                  | SST [11] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| LSTM NN       | MIMO            | World            | NOAA           | January 1950 to October 2017 | RMSE, MAE             | SST, SS, SS [16] Spatio-temporal parameters SST, SST, SS [16] |
| MLP CEEMD-BPNN |                 | South China Sea  | OSTIA          | 1985-2018            | Bias, RMSE, STD       | SST [11] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| MLP BPN         |                 | North Pacific    | NOAA           | 1982-2016            | RMSE, ERR             | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| Convolutional LSTM | SVR, LSTM      | East China Sea   | AVHRR          | 1982-2015            | R, RMSE, MAPE, P-Value | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| LSTM AdaBoost  | SVR, BPNN, LSTM, AdaBoost | East China Sea | AVHRR          | 1982-2017            | RMSE, MAE, R          | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| LSTM GED       | SVR, GED        | Bohai Sea China, South China Sea | NOAA           | 1997-2018            | MSE, MAE               | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| CNN           | SVR, LSTM, XGBoost, SVM, MLP | Pacific Ocean | AVHRR | 2004-2015 | R2, MSE | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| NARX-NN       |                 | Pacific Ocean    | NOAA, buoys    | 1985-1995            | R, RMSE, MAPE, MAE    | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| M-LCNN        | CNN-LSTM, SVR, CFCC-LSTM, RF, MLPXGBoost, SVM, ARIMA, BPNN, RBFNN, RNN, GRU, LSTM, GRU-SVM | Yellow Sea, Bohai Sea | NOAA | 1981-2019 | ACC, RMSE | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| LSTM          |                 | North Atlantic   | 2002-2018      | MAE, MAPE            | SST [19]              | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| DGC network   |                 | East China Sea   | Yellow Sea     | 2001-2017            | RMSE, RMSPE, MAPE, MAE, Acc | SST [20] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| CNN           |                 | Southern coast of France and Corsica | AVHRR | 1985-2009 | RMSE, CRMSE, Bias | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| GRU-NN        |                 | Bohai Sea        | OISST (AVHRR)  | 1982-2019            | R, RMSE, MAE, R, RMSE | SST, SS, SS [16] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| LSTM          |                 | Indian Ocean     | NOAA           | 1870-2018            | R, RMSE, MAE, Bias    | SST [23] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| LSTM          |                 | China Sea        | OSTIA          | 1998-2014            | SD, RMSE              | SST [24] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |
| 3D-CNN and LSTM | LSTM and Conv LSTM | Bohai Sea and the South China Sea | NOAA | January 1, 1982 to December 31, 1982 | R2, RMSE, MAE | SST [25] Decomposition of SST, spatio-temporal parameters SST, SST, SS [16] |

The LSTM is a gradient-based time series prediction model that combines long and short-term sequences to solve sequence prediction problems. In particular, it is a stable model incorporating Recurrent Neural Network (RNN) [28] for solving problems. Besides, LSTM can store the information for the long term than RNN [29]. The memory cell ($C_{t-1}$) is the unique feature of LSTM, which works as an accumulator for memory buffer. It self-characterizes on a control gate for accessing its unit for the further process. In case of new information arrival, it gets accumulated in $C_{t-1}$ and unlocks the input gate. Furthermore if the forgotten gate ($F_t$) is enabled, the former moments...
(C_{t-1}) is “forgotten”. The output gate controls the final output (H) when the information is propagated to the last cell. Unlike CNN, the interconnection between different neurons is introduced in the same network layer of RNN to share the network layer’s weighted parameters. The hidden layer of RNN is defined by the previous layer output and the time step of the hidden layer. Hence, LSTM is known for the correlation of temporal data sequence. The structure of HM-LSTM is divided into input, convolutional LSTM, and output layers. In the input layers, the variables are initialized in the stack. This proposed model captures both spatio-temporal and hidden layers correlations at different inputs.

In this paper, climate change of oceans is taken into account by predicting the ocean properties to preserve the ocean environment. Its species in the future is taken into account to preserve the ocean environment and its species by predicting the ocean parameters. Previously, technologies also developed for spatial correlation forecasting, regional forecasting, offshore forecasting [30], predicting sensor location [31] and the ocean environment is analyzed using discriminatory model [32]. Previously, technologies also developed for spatial correlation forecasting, regional forecasting, offshore forecasting [30] and the ocean environment is analyzed using discriminatory model [32]. For predicting future oceanic parameters, the Ocean observation system and underwater communication systems are interconnected with a network of the Internet of Underwater Things (IoUT) to preserve the Ocean resources. Due to the ocean’s complex nature, Underwater Acoustic Communication (UWAC) plays an essential role in networking multiple underwater networks in IoUT.

As the velocity of sound in water depends [33] on the ocean parameters like temperature, pressure, salinity, and density, its variations define the transmission and communication performance of IoUT [34]. In recent times, the prediction of sea surface temperature has become a rising interest in different ocean fields [35]. The prediction models are of two types in neural networks; iterative and non-iterative training mechanisms. The bidirectional stochastic configuration network (BSCN) performs by dividing the model into forwarding and backward learning until good prediction accuracy is achieved. Here, to improve the efficiency of SCN and optimized BSCN is used to speed up the model. The study on the performance of random weight neural network (RWN) discusses that the performance of the model increases once it reaches the input threshold, and also the degree of matrix information distribution (DDMID) evaluates the model without training. Further, the neural networks with random weights (NNRW) initialize the weights between hidden and input layers to lower the training complexity compared to the traditional iterative neural networks. In the above non-iterative methods achieve their accuracy only when the analytically initialized input weights reach the threshold. Since the weights vary depending on the dataset, the initialization of weights for each process is tedious. The iterative training mechanisms undergo several epochs to update their weights automatically for every loop to achieve prediction accuracy.

The non-iterative methods are preferred to reduce the time consumed during the iterative process. But, the proposed iterative model HM-LSTM uses the early stopping method to avoid unnecessary iterations and produce excellent prediction accuracy without any add-on optimizers. From the iterative model literature studies, a detailed comparison is made in table 1. The list of abbreviations and acronyms used in the literature survey is given in table 2. The common limitation of all the literature surveys mentioned is that only the SST parameter is predicted as their research findings, though oceans have many other parameters for consideration. In this paper, pressure, salinity, and density are predicted along with subsurface temperature for a sustainable marine environment. And also, the proposed algorithms in the literature predict SST only for a single ocean and rarely for two oceans. Here, the HM-LSTM is implemented at three oceans for all four parameters. Good prediction accuracy and better efficiency of all the parameters for three different oceans are the unique research idea proposed in this paper. The physical properties of the ocean are predicted mainly to preserve the ocean wealth. By conserving the ocean resources: 1) Ocean generates more oxygen than Amazon, 2) Ocean determines the earth climate, 3) It is the main source of food, 4) Many species rely on and survive in the ocean, 5) Ocean has therapeutic properties 6) Ocean environment supports our economy. To achieving the above things, Oceanic parameters should be sustainable. To maintain a sustainable Ocean environment, monitoring the ocean parameters plays a major role.

Prediction of these four ocean parameters can protect coastlines from erosions, sea level rise, weather pattern

| TABLE 2. List of abbreviations. |
|-------------------------------|---------------------------------------------------------------|
| Abbreviations                 | Description                                                  |
| AVIRR                         | Advanced Very High-Resolution Radiometer                     |
| AVISO                         | Archiving, Validation and Interpretation of Satellite         |
| Oceanographic data            |                                                                |
| BPNN                          | Back-Propagation Neural Network                               |
| CEBMD                         | Complementary Ensemble Empirical Mode Decomposition          |
| CNN                           | Convolutional Neural Network                                  |
| DGC                           | Deep Gated Recurrent Unit                                    |
| DINCAE                        | Data Interpolating Convolutional Auto-Encoder                |
| EMD                           | Ensemble Empirical Mode Decomposition                       |
| ECMWF                         | European Centre For Medium Range Weather Forecasts            |
| ENSO                          | El Niño-Southern Oscillation                                 |
| FCC                           | Fully Connected Convolutional                                 |
| GHRSSST                       | Group for High Resolution Sea Surface Temperature              |
| GRU                           | Gated Recurrent Unit                                         |
| LSTM                          | Long Short Term Memory                                       |
| MIMO                          | Multiple Input-Multiple Output                               |
| MLP                           | Multilayer Perceptron                                        |
| MLCNN                         | Multi Long Short Term Memory Convolution Neural Network       |
| NOAA                          | National Oceanic and Atmospheric Administration               |
| NARX                          | Nonlinear Autoregressive Exogenous                          |
| RNN                           | Recurrent Neural Networks                                    |
| OISST                         | Optimum Interpolation Sea Surface Temperature                |
| OSTA                           | Operational SST And Ice Analysis                            |
| FSO                           | Particle Swarm Optimization                                  |
| SVR                           | Support Vector Regression                                    |
| SVM                           | Support Vector Machine                                       |

The physical properties of the ocean are predicted mainly to preserve the ocean wealth. By conserving the ocean resources: 1) Ocean generates more oxygen than Amazon, 2) Ocean determines the earth climate, 3) It is the main source of food, 4) Many species rely on and survive in the ocean, 5) Ocean has therapeutic properties 6) Ocean environment supports our economy. To achieving the above things, Oceanic parameters should be sustainable. To maintain a sustainable Ocean environment, monitoring the ocean parameters plays a major role.

Prediction of these four ocean parameters can protect coastlines from erosions, sea level rise, weather pattern...
challenging, atmospheric warming etc. To preserve the Ocean resources by predicting the above mentioned change, this paper proposes a multiple-layer convolutional High speed-LSTM (HM-LSTM) for forecasting the future values of temperature, pressure, salinity, and density in three different oceans like Bay of Bengal, Indian Ocean, and the Arctic Ocean to observe these parametric variations below 2000m in both horizontal and vertical directions. The present and the future abnormal rise and fall parameters should be properly monitored so that former reasons will not occur. The Indian National Centre for Ocean Information Services (INCOIS) data from thermocline, pycnocline, and halocline layers estimate the performance metrics. Predicting the subsurface temperature can avoid natural disasters [36]like global warming, heavy rain, and floods. The rise in ocean pressure can be tolerable only to specific species, such as whales and sharks since they can withstand high pressure due its physical structure. The variation in the temperature affects the ocean’s thermocline layer. Predicting the ocean’s pressure helps find that a small variety of species can be culture or not in species cultivation. Forecasting the future salinity is important for two reasons. One is that it directly affects the temperature affecting the circulation of ocean current by producing heat. Another is linked with the overall evaporation and precipitation process in the earth’s water cycle. Oceanographic organizations are recommended to predict the future salinity to calculate the freshwater levels in the pycnocline. By predicting the density of the ocean in halocline, the ocean currents and the heat circulation in the ocean can be calculated. The temperature, pressure, salinity, and density are the ocean’s physical parameters for saving marine and human life. The Oceanographic institutes are advised to predict these parameters to avoid human and property loss due to the sudden climatic variations. The researchers in the literature have concentrated only on the observation and prediction of SST for saving human life. The innovation of the paper is that it addresses the application of both the marine and human points of view under three layers-thermocline, pycnocline, and halocline layers. The proposed workflow is shown in figure 1. It consists of four modules. 1)Data processing: sensor observations are collected and normalized for further processing. 2)Modeling: The past observation inputs (HM-LSTM) are simulated with tuning for effective output. 3)Application: The task is evaluated with the observed and collected ocean datasets. Some machine learning algorithms are compared for the parameter execution of time-series predictions. 4)Visualization: Simulated outcomes reveal that the

HM-LSTM performs better than other algorithms. The key features in this paper are as follows:

i) Proposed a High-speed multilayer convolutional LSTM(HM-LSTM) to predict four physical properties of the ocean using time series prediction algorithm which can accommodate a wide range of applications based on raw and historical observations.

ii) Implemented HM-LSTM neural network to predict the future states and trends for three different oceans like the Bay of Bengal, Indian Ocean, and the Arctic Ocean.

iii) Evaluated and compared the results with current state-of-the-art. The results revealed the effectiveness and performance of HM-LSTM.

The workflow of this paper is organized as follows. Section II explains the Proposed Methodology HM-LSTM and its structure. Section III describes the experimental analysis and the results. Finally, the conclusion is drawn in Section IV.

II. PROPOSED METHODOLOGY

In this paper, for predicting thermocline, pycnocline, and halocline, high-quality temperature, pressure, salinity, and density datasets are considered at the same latitude and longitude for different oceans at different depths. The multi-layer convolutional LSTM are the main components in this proposed structure. This structure involves both the state-to-state and input-to-state connections. In this regard, $F_1 \ldots F_t$
inputs, $C_1 \ldots C_t$ output cells, $H_1 \ldots H_t$ hidden cells and the $F_t, I_t,$ and $O_t$ of the convolutional LSTM structure serve temporal and spatial variations. The output of the convolutional model entirely depends on the neighbor’s actual inputs. The layout of the HM-LSTM is shown in Figure 2. The structure of single-layer LSTM is given in figure 3 for better understanding. The input information $x_t$ enters the same time cell as the previous time cell for each layer ($A$). It first activates the feature “tanh” before passing it on to the next time cell. The hidden layer state $h_{t-1}$ in the last moment is included in the data obtained by each cell of the LSTM. The previous time’s input $x_t$ and output go through four separate activation functions. The information from both the input and forget gate of HM-LSTM cell is obtained from the present input ($X_t$), previous time cell of hidden state ($H_{t-1}$) and the previous cell ($C_{t-1}$) as given in figure 2. Both input and forget gate define the information of the output gate. The activation function tanh ($\sigma$) of each control gate decides the information to pass through each cell. Digital signal to mapping ($0 - 1$) conversion as the key factor in linear to non-linear conversion. The training set determines the initial time of the input. In HM-LSTM process, each cell of present time ($X_t$) and the hidden state ($H_t$) is trained automatically. The key formulas for each HM-LSTM module are given as follows:

$$F_t = \sigma_F(W_{XF} * X_t + W_{HF} * H_{t-1} + W_{CF} \odot C_{t-1} + B_F)$$ (1)

$$I_t = \sigma_I(W_{XI} * X_t + W_{HI} * H_{t-1} + W_{CI} \odot C_{t-1} + B_I)$$ (2)

$$C_t = F_t \odot C_{t-1} + I_t \odot \tanh(W_{XC} * X_t + W_{HC} * H_{t-1} + B_C)$$ (3)

$$O_t = \sigma_O(W_{XO}X_t + W_{HO}H_{t-1} + W_{CO} \odot C_t + B_O)$$ (4)

$$H_t = O_t \odot \tanh(C_{t-1} + B)$$ (5)

During training the HM-LSTM characteristics are defined as $W$: weighted matrix; $B$: input to output gate offset; $I_t$: input gate; $F_t$: forget gate; $O_t$: output gate; $C_t$: Cell state; $\odot$: Hadamard product; $\sigma$: Logistic sigmoid functiona and *: conventional operator. The convolutional filters used in this model captures different variable interaction during the training phase. The number of filters can be personalized according to the depth of the network and the applications used. The input variables impact is less than the output as the convolutional operation ends once it reaches the edge. The output of the ith layer is obtained by padding the information in the filter. The HM-LSTM model trains the Spatio-temporal features to predict the output. The multivariant observations are stacked throughout the prediction. Thus the proposed model produces good accuracy in the Spatio-temporal predictions.

### III. Experimental Analysis

The algorithm used in this work is implemented in Google Colab, python - 3.7.10 on 8GB Intel(R) Core(TM) i3-3110M CPU @ 2.40GHz. For qualitative work, the dataset for three oceans (i.e.) Bay of Bengal, the Indian Ocean, and the Arctic Ocean is taken for prediction. On the other hand, how the proposed model works for all three Ocean environments at different climatic conditions is discussed. The experimental results show that the HM-LSTM model performs efficient time series prediction tasks for a large dataset at different oceanic conditions in various ocean parameters.

One of the factors that influence the proposed algorithm is no of iterations. Researchers have proposed their model for accuracy in the literature surveys with epochs ranging from 100 to 1000. Since they use more epochs to train the model, it consumes more time for a prediction. The computational time in HM-LSTM is reduced by training the model with only 50 iterations, and it can be increased only in case of high prediction error. This is achieved by the early stopping method by solving the problem of overfitting and underfitting. In the previous studies, researchers have used LSTM for limited period with nearly 100 to 1000 epochs. Here, the input data set with neurons 60,80,80,120,120 is taken from January 2016-December 2019. This dataset is simulated for 50 epochs. The epochs used in this model are less than other methods with a large dataset, and thus the model is known to be High speed-LSTM (HS-LSTM). HS-LSTM neural network is proposed for a more accurate, robust, and efficient prediction model for a large dataset. The Early stopping method is used in this model to avoid overfitting and underfitting. The R2 for each model is the final output after cross-validation. The parameters at each algorithm are taken for comparison, which works as an optimal model to
evaluate the test set. The detailed flowchart for the working of HM-LSTM is explained in figure 4.

**A. DATASET**
The Indian National Centre for Ocean Information Services (INCOIS) under the unit of the Earth System Science Organization (ESSO) provided the Array for Real-time Geostrophic Oceanography (ARGO) dataset for this experiment. The provided dataset contains temperature, pressure, salinity, and density parameters of the Bay of Bengal (BOB), the Indian Ocean, and the Arctic Ocean from January 2016 to December 2019 (4 years), covering $13 \times 97 \times 2000$ (Depth) space-time grid. As Indian Ocean is a part of Bay of Bengal, the data from the Indian Ocean is observed as per latitude and longitude. Each ocean contains a sample of latitude, longitude, depth, temperature, pressure, salinity, and density. The dataset are divided in the ratio of 6:2:2 for training, verification and validation. There are 60,000 raw historical interpretations from 2000 m depth.

**B. EVALUATION METRICS**
In this analysis, different metrics are indexed to evaluate the prediction results [11], performance, Mean absolute error (MAE), Root Mean Squared Error (RMSE), and determination coefficient $R^2$ [20], [37].

Mean Absolute Error (MAE):

$$MAE = \frac{1}{N} \sum_{i=0}^{N-1} |Z_i^{pre} - Z_i^{true}|$$

(6)

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Z_i - \bar{Z}_i)^2}{N}}$$

(7)

Co-efficient of Determination ($R^2$):

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (Z_i - \bar{Z})^2}{\sum_{i=1}^{N} (Z_i - \bar{Z})^2}$$

(8)

Accuracy (ACC):

$$ACC = \frac{1}{N} \sum_{i=1}^{N} \frac{|Z_i^{pre} - Z_i^{true}|}{Z_i^{true}}$$

(9)

where $Z_i$ and $\bar{Z}_i$ represents the true and predicted values of $i^{th}$ samples. While $Z$ denotes the mean of all samples and $N$ is several samples. In paper [38], [39], RMSE value of $i = 2$ shows that the model is highly efficient. In the proposed HM-LSTM model, the parameter MAE and RMSE prove good with their values close to 0 implies that the prediction model gives high accuracy. The model proves better performance with accuracy results closer to 1, showing that HM-LSTM is a better forecasting model for prediction. The survey related to this works explains that these metrics are required to evaluate a forecasting model [40], [41].

**C. RESULTS AND DISCUSSION**
Here the performance of the predicted model HM-LSTM is compared with the existing prediction methods like Logistic
regression (LR), Support Vector Machine (SVM), K-nearest neighbor (KNN), Adaboost model (AB), Naive Bayes (NB), LSTM, Particle Swarm Optimization (PSO) LSTM (P-LSTM), Multi Layer Perceptron (MLP). The HM-LSTM algorithm performs better than current algorithms. The existing methods have the limitations like non-linearity, large dataset, overlapping, overfitting, and low memory. HM-LSTM overcomes these limitations providing good simulation results explained as follows. The HM-LSTM algorithm is tested for three different oceans for four dominant parameters. The performance is evaluated by calculating RMSE, Mean Absolute Error, and $R^2$ score. The RMSE is a good measure of accuracy and the more suitable evaluation metric to calculate the prediction error. Calculating RMSE is more useful when large errors are particularly undesirable as in (Eq.7). Lower the values of RMSE better the model fits the prediction. The $R^2$ score explains the correlation between the actual and predicted values. Higher the values of $R^2$ score better the prediction model as per (Eq.8). The $R^2$ score closer to 1 proves that the model predicts better. Further, the MAE represents the average of the absolute difference between the actual and predicted values in the dataset as in (Eq.6). MAE also finds the difference between the forecasted value and the actual value, which helps understand the amount of error during the forecast. So, evaluating these metrics is essential for analyzing whether the model serves good for prediction.

The ARGO dataset for all four parameters from January 2016 to December 2019 is trained and tested for the BOB, the Indian Ocean, and the Arctic Ocean using the proposed HM-LSTM model. The dataset has temperature, pressure, salinity, and density observations. As per the ministry of earth science report, the BOB is the most vulnerable Ocean, which has faced a maximum number of cyclones in 1981 and 2018. And also, BOB got hit with many disasters like hurricanes, thunderstorms, floods, etc., caused by the abnormal rise in the parameters like pressure, salinity, temperature, and density which leads to the loss of life affecting economic activities. To avert this condition, forecasting the future climate of the BOB is performed in this paper. For the BOB, the model is trained by assigning the real temperature values ranging from 0 to 30°C, pressure from -100 to 2000 pa, salinity from 31 to 35 psu, and density values from 1010 to 1030 kg/m$^3$.

The Indian Ocean, the third-largest among the global divisions, has unusual climate variability causing several floods and droughts. Therefore it is vital to make a prior prediction to avoid property and human loss. In the case of the Indian Ocean, the temperature observations from -5 to 35°C, pressure 960 to 1040 pa, salinity 31 to 36 psu, and density values from 1000 to 1050 kg/m$^3$ are assigned. The Arctic Ocean, the smallest and coldest among all the oceans, is mainly surrounded by land. Owing to high latitudes, the climate of the Arctic ocean varies drastically. Due to the dynamic change in the weather conditions, there is a severe risk that can produce highly complex ice conditions, icebergs, climate change, pollution, seismic hazards (leading to earthquake), and melting permafrost. To avoid the loss from the above disaster, predicting ocean parameters is essential to warn nearby areas. And in the Arctic Ocean, temperature -10 to 140 °C, pressure variations from 0 to 8000pa, salinity -5

FIGURE 6. Prediction results of HM-LSTM and real time data with respect to depth at Indian Ocean for (a) Temperature (b) Pressure (c) Salinity (d) Density.
to 35 psu, and density observations from -500 to 6000 kg/m³ are initialized inputs for the training model. For all the four parameters in three oceans, the assigned neurons vary in each convolutional layer.

The early stopping method reduced the time consumed for iterations and produce better training results. With the past real values, the model outperforms the best-predicted results for 2020. Figure 5 gives the simulated graph for

**TABLE 3.** Evaluation of temperature, pressure, salinity and density for different metrics in existing algorithms compared to the proposed HM-LSTM at Bay of Bengal.

| Parameter | Metrics | LR  | SVM | KNN | Adaboost | Naive bayes | LSTM | PSO-LSTM | MLP | HM-LSTM |
|-----------|---------|-----|-----|-----|----------|-------------|-------|----------|-----|---------|
| Temperature | RMSE  | 0.369 | 0.397 | 0.364 | 0.338 | 0.156 | 0.225 | 0.105 | 0.124 | 0.092 |
|           | R²Score | 0.710 | 0.625 | 0.526 | 0.684 | 0.895 | 0.885 | 0.925 | 0.957 | 0.985 |
|           | MAE    | 0.268 | 0.448 | 0.860 | 0.222 | 0.432 | 0.139 | 0.188 | 0.105 | 0.033 |
| Pressure  | RMSE  | 0.855 | 0.398 | 0.395 | 0.482 | 0.715 | 0.281 | 0.215 | 0.118 | 0.095 |
|           | R²Score | 0.699 | 0.572 | 0.799 | 0.624 | 0.719 | 0.905 | 0.937 | 0.957 | 0.987 |
|           | MAE    | 0.338 | 0.359 | 0.146 | 0.196 | 0.247 | 0.189 | 0.185 | 0.095 | 0.048 |
| Salinity  | RMSE  | 0.870 | 0.539 | 0.92 | 0.475 | 0.681 | 0.397 | 0.325 | 0.278 | 0.197 |
|           | R²Score | 0.513 | 0.501 | 0.693 | 0.687 | 0.762 | 0.859 | 0.847 | 0.875 | 0.909 |
|           | MAE    | 0.489 | 0.349 | 0.333 | 0.258 | 0.367 | 0.285 | 0.208 | 0.157 | 0.085 |
| Density   | RMSE  | 0.728 | 0.676 | 0.505 | 0.423 | 0.361 | 0.392 | 0.288 | 0.248 | 0.192 |
|           | R²Score | 0.752 | 0.685 | 0.591 | 0.308 | 0.749 | 0.854 | 0.902 | 0.947 | 0.976 |
|           | MAE    | 0.459 | 0.394 | 0.333 | 0.587 | 0.311 | 0.222 | 0.199 | 0.147 | 0.126 |

**TABLE 4.** Evaluation of temperature, pressure, salinity and density for different metrics in existing algorithms compared to the proposed HM-LSTM at Indian Ocean.

| Parameter | Metrics | LR  | SVM | KNN | Adaboost | Naive bayes | LSTM | PSO-LSTM | MLP | HM-LSTM |
|-----------|---------|-----|-----|-----|----------|-------------|-------|----------|-----|---------|
| Temperature | RMSE  | 0.789 | 0.329 | 0.437 | 0.325 | 0.369 | 0.159 | 0.105 | 0.399 | 0.059 |
|           | R²Score | 0.752 | 0.803 | 0.452 | 0.587 | 0.600 | 0.859 | 0.907 | 0.915 | 0.959 |
|           | MAE    | 0.194 | 0.254 | 0.248 | 0.570 | 0.220 | 0.250 | 0.198 | 0.111 | 0.096 |
| Pressure  | RMSE  | 0.722 | 0.593 | 0.442 | 0.562 | 0.627 | 0.322 | 0.290 | 0.235 | 0.248 |
|           | R²Score | 0.581 | 0.756 | 0.689 | 0.552 | 0.681 | 0.788 | 0.800 | 0.828 | 0.915 |
|           | MAE    | 0.466 | 0.242 | 0.321 | 0.330 | 0.210 | 0.188 | 0.154 | 0.112 | 0.098 |
| Salinity  | RMSE  | 0.64 | 0.358 | 0.441 | 0.675 | 0.216 | 0.224 | 0.210 | 0.147 | 0.099 |
|           | R²Score | 0.626 | 0.74 | 0.765 | 0.771 | 0.700 | 0.750 | 0.781 | 0.897 | 0.929 |
|           | MAE    | 0.21 | 0.256 | 0.39 | 0.451 | 0.321 | 0.223 | 0.215 | 0.157 | 0.013 |
| Density   | RMSE  | 0.401 | 0.592 | 0.517 | 0.588 | 0.412 | 0.401 | 0.399 | 0.327 |
|           | R²Score | 0.374 | 0.725 | 0.705 | 0.818 | 0.826 | 0.854 | 0.899 | 0.902 | 0.945 |
|           | MAE    | 0.346 | 0.26 | 0.323 | 0.200 | 0.199 | 0.185 | 0.122 | 0.171 | 0.041 |

**TABLE 5.** Evaluation of temperature, pressure, salinity and density for different metrics in existing algorithms compared to the proposed HM-LSTM at Arctic Ocean.

| Parameter | Metrics | LR  | SVM | KNN | Adaboost | Naive bayes | LSTM | PSO-LSTM | MLP | HM-LSTM |
|-----------|---------|-----|-----|-----|----------|-------------|-------|----------|-----|---------|
| Temperature | RMSE  | 0.369 | 0.397 | 0.364 | 0.364 | 0.350 | 0.258 | 0.210 | 0.115 | 0.094 |
|           | R²Score | 0.610 | 0.425 | 0.772 | 0.820 | 0.889 | 0.802 | 0.816 | 0.938 | 0.797 |
|           | MAE    | 0.568 | 0.448 | 0.306 | 0.258 | 0.216 | 0.200 | 0.189 | 0.112 | 0.023 |
| Pressure  | RMSE  | 0.440 | 0.423 | 0.326 | 0.308 | 0.272 | 0.360 | 0.204 | 0.282 | 0.246 |
|           | R²Score | 0.689 | 0.575 | 0.698 | 0.702 | 0.789 | 0.809 | 0.869 | 0.934 | 0.972 |
|           | MAE    | 0.466 | 0.429 | 0.391 | 0.335 | 0.314 | 0.258 | 0.201 | 0.110 | 0.009 |
| Salinity  | RMSE  | 0.335 | 0.469 | 0.363 | 0.301 | 0.239 | 0.225 | 0.219 | 0.209 | 0.194 |
|           | R²Score | 0.558 | 0.666 | 0.691 | 0.785 | 0.708 | 0.869 | 0.925 | 0.931 | 0.979 |
|           | MAE    | 0.271 | 0.3929 | 0.333 | 0.225 | 0.269 | 0.210 | 0.188 | 0.111 | 0.072 |
| Density   | RMSE  | 0.245 | 0.325 | 0.304 | 0.258 | 0.210 | 0.195 | 0.150 | 0.123 | 0.059 |
|           | R²Score | 0.654 | 0.741 | 0.652 | 0.785 | 0.799 | 0.864 | 0.928 | 0.948 | 0.977 |
|           | MAE    | 0.887 | 0.236 | 0.290 | 0.256 | 0.212 | 0.199 | 0.185 | 0.132 | 0.106 |
real and predicted values at the BOB. Figure 6 shows the correlation of real and predicted results in the Indian Ocean.

Figure 7 shows the accuracy of real and prediction results at Arctic Ocean. In figure 6 and 7 prediction of Indian Ocean
pressure and Arctic Ocean density are not much correlated in such case optimization helps to predict better in future. The prediction results of the proposed model are compared with the current state-of-the-art algorithms mentioned above. The evaluation results and their categorical representations of those parameters are displayed in table 3 and figure 8 for
BOB, table 4 and figure 9 for the Indian Ocean, and table 5 and figure 10 for the Arctic Ocean. The results prove that HM-LSTMs R2score is better than other algorithms with an average of 98% accuracy for the BOB, 95% accuracy for the Indian Ocean, and 97% accuracy for the Arctic Ocean. The simulated outcome gives the predicted data from
FIGURE 13. The HM-LSTM prediction loss at the Bay of Bengal, Indian Ocean, and Arctic Ocean obtained during 20% verification test for 50 epochs in four parameters (a) The loss results of temperature at three oceans (b) The loss results of pressure at three oceans (c) The loss results of salinity at three oceans (d) The loss results of density at three oceans.

FIGURE 14. The HM-LSTM prediction MAE at the Bay of Bengal, Indian Ocean, and Arctic Ocean obtained during 20% verification test for 50 epochs in four parameters (a) The MAE results of temperature at three oceans (b) The MAE results of pressure at three oceans (c) The MAE results of salinity at three oceans (d) The MAE results of density at three oceans.

January 2020 to December 2020 for all four parameters. The validation of all the learning curve results is plotted in Figures 11, 12, and 13 for all three oceans. The maximum epochs used in the HM-LSTM model is 50. The Loss, RMSE, and MAE decrease as the epochs increase. The HM-LSTM
curve in Loss, RMSE, and MAE representation proves that the model has less prediction error for all four parameters at three Oceans. Figure 11 gives the accurate results of the HM-LSTM model for all three oceans. Thus, from all the evaluated results, HM-LSTM proves best in terms of time series prediction at all three Oceans (Bay of Bengal, Indian Ocean, and Arctic ocean) for all four parameters (temperature, pressure, salinity, and density).

IV. CONCLUSION

In this article, an HM-LSTM model for Ocean parametric time series prediction is proposed at three different oceans environments. The proposed model can capture horizontal and vertical (spatial) components with past and recent (temporal) dependencies for all four parameters at three ocean conditions. Compared with the current state-of-the-art, the HM-LSTM outperforms a good accuracy of 98% with less than 0.1 prediction error on average during the thermocline, pycnocline, and halocline layer parameter forecast without any over and underfitting. In the future, the model can be improved to train the large dataset with minimize prediction error in other oceans for different physical properties.

ACKNOWLEDGMENT

The authors would like to thank the Ministry of Earth Science through INCOIS for providing ARGO dataset for supporting this research.

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