Machine Learning Based ENSO Prediction Using Multivariate Ocean Atmosphere Data

Dibyadarshini Maharatha[1], Prashant Kumar*[1], Yukiharu Hiasaki[2], and Rajni Rajni[3]

[1] Department of Mathematics, National Institute of Technology, Delhi-110040, India
[2]Department of Physics and Earth Sciences Faculty of Science, University of the Ryukyus, Japan
[3]Jindal Global Business school, O.P. Jindal Global University, Haryana-131001, India

(*Corresponding Author E-mail: prashantkumar@nitdelhi.ac.in)

Abstract. El Niño–Southern Oscillation (ENSO) is a major driver of global climate variability that influences extreme weather, agriculture, water resources, and socio-economic systems. Predicting ENSO is challenging because of the complex interactions between the ocean and atmosphere. This study assesses the ENSO prediction capabilities using a number of machine learning techniques applied to a wide range of oceanic and atmospheric variables spanning 1980–2023. These variables include, but are not limited to, surface and subsurface temperatures, pressures, depths, winds, heat content, and outgoing longwave radiation. To predict the Niño 3.4 index and Niño 4 index, six models are tested; they are Random Forest, Gradient Boosting, Support Vector Regression, XGBoost, LSTM, and 1D-CNN. The results show that deep learning models particularly the 1D-CNN and the LSTM are effective more than the conventional methods. Niño 3.4 SST, thermocline depth, and ocean heat content are also found as the most significant predictors through the feature analysis, to enhance the process of prediction of ENSO and climatic early-warning systems.

Keywords: ENSO, El Niño southern oscillation, machine learning, LSTM, random forest, gradient boosting, sea surface temperature, sea level pressure

1 Introduction

El Niño-Southern Oscillation (ENSO) is a massive atmospheric impact of regular change in the temperature and pressure of the Pacific at the equator. It is very significant in terms of its effects on weather patterns in the world, agriculture, water resources and the socio-economic status in both warm (El Niño) and cold (La Niña) conditions [1]. ENSO should be accurately predicted hence disaster preparedness and climate adaptation. The standard statistical and dynamical models tend to be unable to resolve the interaction between the ocean and the atmosphere which is highly nonlinear. Machine learning approaches have recently demonstrated a great potential in analysis processes of large bodies of climate data as well as enhancing prediction quality. This paper will compare six machine learning models that find the Niño 3.4 and Niño 4 indices by using various oceanic and atmospheric predictors [2], as well as, determining the most influential predictors and their seasonal effects on ENSO predictability that influences the ENSO predictability [3].

A. Agnihotri et al. (eds.), *Proceedings of the Conference on Bridging Engineering Disciplines with AI and Machine Learning (BEDAIML 2026)*, Advances in Intelligent Systems Research 209,
https://doi.org/10.2991/978-94-6239-697-5_29

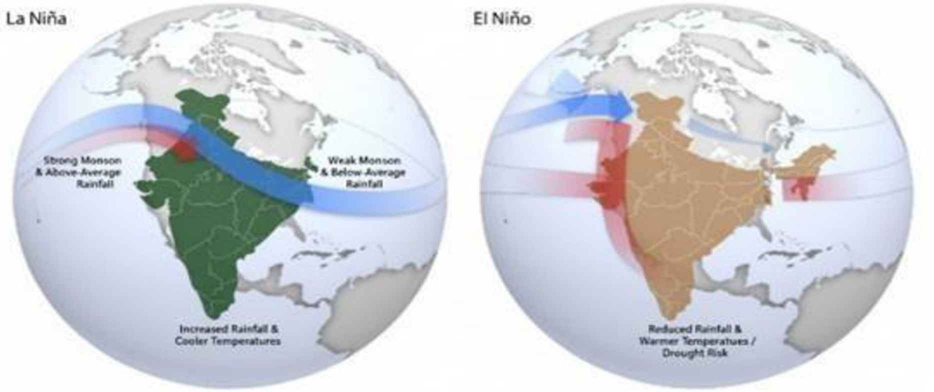

Fig. 1. La Niña and El Niño Effects on Weather [4]

2 Literature Review

Recent studies have paid more attention to the consideration of machine learning (ML) methods to enhance predictability of the ENSO. In a study by 2024 [5], global climate reanalysis datasets were used and predictors of SST, OHC, and zonal wind at 10 m (U10) were used as part of a machine learning-based regression model. The findings revealed that SST has a leading role in the variability of ENSO whereas the addition of the atmospheric wind variables increases forecasting ability to up to approximately 21 months lead time. In 2019 [6], tropical Pacific observational data was summarized with artificial neural networks (ANNs) having SST and network-derived features as inputs. The results suggested that the ML-based models were able to perform better than the traditional dynamical climate models, especially in making future predictions of more than a 12-month lead time. Previous literature in 2015 [7] used SST indexes as predictors to regularized regression done on ENSO observational data to improve the long-range forecasting ability but it was difficult to predict extreme events of ENSO. In 2018, another study [8] used machine learning algorithms on SST anomalies and indices of the ENSO, illustrating a higher predictive power in ENSO Modoki occurrences. Additionally, research conducted in 2019 [9] used deep learning models with climate reanalysis data that included SST and wind variables, achieving notable improvements in long-lead ENSO forecasting skill. Summarizing, these research show that deep learning and machine learning are becoming better at predicting extended-range ENSO events and capturing complicated climatic linkages.

3 Methods

The ML and DL techniques effectively model nonlinear, time-dependent and complex climate processes such as ENSO. This paper uses a series of ML models to measure ENSO predictability using a comprehensive set of oceanic and atmospheric predictors based on long-term observations and reanalysis records.

3.1 Data Sources and Experimental Setup

The variability in the interannual and decadal ENSO is captured using monthly climatic data between 1980 and 2023. SST, atmospheric and subsurface ocean data are obtained from NOAA OISST [9] ERA5 reanalysis [10] and Argo/ORAS5 datasets [11], [12] respectively. All the variables are standardized and aggregated to the monthly level.
The targets of prediction include the Niño 3.4 and Niño 4 [13] sea surface temperature anomaly, the central and western Pacific ENSO variability.

3.2 Predictor Variables and Preprocessing

Let $X_t = (x_{1,t}, x_{2,t}, \dots, x_{n,t})$ represent the time-dependent set of predictors including SST anomalies, sea level pressure, subsurface temperature, thermocline depth, wind stress, ocean heat content, sea surface height, and outgoing longwave radiation. Missing values are filled using the K-Nearest Neighbours (KNN) method, and all variables are standardized to maintain consistency. All predictors are standardized as

$$X'_{i,t} = (X_{i,t} - \mu_i) / \sigma_i \tag{1}$$

where $\mu_i$and $\sigma_i$represent the mean and standard deviation of the i-th predictor respectively. Monthly climatology is used to eliminate seasonal variation to achieve seasonalized anomalies.
In order to include delayed ocean-atmosphere feedback, lagged predictors are built as

$$X_t^{(L)} = \{X_{t-1}, X_{t-2}, \dots, X_{t-L}\} \tag{2}$$

where $L \in \{1,2,\dots,12\}$ months. PCA, is used in high dimensional fields to recover major variability modes.

3.3 Machine Learning Models

Random Forest (RF) :
Random Forest consists of a number of decision trees $\{T_b\}_{b=1}^{B}$, and the prediction is given by

$$\hat{y}_t = \frac{1}{B}\sum_{b=1}^{B} T_b(X_t^{(L)}) \tag{3}$$

where B=300 trees. RF captures nonlinear interactions through bootstrap aggregation and random feature selection.
Gradient Boosting (GB):

Gradient Boosting models predictions as an additive expansion:

$$\hat{y}_t = \sum_{m=1}^{M} \gamma_m h_m(X_t^{(L)}) \tag{4}$$

where h_m denotes the m-th weak learner and γ_m represents its learned weight. The model iteratively minimizes a differentiable loss function using gradient descent. In this study, the mean squared error (MSE) loss is adopted:

$$\mathcal{L} = \frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2 \tag{5}$$

where $y_t$and $\hat{y}_t$denote the observed and predicted values, respectively

Support Vector Regression (SVR):
SVR estimates a function

$$f(X_t) = w^T\phi(X_t) + b \tag{6}$$

where X_t denotes the input predictor vector, $\phi(X_t)$ represents the nonlinear feature mapping, w is the weight vector, b is the bias term. By minimizing the regularized risk with an ε -insensitive loss:

$$\min_{w} \frac{1}{2}||w||^2 + C \sum_{i=1}^{\cdot\cdot} max\ (0, |y_i - f(X_i)| - \varepsilon) \qquad (7)$$

A radial basis function kernel is used to model nonlinear dependencies.

Extreme Gradient Boosting (XGBoost):
XGBoost minimizes the following regularized objective:

$$L = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \qquad (8)$$

where l(·) is the loss function and $\Omega(f_k)$ penalizes model complexity [19]. This formulation enables efficient learning and robust feature importance estimation.

Long Short-Term Memory (LSTM) :
LSTM networks are a type of networks that represent time associations with the help of the gated memory cells:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (9)$$

$$\tilde{c}_t = \tanh\ (W_c[h_{t-1}), x_t] + b_c) \qquad (10)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \qquad (11)$$

$$o_t = \sigma(W_{o[h_{t-1}, x_t]} + b_o) \qquad (12)$$

$$h_t = o_t \odot \tanh(c_t) \qquad (13)$$

where x_t denotes the input predictor vector at time t, h_t and c_t represent hidden state and cell state respectively, f_t, i_t, and o_t denote the forget, input, and output gates, $\tilde{c}_t$ is the candidate cell state, W_f, W_i, W_c, W_o are learnable weight matrices, b_f, b_i, b_c, b_o are bias vectors, $\sigma(\cdot)$ is the sigmoid activation function, tanh (·) denotes the hyperbolic tangent function, $[\cdot,\cdot]$ indicates vector concatenation, and $\odot$ represents element-wise multiplication.

One-Dimensional Convolutional Neural Network (1D-CNN) :
1D-CNN applies temporal convolution:

$$z_{(k)} = \sum^{K} w_{(k)} X \quad + b^{(k)} \qquad (14)$$

involving nonlinear activation and pooling functions for the extracted features from the lagged values of the predictors [14].

3.4 Model Training and Validation

Models are trained through rolling origin cross-validation, and training and testing happen over past periods and unknown future data [15]. Hyperparameters for different models are tuned through a grid search method.

4 Experimental Study

This study analyses monthly ocean–atmosphere data from 1980–2023 to investigate ENSO variability. The dataset combines sea surface temperature from National Oceanic and Atmospheric Administration OISST, atmospheric data from ERA5, and subsurface ocean data from Argo Program and ORAS5. The data are divided into training (1980–2014), validation (2015–2018), and testing (2019–2023)[16]. Six models are compared: Random Forest, Gradient Boosting, SVR, XGBoost, LSTM, and 1D-CNN. Traditional ML models use the same predictors, while deep learning models process sequential inputs. Model performance is evaluated using RMSE, MAE, correlation, and error analysis based on Niño 3.4 thresholds.

.

5 Experimental Results and Analysis

5.1 Evaluation Matrix

Since ENSO prediction is cast as a regression task, its performance is measured on continuous statistics related to the accuracy of predictions concerning the phase of Niño indices.

Root Mean Square Error (RMSE):

RMSE is calculated as square root of the mean squared errors and it is more sensitive to the large errors rather than the actual ones.

Mean Absolute Error (MAE):

MAE is used to measure the prediction accuracy by using the average of the absolute values of the deviation between observed values and the model values.

Correlation Coefficient (R):

This coefficient calculates the relationship between observed and predicted Niño indices, demonstrating the skill of the model in Phase transitions of ENSO.

5.2 Model Performance Comparison

The comparison of six machine learning models in predicting the Niino.

The 1D-CNN model has the best results as indicated by the 3.4 index shown by minimum RMSE and MAE and maximum correlation as shown in Table 1.

Table 1. Model Performance Metrics for Niño 3.4 Index Prediction at 12-Month Lead Time

Model	**RMSE (°C)**	**MAE (°C)**	**R**
RF	0.68	0.52	0.87
GB	0.62	0.49	0.89
SVR	0.64	0.50	0.88
XGBoost	0.60	0.47	0.90
LSTM	0.59	0.46	0.91
1D-CNN	0.58	0.45	0.92

5.3 Feature Importance Analysis

Based on the XGBoost model, feature importance analysis has indicated that Niño 3.4 SST, thermocline depth (D20), and oceanic heat content are the chief variables controlling ENSO variability [17].

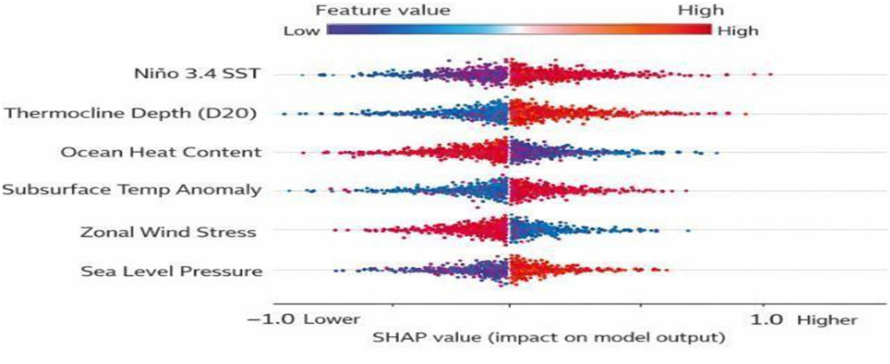

Fig. 2. SHAP summary (bee swarm) plot showing feature importance for ENSO

These variables describe several physical processes pertaining to surface warming, subsurface recharge of heat, and thermocline adjustment. As shown in Fig. 2, thermocline depth, ocean heat content, subsurface temperature anomalies, and zonal wind stress significantly contribute to ENSO predictability.

5.4 Seasonal Predictability Analysis

Results for the best-performing 1D-CNN model display quite strong seasonal variability in ENSO prediction skill, as shown in Table 2 [18].

Table 2. Seasonal Predictive Skill of the 1D-CNN Model

Season	**RMSE (°C)**	**R**
DJF	0.56	0.93
MAM	0.61	0.90
JJA	0.63	0.88
SON	0.59	0.91

The model is most skillful during the DJF season, with an RMSE of 0.56 °C and a correlation coefficient of 0.93, as anticipated from the known phase-locking of ENSO during boreal winter when ocean–atmosphere coupling is strongest.

5.5 Error Distribution and Confusion-Matrix–Style Visualization

Although ENSO forecasting is formulated as a regression problem for predicting continuous Niño index values, phase-wise evaluation requires categorical interpretation [19]. Therefore, both predicted and observed Niño indices are discretized into four predefined classes using threshold-based binning. A binned phase classification heatmap is then constructed to analyze phase-wise prediction accuracy and misclassification patterns. In this heatmap, there is a pronounced cluster of data along this diagonal, which shows there to be a significant level of consistency between the predicted and actual classification of ENSO intensity. What this does indicate is that the 1DCNN model has been successful in capturing the phase transitions of ENSO in addition to being highly effective during extreme La Niña or El Niño events. The off diagonal errors are minimal take place in a manner indicating a continuum in ENSO variability as opposed to prediction errors in Fig 3.

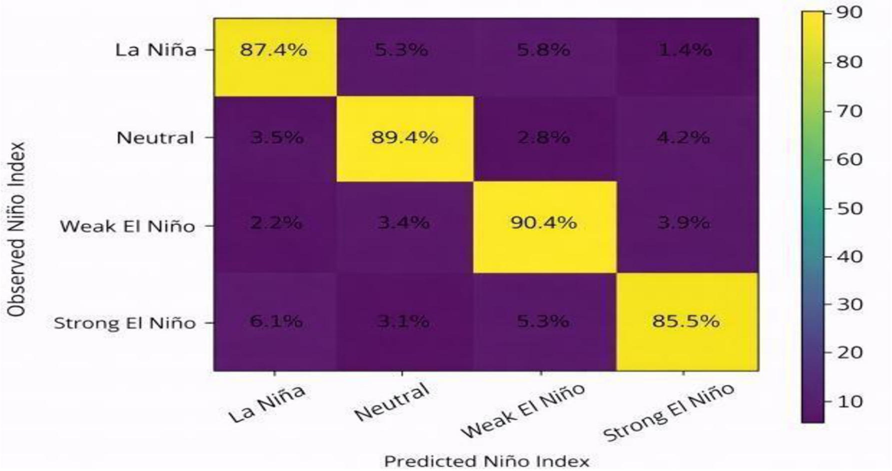

Fig. 3. Binned Error Heatmap for ENSO Phase Prediction Using the 1D-CNN Model.

6 CONCLUSION

This study examines the performance of different ML and DL algorithms in predicting ENSO based on ocean and atmospheric observations from 1980 to 2023. Since deep learning models, especially 1D-CNN and LSTM, were able to expertly recap the complex and ever-changing interactions between the ocean and the atmosphere, they outperformed traditional machine learning in predicting the Niño 3.4 and Niño 4 indices. It is also indicated in the analysis that the ocean heat content, thermocline depth, and sea surface temperature anomalies are some of the factors that drive predictability of ENSO. The boreal winter has a higher accuracy of prediction compared to the boreal summer because it is more variable. In general, the given framework can enhance the credibility of the long- lead climate forecast and assist in creating more efficient climate early warning systems. The work in the future will be devoted to the increase of prediction lead times and the use of more climate indicators which will help to enhance the performance of prediction, including the Indian Ocean Dipole.

References

1. Ibeabuchi, C. C., Rainey, S., Obarein, O. A., Silva, A., & Lee, C. C. (2024). Comparison of machine learning models in forecasting different ENSO types. *Physica Scripta, 99*(8), 086007.

2. Li, T., Tang, Y., Lian, T., & Hu, A. (2024). Quantifying the relative contributions of the global oceans to ENSO predictability with deep learning. *Geophysical Research Letters, 51*(5), e2023GL106584.

3. Liu, Y., Duffy, K., Dy, J. G., & Ganguly, A. R. (2023). Explainable deep learning for insights in El Niño and river flows. *Nature Communications, 14*(1), 339.

4. National Oceanic and Atmospheric Administration. (2026). *El Niño & La Niña*. Retrieved February 4, 2026, from https://www.noaa.gov/education/resource-collections/weather-atmosphere/el-nino-la-nina

5. Colfescu, I., Christensen, H., & Gagne, D. J. (2024). A machine learning-based approach to quantify ENSO sources of predictability. *Geophysical Research Letters, 51*(13), e2023GL105194.

6. Dijkstra, H. A., Petersik, P., Hernández-García, E., & López, C. (2019). The application of machine learning techniques to improve El Niño prediction skill. *Frontiers in Physics, 7*, 153.

7. Lima, H., Lall, U., Jebara, T., & Barnston, A. G. (2015). Machine learning methods for ENSO analysis and prediction. In *Proceedings of the 4th International Workshop on Climate Informatics: Machine Learning and Data Mining Approaches to Climate Science* (pp. 13–21). Springer.

8. Nooteboom, P. D., Feng, Q. Y., López, C., Hernández-García, E., & Dijkstra, H. A. (2018). Using network theory and machine learning to predict El Niño. *Earth System Dynamics, 9*(3), 969–983.

9. Ham, Y.-G., Kim, J.-H., & Luo, J.-J. (2019). Deep learning for multiyear ENSO forecasts. *Nature, 573*(7775), 568–572.

10. Pal, M., Maity, R., Ratnam, J. V., Nonaka, M., & Behera, S. K. (2020). Long-lead prediction of ENSO Modoki index using machine learning algorithms. *Scientific Reports, 10*(1), 365.

11. Patil, K. R., Doi, T., Jayanthi, V. R., & Behera, S. K. (2023). Deep learning for skilful long-lead ENSO forecasts. *Frontiers in Climate, 4*, 1058677.

12. Tang, Y., et al. (2018). Progress in ENSO prediction and predictability study. *National Science Review, 5*(6), 826–839.

13. Wang, B., Feng, P., Waters, C., Cleverly, J., Liu, D. L., & Yu, Q. (2020). Quantifying the impacts of pre-occurred ENSO signals on wheat yield variation using machine learning in Australia. *Agricultural and Forest Meteorology, 291*, 108043.

14. Reynolds, R. W., Smith, T. M., Liu, C., Chelton, D. B., Casey, K. S., & Schlax, M. G. (2007). Daily high-resolution blended analyses for sea surface temperature. *Journal of Climate, 20*(22), 5473–5496.

15. Hersbach, H., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society, 146*(730), 1999–2049.

16. Roemmich, D., et al. (2009). The Argo program: Observing the global ocean with profiling floats. *Oceanography, 22*(2), 34–43.

17. Zuo, H., Balmaseda, M., & Mogensen, K. (2019). The new eddy-permitting ORAS5 ocean reanalysis. *ECMWF Technical Report.*

18. Naisipour, M., Saeedpanah, I., & Adib, A. (2024). Novel deep learning method for forecasting ENSO. *Journal of Hydraulic Structures*, 14–25.

19. Chen, Y., et al. (2023). Prediction of ENSO using multivariable deep learning. *Atmospheric and Oceanic Science Letters, 16*(4), 100350.