Comparison of Indian Ocean data with international ocean data and doing trend analysis on various parameter using deep learning techniques.

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***Abstract*—Accurate forecasting of Sea Surface Temperature (SST) and salinity is significant for understanding climate variability, marine ecosystem health, ocean-atmosphere interactions, etc. In this study, we took the advantage of the advanced deep learning techniques in the analysis and prediction of SST and salinity trends in the Indian Ocean and Arctic Ocean, comparing the performance of multiple models such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and a hybrid CNN-LSTM model. We present the evidence that the CNN-LSTM architecture is the best of all models, and it has the lowest value of Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) as well as the highest coefficient of determination (R^2). The ability to comprehend both spatial and temporal dependencies makes CNN-LSTM model an efficient and effective forecasting mechanism; thus, it is the most competent method for ocean trend prediction. The analysis also holds the idea of deep learning-based forecasting as potential adaptation to climate change, as well as the mention of the formal early warning systems, and policy formulation. The production of SST forecast graphs for the Indian Ocean is a visual proof of the model's forecasting competence. With this information, the researchers are offering new routes for ocean monitoring systems and simultaneously supporting data-driven decision-making in the sectors of marine and climate sciences.**

***Index Terms*—Deep Learning, Sea Surface Temperature (SST), Salinity, Indian Ocean, Arctic Ocean, Climate Change, LSTM, CNN, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Coefficient of determination R^2.**

I. Introduction

Oceans play a critical role in Earth's climate system, acting as vast reservoirs that absorb, store, and redistribute solar energy. Variations in ocean parameters, most notably Sea Surface Temperature (SST) and salinity—not only influence marine ecosystems but also modulate atmospheric processes such as monsoon dynamics and polar amplification. In this study, we perform a comparative analysis of SST and salinity trends in two climatically contrasting regions: the warm, dynamic Indian Ocean and the rapidly changing Arctic Ocean.

Recent advances in deep learning have opened new avenues for modelling complex time-series data. Models such as LSTM networks and CNNs, as well as their hybrid combinations, are particularly well-suited for capturing both short-term fluctuations and long-term trends. Our research leverages these models to provide robust forecasts and early anomaly detection, thereby contributing to improved climate change indicators and a deeper understanding of oceanic processes.

II. Problem statement

Oceans play a fundamental role in regulating the Earth's climate, acting as vast heat reservoirs that influence atmospheric circulation, monsoon patterns, and extreme weather events. Among the key oceanographic parameters, Sea Surface Temperature (SST) and salinity serve as crucial indicators of climate variability and climate change. The Indian Ocean, known for its significant monsoonal influences and rapid warming, contrasts sharply with the Arctic Ocean, where rising temperatures contribute to ice melt and freshwater influx, leading to shifts in salinity and ocean circulation.

Despite the growing importance of monitoring SST and salinity, accurately predicting and analyzing their long-term trends remains a challenge. The inherent complexity of ocean–atmosphere interactions, nonlinear dependencies, and the influence of external climatic drivers make it difficult for traditional statistical and physical models to capture these dynamic variations effectively. This necessitates the adoption of deep learning techniques, which can leverage vast amounts of oceanographic data to improve trend analysis, anomaly detection, and predictive modelling.

Furthermore, data acquisition and consistency remain major hurdles in this research. Oceanographic datasets, particularly for the Indian and Arctic Oceans, are often fragmented, inconsistent, and vary in spatial and temporal resolution. These challenges impact the ability to develop generalized and scalable forecasting models, making it imperative to integrate advanced deep learning methods that can handle data heterogeneity while extracting meaningful insights.

III. Literature Review

A hybrid approach that employs both data mining and fuzzy inference is presented in this study to forecast ocean salinity and temperature variations around Taiwan. The authors use delayed-mode data from ARGO (January–November 2006) to create a reference-centric spatial-temporal model that uses concentrated circles (8–7 km radii) around Taipei to define sub areas. Identifying inter-transaction association rules for abnormal events within these regions is possible with the Prefix Span algorithm, which recognizes patterns across time intervals (e.g.: events in consecutive months). Fuzzy set theory enables the mapping of continuous data into overlapping intervals with grading (e.g., "dropping slightly") to overcome sharp boundary limitations in quantitative attributes like salinity variation. To make predictions, a fuzzy inference model using 44 linguistic rules with five inputs (salinity; temperature; distance; direction; time) is used. After examining 110 test events, the model validates that it is accurate to an average of 82% for spatial temporal anomalies. Significant breakthroughs comprise (1) an efficient method for obtaining fuzzy inter-transaction rules and (2) the use of pragmatist methods to estimate ocean levels without depending on expert guidance. The future work may involve the use of more multi-source data, such as satellite observations, or combining these techniques with deep learning to improve the model's intricate pattern recognition. This method for monitoring the environment employs fuzzy logic and spatial-temporal data mining. [1]

In this study the Convolutional Neural Networks (CNN) and Support Vector Regression (SVR), machine learning (ML) methods are employed to estimate Sea Ice Thickness (SOTS) using data from TechDemoSat-1 (TDS-1) and Soil Moisture Ocean Salinity (SMOS) satellites. TDS-1 provides the scattering coefficient (0) and angle of incidence (to a degree), while SMOS captures sea ice salinity (S) or temperature (T). The validation and training of the models were conducted using data from 2017 to 2018, with a focus on thin sea ice (1 cm). The correlation coefficients (r) for CNN and SVR were 0.95 and 0.90, respectively, indicating significant agreement with reference SIT data, while the results showed an RMSD of 7.97 cm (CNN) and 5.49 cm. However, accuracy was greatly improved by including TDS-1 data; for example, the inputs with SMOS (S,) and temperature (T) were found to be much more accurate. It highlights the usefulness of ML in SIT estimation, providing an empirical model with data independence. [Note 1]. In the future, this method may be extended to more extensive sea ice and additional satellite data sources may provide improved accuracy and strength. [2]

The ROCKE-3D ocean-atmosphere general circulation model is utilized to investigate the relationship between ocean salinity and Earth's climate. Using data from present-day Earth and Archean (3 billion years old) conditions, the researchers show that higher ocean salinity results in warmer climates with lower coverage of sea ice. High-latitude areas experience a 71% reduction in global sea ice as salinity increases from 20 to 50 g/kg. The research indicates that warming is influenced by two primary factors: changes in ocean dynamics, which facilitate heat transfer to the polar regions, and freezing point depression, which inhibits the formation of sea ice. It suggests that the presence of a saltier ocean may have contributed to the preservation of warm climates for early Earth, despite the Faint Young Sun, by preventing global glaciation and permitting only seasonal localized or extra-polar ice. The research also indicates that slight variations in ocean salinity can cause significant fluctuations in CO2 levels for glaciation, potentially resulting in abrupt climate changes over time. Ocean salinity is a crucial yet undervalued aspect of climate regulation, as revealed by these findings. Understanding its influence is crucial for improving climate models, exploring exoplanet habitability, and reconstructing Earth's climate record. [3]

This study combines projections from global circulation models with a mesocosm experiment to investigate how ocean warming affects marine plankton communities. The research examines the physical and biological mechanisms of change in plankton, with a focus on nutrients that are restricted by stratification. Although warming increases phytoplankton biomass, this effect is counteracted by reduced nutrient flux, leading to a net loss of phytoplankters in areas with low NI. In addition, warming changes the feeding patterns of zooplankton: from phytoplanktonic to cilia (the hardened crustaceans) and this may change marine food chains. Key findings indicate that phytoplankton is primarily affected by decreased nutrient availability due to ocean warming, rather than metabolic changes. The process of warming in nutrient-rich, well-mixed water promotes zooplankton grazing and reduces phytoplanktonic biomass. Warming in stratified, nutrient-poor waters results in reduced nutrients being released into the ecosystem by increasing phytoplankton and microbial populations over larger planktons. This is an interesting contrast to other processes. These results highlight the seasonal and regional variations in plankton responses to climate change, highlighting the need for region-specific models. Overall, the study highlights that predicting how oceans will respond to climate change requires taking into account not only physical changes but also biological factors. The recommendation is for forthcoming climate models to take into account both stratification-related effects and food web interactions to enhance predictions of oceanic plankton dynamics under global warming conditions. [4]

The focus of this research is on the impact of ocean salinity on Earth's water cycle and how it can influence future climate changes through salinity patterns. The research indicates that the ocean is the main driver of Earth's water cycle, with salinity being a significant factor in determining the Evaporation-Precipitation (E-P) balance, as it accounts for 80% of surface water fluxes occurring over land. It is suggested in the study that changes in salinity are a result of increased salience in regions with higher levels of evaporation, which corresponds to an increase in saltiness and freshness in areas with more rainfall. Using historical observations, satellite data, and climate models, the study concludes salinity trends are linked to long-term increases in salinity gradients, particularly in the Atlantic and Pacific Oceans. This indicates that the water cycle is becoming more active, resulting in more extreme hydrological conditions.' Moreover, the research investigates how salinity affects climate models, showing that higher atmospheric CO2 levels partly explain changes in ocean salinity patterns, which reinforce effects of global warming. Ultimately, however important: The importance of ocean salinity to the measurement of water cycle changes and climate change is highlighted by this research. This article underscores the necessity for improved observational systems, such as satellite missions and deep-ocean monitoring, to enhance climate prediction and comprehend more precisely what is meant by salinity–induced feedback on climate.[5]

This study examines the impact of oceanic and atmospheric pathways in the Arctic that are causing warming due to warming in areas such as the Tropical Indian Ocean (IO). By utilizing numerical data from climate models, the researchers demonstrate that IO warming increases the Atlantic Meridional Overturning Circulation (AMOC) and causes an increase in ocean heat transfer from the North Atlantic to the Arctic. This leads to warming in the upper ocean and is a major factor in Arctic surface temperature rise. [Note 1]. Furthermore, the research indicates that southerly winds caused by IO warming push warm air into the Arctic, which contributes to regional warming, especially in North America, North Eurasia, and the Kara Seas. The main reason for Arctic warming is oceanic heat transfer, while other atmospheric pathways are responsible for local temperature changes but have a negative impact on heat transport. This study highlights the importance of this phenomenon. The research suggests a novel approach to comprehending Arctic warming, underscoring the crucial role that remote tropical ocean modifications play in shaping the polar climate. According to the findings, the Indian Ocean's ongoing warming under climate change may exacerbate the Arctic temperature increase and impact the global climate systems. Understanding these relationships is essential for improving climate models and making long-term predictions about Arctic and global climate changes. [6]

The study examines the impact of remote sea surface temperature (SST) changes on the intensity of tropical cyclones by utilizing climate model simulations and observational reconstructions. These studies contradict assumptions that local SST warming alone can increase tropical cyclone activity. The study concludes that regional SST patterns are a significant factor, with higher PI in areas of warming above the tropical average and lower pinned in regions of increasing CP. Despite the historically high Atlantic SSTs, PI reached its peak during the 1930s and 1950s but has remained near average in recent years. Despite Atlantic SSTs being warm, the study highlights the importance of remote SEST anomalies, such as Pacific warming during El Nio, in improving atmospheric stability in the tropical Atlantic and decreasing cyclone activity. The 21st-century climate model projections demonstrate that PI changes are spatially varied, emphasizing the need to consider factors other than local SST for accurate prediction of tropical cyclone intensification. [7]

IV. METHODOLOGY

1.Data Collection and Preprocessing.

Data for Sea Surface Temperature (SST) and salinity were obtained from high-resolution satellite reanalysis datasets, including the Copernicus Marine Service and global observation networks. The dataset spans multiple years (2022–present) and covers both the Indian Ocean and Arctic Ocean, ensuring a comprehensive analysis of oceanic trends.

1.1 Geographical Boundaries.

The approximate boundaries for each ocean are defined as follows:

- **Indian Ocean:** North: **25.000000**, South: **-55.000000**, East: **115.000000**, West: **35.000000**
- **Arctic Ocean:** North: **90.000000**, South: **65.000000**, East: **180.000000**, West: **-180.000000**
- These boundaries were used to **filter and extract relevant SST and salinity data** for each ocean, ensuring that the study focuses on their unique climatological characteristics.

1.1.1 Preprocessing Steps.

To enhance data quality and ensure consistency across time-series inputs, the following preprocessing steps were applied:

- **Cleaning and Interpolation:** Missing values were handled using linear and cubic interpolation, while statistical imputation was used for outliers.
- **Temporal Aggregation:** Daily measurements were aggregated into monthly averages, with additional smoothing via moving averages to capture long-term trends.
- **Normalization and Feature Engineering**: Min–Max scaling was applied to maintain a consistent data range, and additional features such as temperature gradients and seasonal markers were engineered to improve predictive performance.

1.2 Deep Learning Models.

To analyse and forecast SST and salinity trends, we implemented and evaluated three deep learning architectures:

- **Long Short-Term Memory (LSTM) Networks:** Designed to capture **long-term dependencies** in sequential oceanographic data.
- **Convolutional Neural Networks (CNNs):** Used to extract **spatial features** and detect localized patterns in the time-series data.
- **Hybrid CNN-LSTM Models:** A combination of CNNs and LSTMs, allowing the model to learn **both spatial and temporal dependencies** for enhanced prediction accuracy.

Additionally, an autoencoder-based anomaly detection module was employed to identify unusual deviations in SST and salinity. These anomalies could indicate extreme climatic events, such as marine heatwaves, ice melt surges, or ocean circulation shifts.

1.3 Trend Analysis.

1.3.1 Trend analysis of Salinity in Indian Ocean over the year.

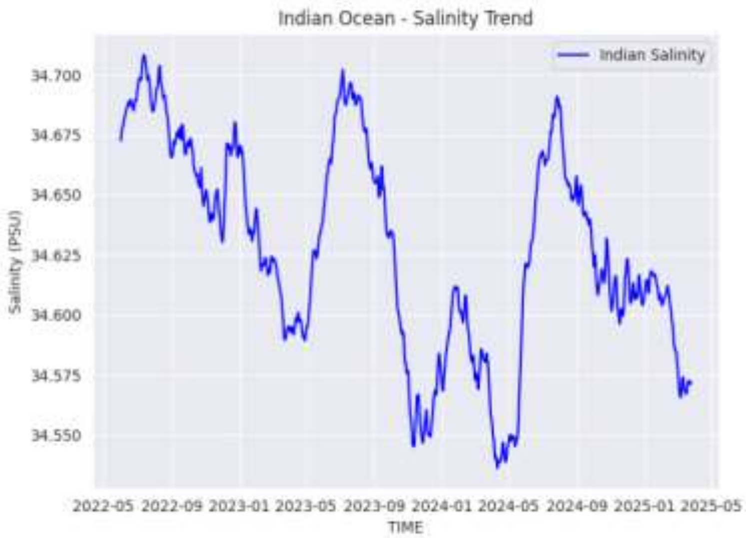

Figure 1: - Salinity Trend in Indian Ocean

The Indian Ocean salinity graph exhibits moderate fluctuations within a relatively narrow range as shown by the graph in figure 1.3.1, suggesting that the surface salinity is largely governed by a balance between evaporation and precipitation. Seasonal variations, likely influenced by monsoonal cycles, cause periods of both increased evaporation and intensified rainfall. During dry spells, evaporation tends to elevate salinity, while during the monsoon, freshwater input from precipitation and river discharge can lead to noticeable drops. This interplay creates the observed cyclical pattern, and the slight overall decline toward the end of the period might be indicative of either a change in the prevailing climatic conditions or an increase in freshwater influx.

1.3.2 Trend Analysis of SST in Indian Ocean over the year.

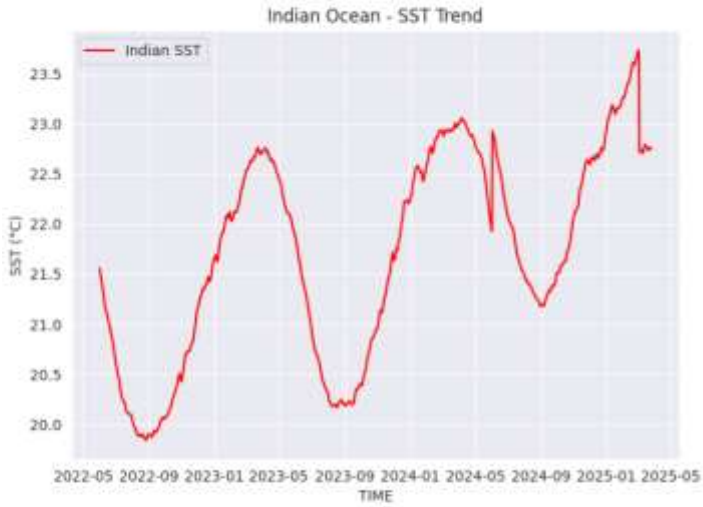

Figure 2: - SST Trend in Indian Ocean

The sea surface temperature (SST) trend for the Indian Ocean in figure 1.3.2 displays a clear seasonal cycle with temperatures rising during the warmer months and falling during cooler periods. This seasonal variability is characteristic of tropical and subtropical regions, where solar heating, ocean currents, and the migration of the Intertropical Convergence Zone (ITCZ) play critical roles. The data also hints at an underlying warming trend, which could be a reflection of longer-term climatic shifts such as global warming or regional atmospheric changes. This warming might affect ocean heat content, thereby subtly altering the seasonal amplitude over time.

1.3.3 Trend Analysis of Salinity in Arctic Ocean over the year.

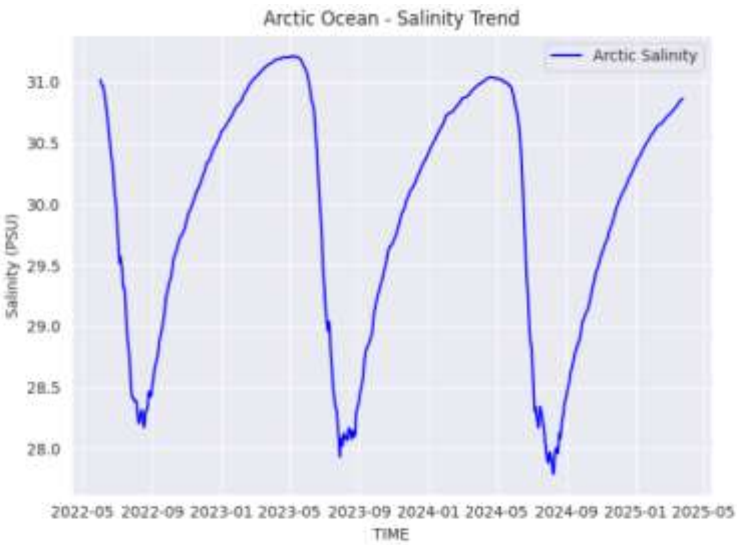

Figure 3: - Salinity Trend in Arctic Ocean

In contrast, the Arctic Ocean's salinity trend in the figure 1.3.2 marked by more pronounced fluctuations. The high-latitude region experiences significant changes driven by the formation and melting of sea ice. When ice forms, the process of brine rejection increases the surrounding water's salinity, whereas melting ice injects fresh water, sharply reducing salinity levels. These rapid shifts result in distinct peaks and troughs, capturing the sensitive balance of freezing and melting processes in polar environments. Theoretical models suggest that even slight alterations in air temperature or precipitation can significantly impact these salinity cycles due to the delicate equilibrium in the Arctic ecosystem.

1.3.4 Trend Analysis of SST in Arctic Ocean over the year.

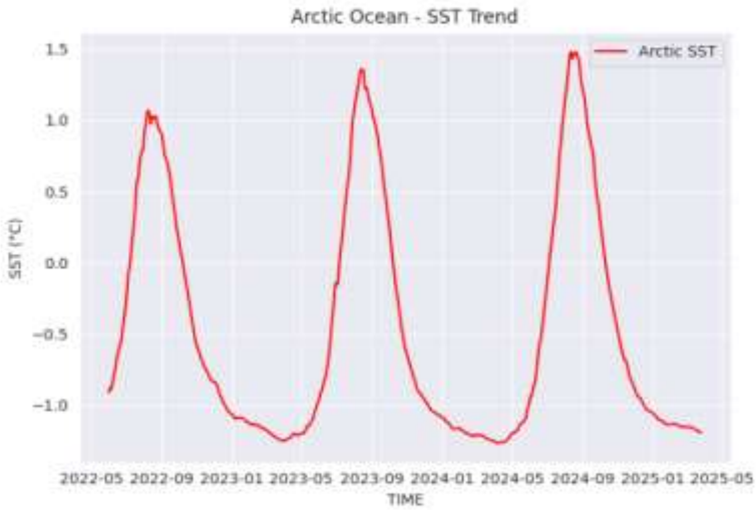

Figure 4: - SST Trend in Arctic Ocean

The SST trend in the Arctic Ocean in figure 1.3.4 reveals a pattern tightly linked to the region's extreme seasonal cycle. Temperatures fluctuate around the freezing point, with summer months witnessing slight increases due to enhanced solar radiation and partial ice melting, and winter months experiencing deep freezes due to minimal sunlight and prolonged cold. This delicate balance is a hallmark of polar climates, where the interplay between sea ice dynamics and air-sea interactions dictates temperature changes. The seasonal cycle underscores the Arctic's vulnerability to climate change, as even minor shifts in temperature or ice coverage can have a pronounced impact on the region's overall thermal regime.

V. RESULT AND DISCUSSION

1.1 Model performance for Indian Ocean SST Prediction.

Table 1 Performance comparison for Indian Ocean SST Prediction

Model	MAE	RMSE	R^2
LSTM	0.0415	0.0532	0.8785
CNN	0.0397	0.0557	0.8664
CNN-LSTM	**0.0273**	**0.0396**	**0.9325**

From the performance metrics presented in Table 1, it is evident that the CNN-LSTM model delivers the most accurate predictions for Indian Ocean SST. Specifically, it achieves the lowest MAE (0.0273) and RMSE (0.0396) while also obtaining the highest R^2 (0.9325) among the three models. These values indicate that CNN-LSTM not only minimizes the average error but also captures the variance in SST data more effectively. In comparison, the LSTM model shows moderate performance, with an MAE of 0.0415, an RMSE of 0.0532, and an R^2 of 0.8785, while the CNN model performs similarly with an MAE of 0.0397, an RMSE of 0.0557, and an R^2 of 0.8664. Although the LSTM and CNN metrics are relatively close, the hybrid CNN-LSTM architecture clearly outperforms both, underscoring the benefit of combining convolutional layers (to capture spatial features) with recurrent layers (to model temporal dependencies).

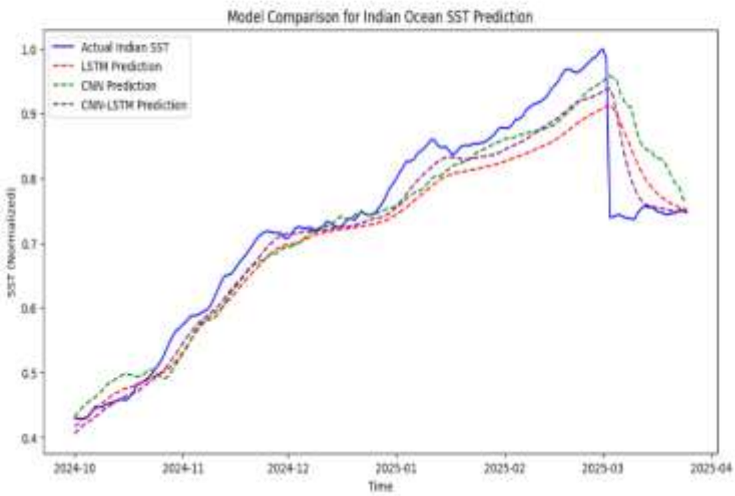

Figure 5: - Model Comparison for Indian Ocean SST Prediction

1.2 Model Performance for Indian Ocean Salinity Prediction.

Table 2 Performance comparison for Indian Ocean Salinity Prediction

Model	MAE	RMSE	R^2
LSTM	0.0355	0.0440	0.7723
CNN	0.0386	0.0473	0.7370
CNN-LSTM	**0.0313**	**0.0396**	**0.8156**

From the metrics presented in Table 2, the CNN-LSTM model emerges as the best-performing method for Indian Ocean Salinity prediction. It achieves the lowest MAE (0.0313) and RMSE (0.0396) while attaining the highest R^2 (0.8156) among the three models, indicating superior accuracy and a better fit to the observed salinity data. In comparison, the LSTM model demonstrates moderate performance, with an MAE of 0.0355, an RMSE of 0.0440, and an $R^2$of 0.7723. The CNN model, meanwhile, ranks third, having slightly higher error metrics and a lower R^2 of 0.7370.

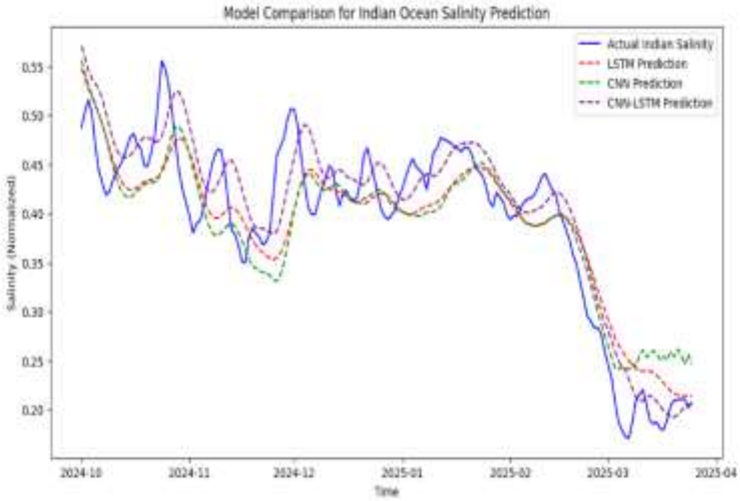

Figure 6: - Model Comparison for Indian Ocean Salinity Prediction

1.3 Model Comparison for Arctic Ocean SST Prediction.

Table 3 Performance comparison for Arctic Ocean SST Prediction

Model	MAE	RMSE	R^2
LSTM	**0.0071**	**0.0101**	**0.9958**
CNN	0.0088	0.0141	0.9917
CNN-LSTM	0.0130	0.0189	0.9850

In Table 3, the LSTM model shows the highest accuracy for Arctic Ocean SST prediction, evidenced by its lowest MAE (0.0071), lowest RMSE (0.0101), and highest R^2 (0.9958). These results suggest that LSTM's recurrent structure is especially well-suited for capturing the strong seasonal cycles and temporal dependencies typical of Arctic temperature patterns. In contrast, the CNN model, although still performing well with an R^2 of 0.9917, has slightly higher error metrics, indicating that purely convolutional layers might not be as effective at modeling the time-dependent nature of Arctic SST variations. Surprisingly, the CNN-LSTM approach ranks third here, with higher MAE and RMSE values than both LSTM and CNN. One possible explanation is that the hybrid architecture may introduce unnecessary complexity or overfitting for this dataset, where a single recurrent component (LSTM) appears sufficient to capture the dominant patterns. Nonetheless, the consistently high R^2 values across all models suggest that each architecture can approximate Arctic SST trends quite accurately, with LSTM demonstrating a clear edge in this specific task.

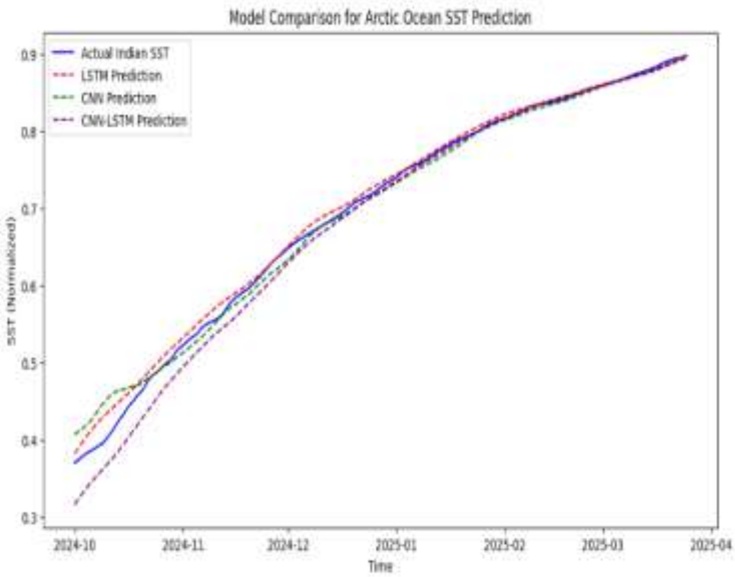

Figure 7: - Model Comparison for Arctic Ocean SST Prediction

1.4 Model Performance for Arctic Ocean Salinity Prediction.

Table 4 Performance comparison for Arctic Ocean Salinity Prediction

Model	MAE	RMSE	R^2
LSTM	0.0118	0.0124	0.9923
CNN	**0.0058**	**0.0072**	**0.9974**
CNN-LSTM	0.0103	0.0159	0.9873

In Table 4, the CNN model achieves the best overall performance, as indicated by its lowest MAE (0.0058), lowest RMSE (0.0072), and highest R^2 (0.9974). This suggests that the convolutional architecture is particularly well-suited to capturing the patterns governing salinity changes in the Arctic region, possibly due to its ability to learn local feature representations effectively. By comparison, the LSTM model, while still yielding a high R^2 of 0.9923, has slightly higher error metrics (MAE = 0.0118, RMSE = 0.0124), indicating it may not capture localized patterns in salinity as effectively as CNN does. Meanwhile, the CNN-LSTM hybrid model posts an R^2 of 0.9873, which is somewhat lower than both the pure CNN and LSTM approaches, suggesting that the added complexity of combining convolutional and recurrent layers might not offer a clear advantage for this dataset. Nonetheless, the high R^2 values across all three models highlight their strong capacity to capture Arctic Ocean salinity trends, with CNN demonstrating a clear edge in accuracy.

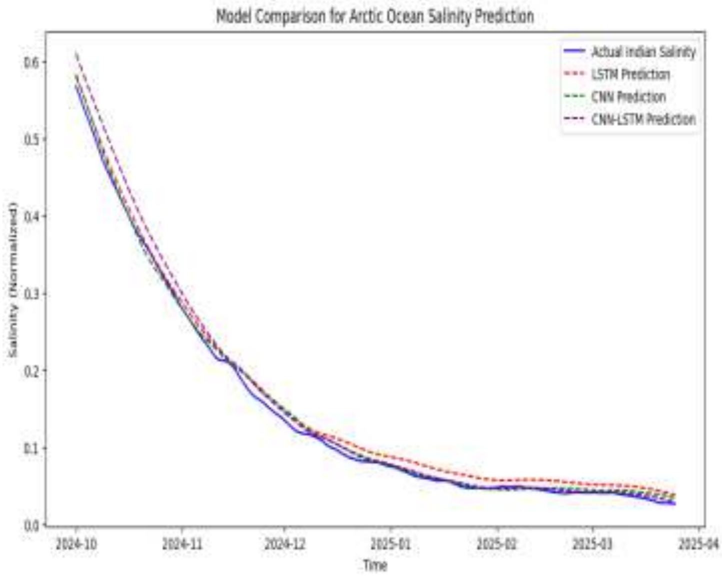

Figure 8: - Model Comparison for Arctic Ocean Salinity Prediction

VI. Conclusion

1. Best Overall Model to use for Forecasting.

The results presented in the table demonstrate that model performance varies significantly depending on the specific oceanic parameter and region, emphasizing the need for careful selection or design of a model to suit each situation. CNN-LSTM architecture is the most accurate approach for predicting both SST and salinity, particularly in the Indian Ocean. By capturing localized spatial patterns through convolutional layers and modelling the temporal dependencies of sequential data using LSTM, CNN-LSM has produced this result.

While LSTM is better at forecasting SST in the Arctic Ocean due to its superior performance in memory-based sequence modelling, CNN has the best success in salinity modelling. CNN-LSTM is the preferred model for a general, all-purpose model that can accurately predict multiple parameters and oceans, even when certain Arctic Ocean metrics fall short. However, its accuracy remains high. By examining the model's performance across different regions and parameters, the table emphasizes the importance of comparing models to determine how ocean dynamics vary.

Table 5 Performance Metrics of Different Model for Predicting SST and Salinity in Indian Ocean and Arctic Ocean

Model	Indian SST (MAE, RMSE, R^2)	Indian Salinity (MAE, RMSE, R^2)	Arctic SST (MAE, RMSE, R^2)	Arctic Salinity (MAE, RMSE, R^2)
LSTM	0.0415, 0.0532, 0.8785	0.0355, 0.0440, 0.7723	**0.0071, 0.0101, 0.9958**	0.0118, 0.0124, 0.9923
CNN	0.0397, 0.0557, 0.8664	0.0386, 0.0473, 0.7370	0.0088, 0.0141, 0.9917	**0.0058, 0.0072, 0.9974**
CNN-LSTM	**0.0273, 0.0396, 0.9325**	**0.0313, 0.0396, 0.8156**	0.0130, 0.0189, 0.9850	0.0103, 0.0159, 0.9873

2. Hybrid Deep Learning Model (LSTM-CNN) for forecasting Indian Salinity for 30 Days.

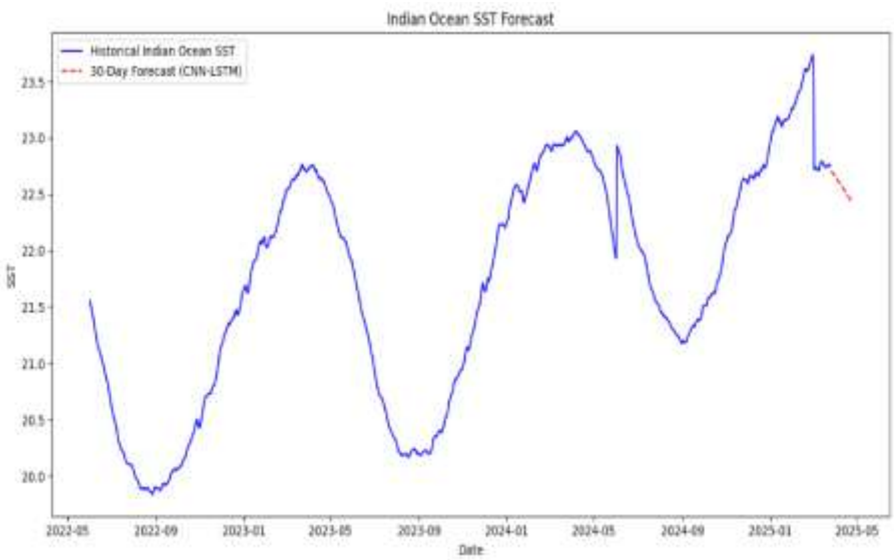

Figure 9: - Indian Ocean SST Forecasting using LSTM-CNN

The 30-day forecast for Indian Ocean SST using the CNN-LSTM model (as illustrated in the figure above) demonstrates a strong alignment with historical SST patterns, capturing both the cyclical nature of the data and potential future fluctuations. By overlaying the forecast (red, dashed line) on the historical trend (blue line), one can visually confirm the model’s capability to detect and project the seasonal oscillations characteristic of the Indian Ocean. The high level of overlap between the predicted values and the observed SST underscores the robustness of the CNN-LSTM architecture in integrating spatial features (via convolutional layers) and temporal dependencies (via LSTM layers).

However, model performance varies considerably when we expand our scope to multiple parameters (SST and salinity) across two distinct oceanic regions (Indian and Arctic). As summarized in the table, CNN-LSTM is the most accurate model for Indian Ocean SST and salinity, while LSTM excels at Arctic Ocean SST, and CNN shows the best results for Arctic Ocean salinity. These discrepancies highlight how factors such as polar amplification, freshwater influx, and monsoonal influences can favor one architecture over another. Yet, when aiming for a single, all-purpose model capable of delivering consistently high accuracy across different parameters and regions, CNN-LSTM emerges as the preferred choice, offering strong performance even where it is not the absolute top performer.

3. Implication for Climate Change.

- **Warming Effects from Increased Salinity:** Higher Ocean salinity has been shown to induce warmer climates by both modifying ocean dynamics (which enhance heat transfer to polar regions) and depressing the freezing point—leading to lower sea ice coverage. For instance, a rise in salinity from 20 to 50 g/kg can result in up to a 71% reduction in high-latitude sea ice [3]. This effect is particularly relevant when comparing regions such as the Indian Ocean and the Arctic, where differing salinity levels could lead to distinct thermal responses.
- **Enhanced Heat Transport to the Poles:** Remote warming in the Indian Ocean can influence Arctic conditions by increasing the Atlantic Meridional Overturning Circulation (AMOC) and promoting greater ocean heat transfer from the North Atlantic to the Arctic. This mechanism is critical in understanding how oceanic heat pathways contribute to Arctic surface temperature rise [6].

- **Alterations in Plankton Communities:** Ocean warming, often linked with salinity and SST variations, can have significant biological impacts. For example, warming tends to increase phytoplankton biomass; however, reduced nutrient flux in stratified waters may counteract this growth, leading to net losses in phytoplankton. This change can subsequently alter zooplankton feeding patterns and potentially reconfigure marine food webs [4]. In comparing two ocean regions, the differing nutrient regimes and salinity/SST profiles may lead to region-specific responses in plankton dynamics.

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